A framework for modelling spatial proximity

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A Framework for Modelling Spatial Proximity

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Declaration

I hereby declare that this submission is my own work and to the best of my knowledge it contains no material previously published or written by another person, nor material which to a substantial extent has been accepted for the award of any other degree or diploma at UNSW or any other educational institution, except where due acknowledgement is made in the thesis. Any contribution made to the research by others, with whom I have worked at UNSW or elsewhere, is explicitly acknowledged in the thesis.

I also declare that the intellectual content of this thesis is the product of my own work, except to the extent that assistance from others in the project's design and the conception or in style, presentation and linguistic expression is acknowledged.

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Abstract

The concept of proximity is an important aspect of human reasoning. Despite the diversity of applications that require proximity measures, the most intuitive notion is that of spatial nearness. The aim of this thesis is to investigate the underpinnings of the notion of nearness, propose suitable formalisations and apply them to the processing of GIS data. More particularly, this work offers a framework for spatial proximity that supports the development of more intuitive tools for users of geographic data processing applications.

Many of the existing spatial reasoning formalisms do not account for proximity at all while others stipulate it by using natural language expressions as symbolic values. Some approaches suggest the association of spatial relations with fuzzy membership grades to be calculated for locations in a map using Euclidean distance. However, distance is not the only factor that influences nearness perception. Hence, previous work suggests that nearness should be defined from a more basic notion of influence area. I argue that this approach is flawed, and that nearness should rather be defined from a new, richer notion of impact area that takes both the nature of an object and the surrounding environment into account. A suitable notion of nearness considers the impact areas of both objects whose degree of nearness is assessed. This is opposed to the common approach of only taking one of both objects, seen as a reference to assess the nearness of the other to it, into consideration.

Cognitive findings are incorporated to make the framework more relevant to the users of Geographic Information Systems (GIS) with respect to their own spatial cognition. GIS users bring a wealth of knowledge about physical space, particularly geographic space, into the processing of GIS data. This is taken into account by introducing the notion of context. Context represents either an expert in the context field or information from the context field as collated by an expert.

In order to evaluate and to show the practical implications of the framework, experiments are conducted on a GIS dataset incorporating expert knowledge from the Touristic Road Travel domain.

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This thesis is dedicated to my husband Luke David Brennan and my little son Karl Ludwig Brennan.

It is also dedicated to my Grandmother,
Else Köhler.

Contents

Chapter 1

Introduction

The world around us is in its nature spatial, and the ability to cope with these spatial surroundings is not only an essential survival skill, but "[h]uman beings [also tend to] think spatially" ([76]:p.357). This spatial thinking is often also the basis for problem solving in non-spatial domains. Given this dominance of spatial thinking, spatial reasoning has played an important part in both cognitive science and Artificial Intelligence research, even though this might not always be explicitly stated. The processing of geographic data, which is in its nature spatial, has also taken a great role in the development of spatial reasoning approaches.

The physics of space has always held a fascination to me; from the more tangible workings of mechanics exploring how bodies move through space, to the more abstract notions of Einstein's relativity theory. Considering that even the tiniest toddler develops a sense of physical space, and skills and abilities to deal with it as a matter of survival has raised many interesting questions as in how does this wonderous machine, that is the human mind, find its grounding in what surrounds its physical embodiment. I will focus in this thesis on the field of spatial reasoning. This field has as its objective to combine the findings of a myriad of disciplines with the common goal to explore and understand how the human mind is able to encompass physical space in all its complexity and develop suitable abstractions. For the purpose of this thesis, I single out the notion of spatial proximiy to make my contribution. Spatial proximity is a difficult notion due to its highly vague nature, that makes it hard to define and and formalise. No comprehensive solution has been found yet despite several good-intentioned efforts to solve the problem. While *Nearness* has been investigated by empirical data collection and analysis ([27, 123]), formal treatment exists only for identifying *nearest neighbours* (e.g., [1, 124]). *Nearest Neighbours* however require ternary relations between objects, while the most common day-to-day nearness queries are of a binary nature. Although nearness is acknowledged as one of the qualitative spatial relations, among topological [33] and directional ones [40], it is harder to formalise because of its context-dependency. Frank [41] introduces reasoning with stipulated nearness notions such as close or far (and similarly Hernández et al. [64]). There are also some operational models using fixed buffer zones (e.g., in GIS applications) or fuzzy membership functions ([48, 57]. However, no formal models incorporating context-dependency exist. Kettani and Moulin [69] suggest an influence area model that is a way towards a contextual model. It is motivated by the psychological concept of an imaginary area surrounding objects perceived in the environment in order to grade proximity. However, their proposed operational model calculates the influence area from the spatial boundaries of an object, which I argue is not flexible enough to account for context-dependency. If only the spatial boundaries are taken into account, but not any of the object's other characteristics or its actual location with respect to its environment, influence area becomes another "fixed-value" buffering method. This thesis proposes a cognitively motivated formal model which incorporates context-dependency. In an effort to put a more tangible moment on this notion, I have, after developing the formal approach to representing a possible cognitive mirage of proximity in physical space, utilised geographic data to show a way of using spatial cognitive information in the particular *context* of Touristic Road Travel.

The goal of this thesis is to examine spatial proximity with a focus on how it is perceived and reasoned about by humans, and to find a representation which mimicks this human mental process, at least to some extent, and is implementable to support the development of more intuitive tools for spatial proxomity analysis in spatial data processing. A reductionist view of physical space as a universe of objects and relations amongst them is adopted. This is done in order to develop a formal, symbolic approach to represent physical space. Further, human cognition is reduced to a data model to make it easily analysable and also applicable to Geographic Data Processing. Such as reductionist view of physical space can be used to derive a useful representation of spatial proximity as perceived and reasoned about by humans. In particular, the introduction of a context variable to the model is asserted to provide a suitable notion of nearness. The hypothesis is that there is a suitable notion based on context that goes beyond fixed buffer zones, fuzzy membership functions and stipulated natural language expressions. This hypothesis will be tested when the framework is applied to GIS data in the specific context of touristic road travel. Two data sets will be used, one as domain specific knowledge in the experiments and the other as verification data. The model can be deemed successful if the results of the experiments correspond to the verification data.

The research presented in this thesis makes three important contributions:

1. It provides a thorough and comprehensive synthesis of the disparate literature that pertains to the topic of proximity. A very wide set of prior works is woven together into a single and clear account of the complexities and nuances of this field.

2. It offers insight into why some of the existing methods for reasoning with proximity work, or do not work, and analyses their strengths and weaknesses. This is carefully reasoned; with clear examples, rhetoric and logic formalism all being used to support the arguments made.

3. The final contribution is the derivation of new proximity measures, and their

evaluation, backed by some personal experiments and reflections. New measures are formally described in a unifying and compelling framework.

The structure of the thesis is as follows. Chapter 2 reviews the general work in the field of qualitative spatial reasoning, in addition to providing the motivation for the choice of qualitative over quantitative approaches. A more specific review of qualitative spatial reasoning about spatial proximity or nearness will be provided throughout the core Chapters 5, 6 and 7 wherever suitable.

Chapter 3 provides an introduction to the data models used in Geographic Information Systems. *Proximity analysis* functions that are commonly available in these systems are discussed with respect to their limitations and possible improvement directions.

Chapter 4 outlines the methodological approach that was taken to carry out the investigations to develop and validate a suitable Framework for Modelling Spatial Proximity.

Chapter 5 introduces and argues for the concept of *Impact Areas* and suitable *Nearness Notions* employing impact areas. A Cognitively motivated Data Model of physical space is proposed that is then adapted to a Geographic Data Model into which these concepts can be placed. This chapter does also provide a thorough review of qualitative spatial reasoning approaches to distance and nearness.

In Chapter 6, the formal framework for modelling spatial proximity based on impact area and context is developed for topological space. Interpretations are provided for the GIS context to illustrate the relevance of this formalism to spatial information science and to provide the background for the experimental validation of the formalism in Chapter 8. It is also in this chapter that the *Impact Area Generation Model* is introduced, which provides the basis for any operational model of the framework.

Chapter 7 identifies several *nearness notions* based on the interrelations between impact areas. Case studies are utilised to illustrate these notions. The specific case of a singleton object is considered in detail to provide a “family” of nearness relations that can be used in the experiments of Chapter 8, where the query objects are points.

Chapter 8 reports on experiments that were conducted to validate both the concept of impact area and the idea of nearness notions being based on these areas. The experiments were conducted for the Touristic Road Travel *context* in *ArcGIS* using a GIS data set and additional context data that was collected from tourist information material. A *Nearness Data Set* was also collected from these kinds of materials to provide data to validate the impact area approach against. The impact area approach was also contrasted with a simple fixed-value or naive approach to emphasise the advantages of the far more flexible and of course contextual impact area model. The results confirmed the model for the given data sets and context, and yielded some interesting additional results.

Chapter 9 summarises the thesis, points out the contributions of the work presented here and suggests future work based on the results.

Chapter 2

Spatial Reasoning

2.1 Artificial Intelligence and Spatial Reasoning

In Artificial Intelligence, space is often defined using notions of location, orientation, shape, size[1], connection, distance and neighbourhood. There are well defined meanings for some of these notions in fields such as physics, topology, geometry and theoretical computer science. Spatial reasoning researchers, building on well defined notions of space used in Artificial Intelligence, set out to tackle issues such as how humans think and talk about these notions, how they represent them to navigate around and successfully reason about their physical environment, and how problems are solved using this reasoning. Traditionally, Artificial Intelligence has treated space mostly implicitly. However, human spatial cognition is very complex and these implicit representations of space can therefore cause problems, because their expressiveness is quite restricted while the complexity of human spatial cognition is high. In order to describe space comprehensively, more explicit representations need to be developed and Artificial Intelligence has therefore shifted to these kinds of models [47].

In Artificial Intelligence and Spatial Reasoning, spatial facts are usually described

[1]height, weight, length and their combination

as relations between entities. These entities could be objects[2], regions[3], intervals[4] or points[5] depending on the level of abstraction required.

In order to reason about anything, an agent needs to have certain knowledge to reason about, to draw conclusions and inferences from. An appropriate representation of knowledge is therefore an important prerequisite for reasoning. This chapter will review both spatial knowledge representation and spatial reasoning approaches, which are often intertwined. The next section will look at qualitative spatial reasoning in general and also aims at motivating qualitative approaches to reasoning and to representing spatial knowledge.

2.2 Qualitative Spatial Reasoning

Generally speaking, reasoning encompasess the process of inferring new information from information already known [62]. For example, if a small child is told that a robin is a bird, it will usually conclude or infer from this information that a sparrow, having wings too, is also a bird.

The objective of spatial reasoning is to develop implementable models [47]. The implementation of reasoning techniques on a computer usually requires quantitative knowledge. For example, if it is known that point A is 12 km from point B and point B 6 km from point C, it can easily be inferred by applying simple mathematical rules about distance in Euclidean space, such as the triangle inequality, that the distance between A and C can be at most 18 km.

Sometimes, precise quantitative descriptions are however not available and therefore qualitative information is used in its place. For example, instead of describing a distance as 5 km, it might be described as a symbolic value such as the word *close*.

However, incomplete information is only one reason for using qualitative repre-

[2]e.g., [65], [59],[37]
[3]e.g., [93], [33]
[4]discussed in more detail in Section 2.5.1
[5]e.g., [31], [13]

sentations. As James Franklin [42] pointed out, there are also efficiency reasons. As with all fuzzy and linguistic concepts, there is a big gain in efficiency of thought and memory, and even more so in communication between persons, if you can get by with a few words without too much loss of information. If we had to communicate spatial concepts in coordinates, we would be talking forever.

To clarify this concept, contemplate the following example[6] description of a spatial situation:

The front-left-bottom corner of a given cubic box with a width and height of 10 units is situated in an imposed coordinate system at position (x, y, z). *The front-left-bottom corner of another cubic box with a size of 1 unit length is situated in the same imposed coordinate system at position* $(x + 1, y + 1, z + 2)$.

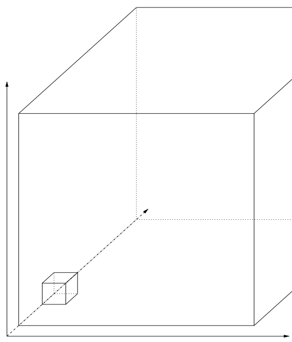


Figure 2.1: Two cubic boxes placed into a coordinate system

The situation is pictured in Figure 2.1. This situation can be much more efficiently described using natural language as its qualitative representation. The sentence *The small box is inside the big box.* is much more comprehensible than the previous description of the scene. This kind of representation is sufficient for many purposes, despite the loss of some of the originally available information, and is clearly much more efficient reasoning purposes.

One of the very early works on qualitative spatial representation and reasoning

[6] similar to [63]:p. 2

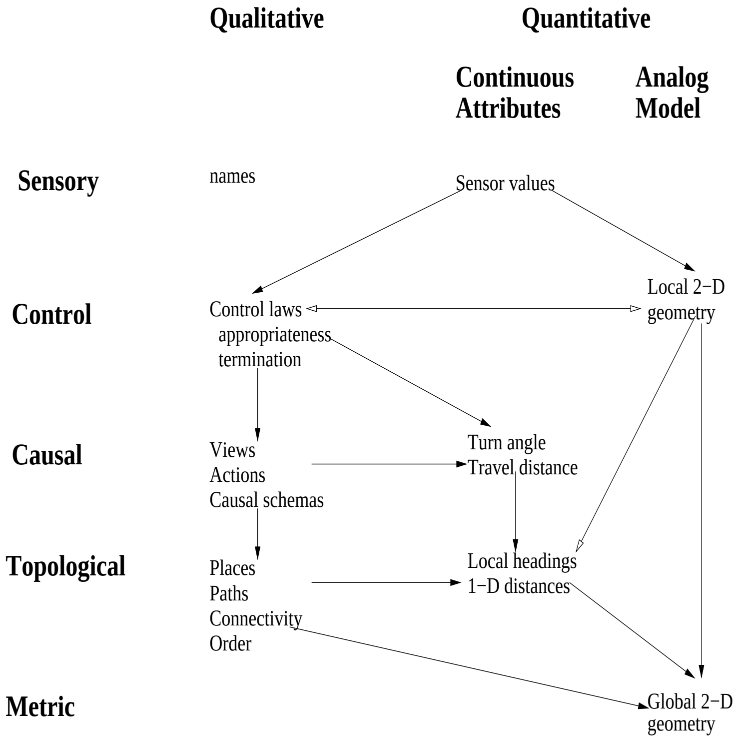


Figure 2.2: Distinct representations of the Spatial Semantic Hierarchy (Figure 1 in [73]). The closed-head arrows represent dependencies, and open-head arrows represent potential information flow paths, but not dependencies.

is that of Kuipers' TOUR model [72] considering issues of navigation in large-scale spaces, i.e., space that cannot be observed from a single point of view. With this model, Kuipers introduced the notion of cognitive maps that can be used to do problem solving in these large-scale spaces. The Spatial Semantic Hierarchy (SSH) [73] is the latest work that came out of Kuipers' original TOUR model deliberations. This hierarchy assumes that "large-scale space consists of several distinct but interacting representations, each with its own ontology ([73],p.192)." The SSH representations are shown in Figure 2.2, where each node in the lattice indicates a particular representation in terms of its ontology and is also classed as a qualitative or quantitative representation. The closed-head arrows represent dependencies, and open-head arrows represent potential information flow paths, but not dependencies. The ontologies can also be grouped into different levels, i.e., the sensory, control, causal, topological and metrical level. The SSH model is an action based representational tool and only works when “motion in qualitatively uniform regions is sufficiently reliable between locally distinctive states ([73],p. 226).” It can therefore not be used as a “pure” knowledge representation device, but is certainly a very interesting potential platform for any more general representation of spatial knowledge.

As previously mentioned, spatial reasoning places a strong emphasis on incorporating aspects of human spatial cognition into their models to develop more flexible, adaptable systems. Spatial cognition attempts to identify the mental representation of spatial knowledge. However, there is no way to directly access cognitive space. It has therefore frequently been the practice to use natural language descriptions of space to access internal representations of spatial knowledge. The next section will therefore concern itself with aspects of natural spatial language and existing computational models for spatial expressions[7].

2.3 Language, Space and Computational Models

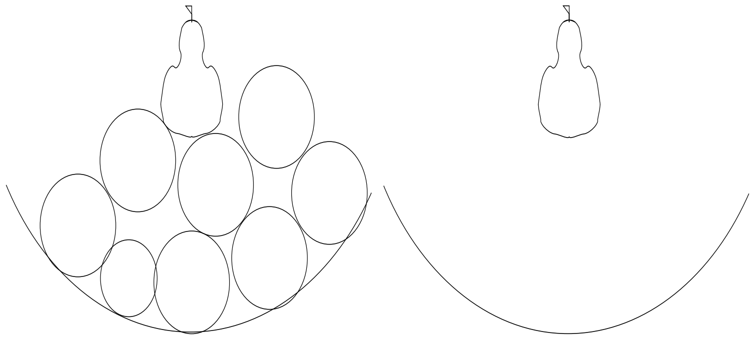
Herskovits [65] examined English spatial prepositions and defined them in terms of geometric relations, assuming their “ideal” meaning. She defined context by modifying the meaning using what she called “use types.” Use types are applied in contexts where the ideal meaning does not sufficiently describe the preposition. She defined her elementary geometric description functions in terms of place, parts, idealisation, good forms, adjacent volumes, axes and projections. These are not formalised notions but they are stipulated, i.e., their symbolic values are assumed to fully represent these functions. Her idealisations stipulated an approximation of objects to points, lines, surfaces, horizontal planes or strips. We will not go into any further detail of the functions, but will have a look at an example of how Herskovits

[7]This part of the survey draws to a great extent on Mukerjee’s 1998 [82] survey, but also incorporates additional and later work.

idealised the meaning of a particular spatial preposition and applied use types. The ideal meaning of the preposition *in* was defined by Herskovits as the *"inclusion of a geometric construct in a one-, two- or three-dimensional geometric construct" (p. 149)* with the following use types:

- Spatial entity in container, e.g., *the milk is in the glass.*
- Gap/object "embedded" in a physical object, e.g., *fish in the water* or *crack in the surface.*
- Physical object "in the air", e.g., *bird in the air.*
- Physical object in outline of another or of a group of objects, e.g., *bird in the tree* or *straw in his hair.*
- Spatial entity in part of space or environment, e.g., *there is a chair in the middle of the room* or *there is no supermarket in the neighbourhood.*
- Accident/object part of physical or geometic object, e.g., *muscles in his legs*, *curve in the road* or *bodies in the solar system.*
- Person in clothing, e.g., *man in a red hat.*
- Spatial entity in area, e.g., *island in the lake* or *boat in the bay.*
- Physical object in a roadway, e.g., *truck in the road.*
- Person or participant in institution, e.g., *The children are in school.*

Herskovits claims that use types can account for all situations that do not conform to the ideal meaning. Coventry [23] however points out that ideal meanings and use types cannot fully account for situations such as the one shown in Figure 2.3(b) leaving the pear in exactly the same situations and in the same relation with the bowl as shown in Figure 2.3(a). Herskovits discussed the peculiar fact that



(a) Situation considered by Herskovits [65]

(b) Situation considered by Coventry [23]

Figure 2.3: Is the pear in the bowl?

the pear is still considered to be in the bowl even though it is not at all in the volume of the bowl. She explains this phenomenon with the fact that the pear is part of a group of objects supported by the ball and some of these objects are strictly *in the bowl*, however there is no generally applicable way to explain this situation with her approach. She has to deal with every such peculiar situation more or less individually. Coventry [23] believes that the variability in spatial expressions can only be accounted for by considering the functional relations between the reference object (RO) and the object to be localised (LO). Pure specifications of meaning, no matter if they are minimal or maximal descriptions, are not sufficient.

There have been many efforts to make the representations of spatial expressions more variable and therefore more flexible in terms of their applications. Some of the approaches have used fuzzy functions, and thus decided with the help of membership functions how "strong" a particular relation is in a particular position. For example, if you take a chair in front of a table, the further you take the chair towards one of the sides of the table, the less "in front" the chair will be. Gapp [50] introduces a 3-D model that computes and evaluates the meanings of basic spatial relations using various kinds of approximations. Gapp differentiates between three classes: topological relations, orientation relations and the relation "between". He uses fuzzy[8] set distributions to define the degree of some relations in particular configurations. As Mukerjee [82] points out, there are several problems with Gapp's model. It seems to be applicable to a very wide range of problems, however his "between" function fails to capture the lesser degree of "betweenness" as objects move further apart. In addition, these fuzzy functions are determined by sometimes hard-to-justify choices, because they have to be both computationally simple and also account for desirable spatial attributes.

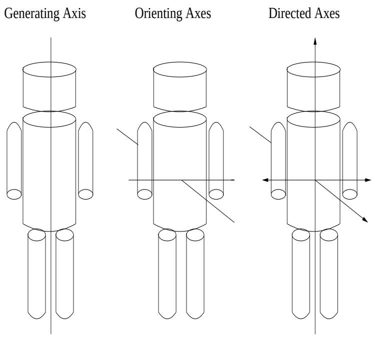


Figure 2.4: Landau and Jackendoff's Axes System ([74],Figure 4)

As could be seen in Herskovits' work, the assignment of axes is a commonly used approach to represent at least part of objects in physical space. Landau and Jackendoff [74], in a study aimed at understanding how humans represent objects and places in space, utilise an axial structure "to account for linguistic terms describing aspects of an object's orientations" ([74],p.221). Most objects have a top and a bottom, a front and a back, and sides and/or ends. For humans, the front of the body can be determined by the fact that one's eyes, nose, feet and navel point in the same direction; and the fact that arms are attached opposite one another and orthogonal to the front determines the sides [74].

Landau and Jackendoff differentiate three layers of axes, the *generating* axis, *orienting* axes and *directed* axes. The generating axis is the principal axis, as described in Marr's [77] vision theory, which is vertical in the case of a human. The orienting axes are orthogonal to the generating axis and each other, they represent the front-to-back and side-to-side axes. Finally, the directed axes indicate inherent regularities that distinguish one end from another (i.e., top from bottom, front from

[8]referring to fuzzy logic

back). Figure 2.4 illustrates the model.

Glasgow [52] uses rectangles as a means of representing objects in space. She developed a multi-scale spatial array model describing the spatial relations between the rectangles in terms of a rectangular grid or lattice of variable size. The best known of the examples that she used to illustrate her approach is that of a map of European countries abstracted into rectangles and yet maintaining the conceptual spatial relations such as which countries border with each other and which countries have larger or smaller areas than others. Glasgow's work has been motivated by the mental imagery philosophy. Her work has had a great influence on areas such as diagrammatic reasoning. Cobb et al. [21] introduced an approach to define fuzzy spatial relationships using minimum bounding rectangle variations.

Independent of Glasgow's work, the idea of representing spatial knowledge pictorially has also been incorporated into hybrid approaches to representing spatial knowledge. These hybrid approaches or systems use analogue spatial representations, i.e., images, in addition to some verbal or formal representation. Pictorial representations have a lot of advantages, such as the ability to use perception-based inferential mechanisms instead of logic-based deductions that require extensive abstractions. These very explicit representations, however, also limit the real world situations they can represent. In addition to that, because images can only represent purely spatial aspects, propositional components need to complement them in hybrid systems. An extensive discussion on pictorial and hybrid approaches for representing spatial knowledge can be found in [60]. Some of the representative systems developed for automatic understanding of natural spatial language were the purely pictorial system of Waltz and Bogess [113] and LILOG-System by Habel and Pribbenow [61].

Mukerjee et al. [83] use Gapp's continuum field model and combine it with a set of constraints specific to their particular domain. These constraints are applied to a large visual database of objects and actions. Visual scenes are then generated from natural language input using the database with its constraints. This way they create some kind of visual semantics for the natural language input. They found support for the choice of fuzzy functions[9], used to visualise the spatial expressions, through the results of psycholinguistic experiments. These experiments were conducted on a computer screen with 47 subjects.

As with previously discussed models in this section, they are quite explicit in their descriptions, therefore limiting the applications of these representations. While many of these approaches have been very influential on the course the work in this thesis has taken, we will now focus on more invariant properties and more implicit representations of physical space; the mission of the project presented in this thesis is geared towards general properties of spatial knowledge rather than the properties of specific sub-domains.

2.4 Defining Notions of Spatial Knowledge

We have already noted that space is often defined in terms of several notions such as topology, orientation, shape, size and distance in Artificial Intelligence in general [47] and also in spatial reasoning [22]. Over the last decades, however, qualitative spatial reasoning research has heavily focused on the notions of connectivity-based topology, orientation and more recently proximity. While the former two notions are well defined, proximity or nearness is heavily context dependent and as we will see throughout this thesis formal models to account for this context dependency are yet to be developed.

Connectivity-based topology by itself has been used on numerous occasions and will be discussed in more detail in Section 2.5. There have been models combining these topological aspects with orientation notions (e.g., [63]). Frank [41] on the other hand believes that orientation and proximity information need to be combined in

[9]for their very limited domain

order to arrive at a sufficient representation of spatial knowledge.

The only model so far that has strived to combine all three of these notions of space is a knowledge-based navigation model that was developed by Kettani and Moulin [69] as part of the GRAAD project. Kettani and Moulin [69] developed a knowledge-based navigation system that incorporated orientation and proximity information to generate routes and also provide natural language descriptions of these routes. A logical and an analogical framework were combined in order to reason about space and time when generating and describing the routes of a virtual predestrian (VP) in a virtual urban environment setting [81]. The analogical framework was based on the notion of spatial conceptual map (SCM), used to describe a spatial environment by its landmark objects and medium objects such as streets. The spatial conceptual map was also used to simulate the displacement of the VP and to generate possible paths between any two positions along medium objects of the SCM. Temporal reasoning, the generation of plans used to compute the VP's displacement in the SCM, and the generation of natural language descriptions was accomplished within a logical framework.

Kettani and Moulin state that pure logical frameworks are useful from a theoretical point of view, but that they are difficult to use for implementation purposes due to efficiency problems. This is why they chose to combine a logical and an analogical framework to deal with static and dynamic spatial properties of route generation. We firmly agree with this kind of approach and although this thesis does focus on logical frameworks, the work conducted is ultimately aiming at providing frameworks that can be incorporated into systems such as Kettani and Moulin's navigation system to help to make them more adaptable to unknown and previously not considered spatial situations.

Kettani and Moulin [69] conducted an analysis of several cognitive studies of human generation of route descriptions. Subsequently, two structural components of *local descriptions* and *paths* were identified, representing places where an orientation change will take place, and connectors between local descriptions along which the pedestrian moves without direction change, respectively. Local descriptions generally refer to landmark objects and their relative spatial positions with respect to other objects or the pedestrian. Spatial relations such as neighbourhood relations, topological relations and orientation relations are used to describe these relative positions of objects. For representing proximity, the GRAAD system grades closeness around objects by the means of influence areas. These will be discussed in more detail when introducing a framework for modelling spatial proximity in Chapters 5, 6 and 7. This framework employs interpretations of topological space. The following section gives an introduction to topology and spatial reasoning models of topological relations.

2.5 Topology

Topology is the study of those properties of geometric forms that remain invariant under certain transformations such as bending and stretching. Topology is a kind of qualitative geometry, unlike "normal" (Euclidean) geometry.

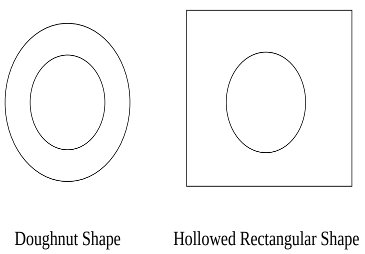


Figure 2.5: Topologically identical shapes

From a topological standpoint, objects or shapes with similar boundaries, holes, hollow spots, and components are identical. For example, topology considers a circle equivalent to a rectangle; and also a "doughnut" is considered to be the same as a hollowed rectangular body (see Figure 2.5). This is because these shapes are topologically equivalent or homeomorphic. This kind of abstraction makes topology a very useful problem solving tool. We will discuss some of its basic properties in a brief review (compiled from [34], [68], [116], [117], [118], [119], [120]) in the following paragraphs.

Topological spaces are structures which facilitate the formalisation of concepts such as convergence, connectedness and continuity. Formally, a topological space is a set X together with a set $\mathcal{T}$ of subsets of X[10] satisfying the following conditions:

1. $\emptyset \in \mathcal{T}$ and $X \in \mathcal{T}$, i.e., the empty set and X are in $\mathcal{T}$.

2. If $U_1 \in \mathcal{T}$ and $U_2 \in \mathcal{T}$, then $U_1 \cap U_2 \in \mathcal{T}$, i.e., the intersection of any pair of sets in $\mathcal{T}$ is also in $\mathcal{T}$.

3. If $\mathcal{A} \subset \mathcal{T}$, then $\cup \mathcal{A} \in \mathcal{T}$, i.e., the union of any collection of sets in $\mathcal{T}$ is also in $\mathcal{T}$.

The set $\mathcal{T}$ is also called a topology on X. The set X is called a *space* and the elements of X are called *points* of the space. All the subsets of X that belong to $\mathcal{T}$ are said to be *open* in the space.

Therefore, the sets in $\mathcal{T}$ are also referred to as open sets, and their complements in $\mathcal{X}$ are called closed sets. Given a topology $\mathcal{T}$ on X, a set is said to be open if it is in T. A set is open if every point in the set has a neighbourhood lying in the set. Intuitively speaking, an open set is a set without its boundary points. For example, an interval in $\mathbf{R}$, i.e., real numbers, is an open interval if its limit points x_0 and x_n, as shown in Figure 2.6, are not part of the interval. A metric space is a space where a distance between points is defined. An open set in a Euclidean metric space, for example, of radius r and center x_0 is the set of all points x such that the distance between x_0 and x is less than the radius. Such an open disk is shown in Figure 2.7 on the following page.

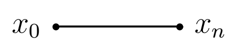


Figure 2.6: Open interval with limit points x_0 and x_n

[10] $\mathcal{T}$ is a subset of the power set of X

A set is called a closed set if its complement is open. Intuitively speaking, a closed set is a set including its boundary points. For example, an interval in **R** is a closed interval if it includes its limit points. A closed set in a Euclidean metric space, for example, of radius r and center x_0 is the set of all points x such that the distance between x_0 and x is less than or equal to the radius.

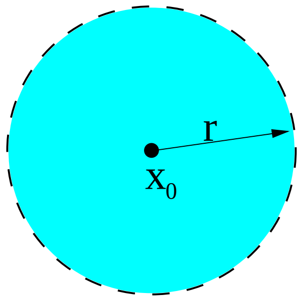


Figure 2.7: An open disk in metric space

The closure of a set is the union of the set and its limit points. A closed set contains its limit points, if any exist. A point x is a closure point of a set A in X if every open set that contains x also contains at least one point from A.

A topological space is connected if it cannot be divided into two disjoint nonempty open sets whose union is the entire space. Since a closed set is the complement of an open set, a connected topological space cannot be divided into two disjoint nonempty closed sets.

The connectivity aspect of topology has been studied and formalised in depth in the area of qualitative spatial and also temporal reasoning, drawing inspiration from mathematical research. The following section will look at temporal interval calculi and their adaption to the spatial domain. We generally experience space as a dynamic entity, i.e., dynamic space, where changes in spatial alignments happen over time. It is therefore often hard to separate the concepts of space and time; and a brief look at some temporal calculi is therefore a good idea.

2.5.1 The Temporal Interval Calculus and its Adaption to Spatial Reasoning

Allen [3] introduced a temporal logic that was based on the idea of time intervals. Comparative relations between these intervals represent the knowledge about time qualitatively.

Freksa [45] introduced the notion of conceptual neighbourhood of topological relations between temporal intervals (i.e., events) directly derived from the temporal interval calculus of Allen [3].

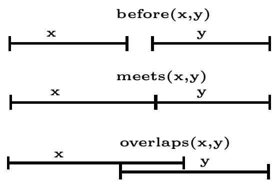


Figure 2.8: Some Interval Relations

Two topological relations are neighbours if they can be *directly transformed* into one another by continuously deforming the events (i.e., intervals) involved. Figure 2.8 shows the relations *before(x,y)*, *meets(x,y)* and *overlaps(x,y)*, a direct transformation from *before(x,y)* to *meets(x,y)* can be performed by for example lenghtening one of the intervals. The same holds for a transformation from *meets(x,y)* to *overlaps(x,y)*. Therefore *before(x,y)* and *meets(x,y)* are neighbours, so are *meets(x,y)* and *overlaps(x,y)*. However, *before(x,y)* and *overlaps(x,y)* are not neighbours, because the lengthening of any of the intervals in the *before(x,y)* relation would have to first become the *meets(x,y)* relation before *overlaps(x,y)* would be achievable. Freksa also used this approach in the spatial domain in some of his later work [46] by employing orientation relations in vector spaces.

Matuszek [26] introduced a calculus in which the endpoints of the intervals rather than the duration of the intervals were considered. For example, Allen's relations START, EQUALS and STARTED BY can be combined to form SWS (i.e., starts when starts) using the end point approach. This allows a much greater freedom in defining relations between time intervals as there is no necessity to consider both end points of the intervals. Although this makes the relations more ambiguous, for some purposes this greater degree of freedom is desirable. Esch [36] uses Matuszek's end point relations for a conceptual graph application. Esch [36] combines Allen's temporal interval calculus and Matuszek's [26] end point relations on temporal intervals into a set of 12 base relations on intervals. The base relations are shown in Figure 2.9. They only specify constraints on one end of each relation, therefore the other end is often not constrained. Visually this is represented as shown in Figure 2.9 and explained in Esch's original text. The unconstrained end of the interval "indicated by the dotted line showing a range of values still possible for the free end of the x interval. The constrained end of the x interval is shown by a vertical bar. Sometimes it may also be a range of values. In that case its range is shown by a dotted line between two vertical bars.([36], p. 368)" As two examples, *x S)S y* stands for *interval x starts before interval y starts* and *x F]S y* stands for *interval x finishes where or before interval y starts.*

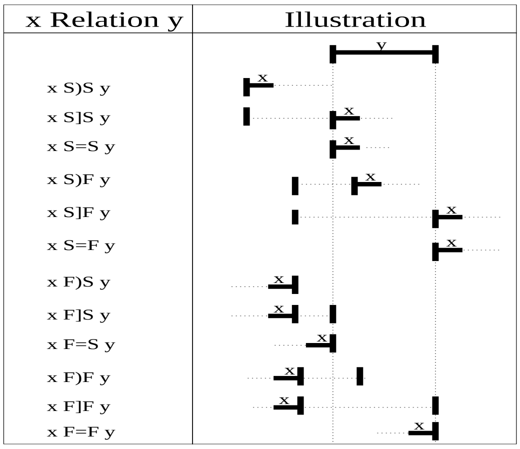


Figure 2.9: Esch's Temporal Base Relations ([36],p. 368)

Allen's original idea has also been extended to represent spatial topological relations. Guesgen [56] projected the boundaries of rectangular objects onto the axes of a two-dimensional coordiante system thus having two corresponding intervals, one on each axis for each object. Spatial relations between two objects were then represented by a pair:

[interval relations on the x axis, interval relations on y axis]

Egenhofer and Franzosa [33] developed a theory of topological spatial relations between sets. The relations in this theory are defined in terms of intersections of boundaries and interiors of two sets, i.e., empty or non-empty. Subsets of a topological space were chosen as the underlying data model. The decision in favour of a point-set approach was justified by its more general properties compared to models previously employed when defining spatial topological relations, such as Pullar and Egenhofer's [91] interval approach.

For similar reasons, however, not considering the point-set nature of topological spaces, the Region Connection Calculus has been developed [93]. This calculus is discussed in more detail in Section 2.5.3.

2.5.2 A Calculus of Individuals based on 'Connection'

The Principia Mathematica [103] is a three-volume work on the foundations of mathematics. It introduced a wide range of philosophically rich notions such as propositional function, logical construction, and type theory, and intitiated the discovery of classical metatheoretic results such as those of Kurt Gödel. It is an attempt to derive all mathematical truths from a well-defined set of axioms and inference rules in symbolic logic. The main inspiration and motivation for the Principia was Frege's earlier work on logic ([43],[44]), which had led to some contradictions discovered by Russell [44]. These were avoided in the Principia by building an elaborate system of types: a set has a higher type than its elements and one cannot speak of the "set of all sets" and similar constructs which lead to paradoxes.

The Principia covered set theory, cardinal numbers, ordinal numbers and real numbers. Theorems from real analysis were not included, however upon completion of the last volume it became clear that mathematics in its known entirety could in principle be developed using the adopted formalism.

However, it was still not possible to answer the question whether a contradiction could be derived from the Principia's axioms, and whether there exists a mathematical statement which could neither be proven nor disproven in the system [121]. Gödel's incompleteness theorems [53] showed that for any formal axiomatic system, there is always a statement about natural numbers which is true, but which cannot be proven in the system [66].

However, the Principia did make very important contributions to fields as diverse as philosophy, mathematics, linguistics, economics and computer science. By using a notation that was in many ways superior to that of Frege, it made modern mathematical logic quite popular. Whitehead and Russell were also able to show how powerful the idea of a formal system can be by giving this clear demonstration of the deductive power of this new logic. Thirdly, Principia Mathematica reaffirmed clear and interesting connections between logicism and two main branches of traditional philosophy, namely metaphysics and epistemology, thus initiating new and interesting work in these and other areas.

While the fourth volume on the Principia Mathematica on geometry was never published, Whitehead did pursue this work further and published with his *Process and Reality* [115] a theory that was based on *Extensive Connection*. The basic idea of this work was that philosophy must explain not only the objective, scientific and logical description of the world but also its connection to the "everyday" world of subjective experience. This matter has also been taken up in the philosophy of space discussed by Bollnow [12], who investigates space as we experience it in addition to mathematical space.

Whitehead's theory was based on the primitive binary predicate *x is extensionally connected with y*, where x and y are regions. Clarke ([19], [20]) devised a calculus of individuals based on this primitive predicate, which is true if two regions share a point.

Asher and Vieu [6] used a variation of Clarke's calculus to describe the topological aspects of spatial relations and related this to natural language. They proposed to develop the foundations of a common-sense geometry using relational mereotopology[11]. They developed a calculus based on Clarke's connection relation together

[11] Mereotopology is a theory that seeks to combine mereology, the theory of part-whole-relations, and topology.

with a formal semantics. Individuals were identified as particular subsets of a particular topological space. Their topological space is however problematic, as Pratt and Schoop [89] pointed out, because it is a non-Euclidean and non-dense space, which makes it hard to assess in the context of mereotopology.

Clarke's calculus was also taken up by Randell [94] in his PhD thesis, who modified its axiom set. This later became the Region Connection Calculus [93], that extended the connectivity primitive of Whitehead [115], Clarke [19] and Randell [94] to be true when the *closures* of two regions share a point. A more detailed summary of the Region Connection Calculus (RCC) is given in the following section.

2.5.3 The Region Connection Calculus

This calculus is generally used for reasoning about 2-dimensional spaces and can theoretically be applied to reasoning about maps and map-like representations. The complexity of its models however makes the full theory intractable for practical applications, see Renz and Nebel [98] for a detailed discussion on the constraint satisfaction problems associated with RCC-8, which is a subset of the region connection calculus. Useful subsets of the theory have been defined (e.g., [98]) however and applied to qualitative spatial databases (e.g., [4]).

While the focus of RCC research has been on 2-dimensional spaces, it can also be extended to 3-dimensional spaces [92]. RCC does not consider the orientation[12] of objects to one another. Hernàndez [63] had therefore previously added orientation to Egenhofer's topological model to create a more holistic representation. However, his resulting model was confined to two-dimensional spaces.

According to Randell et al. [93], the Region Connection Calculus (RCC) was devised as an interval logic for reasoning about space, in particular reasoning about the relations between the boundaries of regions. The primitive dyadic relation $C(x, y)$, standing for x *connects with* y, is assumed and every other relation in the theory

[12] "Orientation relations describe where objects are placed relative to one another." [63],p. 39

is based on this relation. Individuals in the theory can be interpreted as spatial or temporal regions. As spatial reasoning is the subject of the work presented in this thesis, we assume, as Randell [94] did in his PhD work that laid the foundations for the later RCC work, that regions representing the space an object occupies, are the primitives.

Several dyadic relations based on $C(x, y)$ were identified and shown to conform to a lattice structure defining a subsumption hierarchy [93]. The relations were defined as follows by Randell et al. [93]:

- $DC(x, y) \equiv_{Def} \neg C(x, y)$, meaning x is disconnected from y
- $P(x, y) \equiv_{Def} \forall z[C(z, x) \rightarrow C(z, y)]$, meaning x is part of y
- $PP(x, y) \equiv_{Def} P(x, y) \wedge \neg P(y, x)$, meaning x is proper part of y
- $x = y \equiv_{Def} P(x, y) \wedge P(y, x)$, meaning x is identical with y
- $O(x, y) \equiv_{def} \exists x[P(z, x) \wedge P(z, y)]$, meaning x overlaps y
- $PO(x, y) \equiv_{Def} O(x, y) \wedge \neg P(x, y) \wedge \neg P(y, x)$, meaning x partially overlaps y
- $DR(x, y) \equiv_{Def} \neg O(x, y)$, meaning x is discrete from y
- $EC(x, y) \equiv_{Def} C(x, y) \wedge \neg O(x, y)$, meaning x is externally connected to y
- $TPP(x, y) \equiv_{Def} PP((x, y) \vee \exists z[EC(z, x) \wedge EC(z, y)]$, meaning x is a tangential proper part of y
- $NTPP(x, y) \equiv_{Def} PP(x, y) \wedge \neg \exists z[EC(z, x) \wedge EC(z, y)]$, meaning x is a non-tangential proper part of y

The inverse relations

- $P^{-1}(x, y) \equiv_{Def} P(y, x)$
- $PP^{-1}(x, y) \equiv_{Def} PP(y, x)$

- $TPP^{-1}(x, y) \equiv_{Def} TPP(y, x)$ and
- $NTPP^{-1}(x, y) \equiv_{Def} NTPP(y, x)$

were also defined.

Figure 2.10 shows the lattice embedding the complete set of relations.

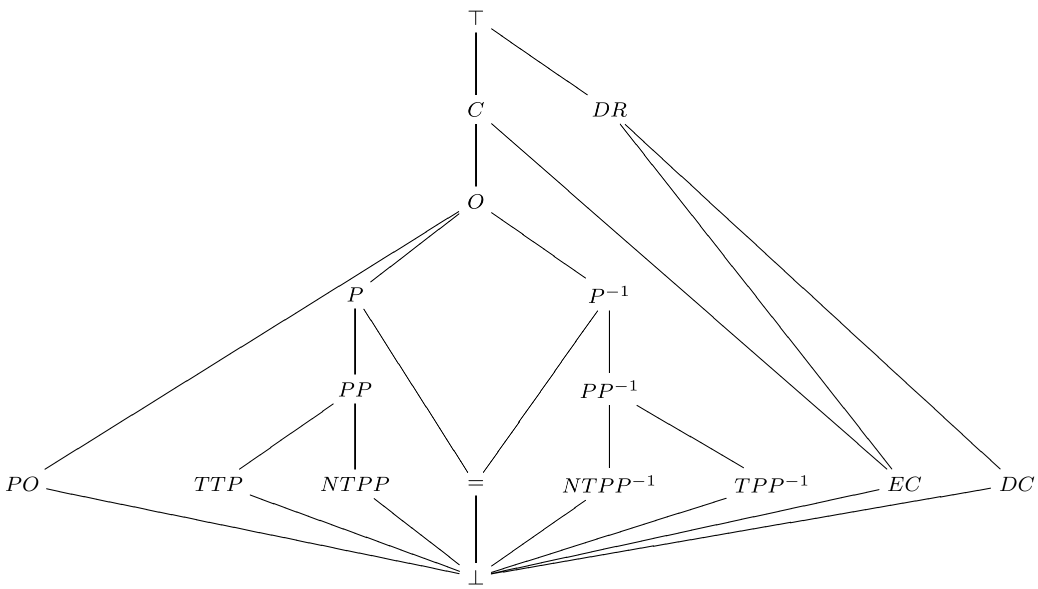


Figure 2.10: Lattice defining the subsumption hierarchy of the RCC relations

RCC does not consider the distance between disconnected regions or the orientation of the regions to one another. Orientation relations with the incorporation of the kind of topological relations considered in RCC were extensively covered by Hernández' [63] work on a qualitative representation of spatial knowledge. Nicoletti and Brennan [86] investigated the automatic learning of orientation relations, which could be of relevance to other qualitative spatial relation types as well.

Let us now move on to operational models of spatial relations. In Geographic Information System (GIS), topological relations are provided as operational models, however the notion of nearness is limited to buffering objects using fixed values. The following chapter will review GIS data models and the limitations of existing proximity analysis tools. These limitations will be addressed in the framework proposed in this thesis.

Chapter 3

Geographic Data Models and Analysis Functions

There are several data models commonly used in Geographic Information Systems (GIS) and also numerous data analysis functions. This chapter introduces those data models and data analysis functions that are relevant to the model of spatial proximity presented in Chapter 5. A detailed discussion on possible geographic coordinate systems is not included as this is a projection issue, which is not relevant to the work presented here.

Generally, the data that is stored in GIS can be thought of as a digital representation of real world objects. These can be abstracted into either discrete objects such as a houses or continuous fields such as elevation; and they are stored in the GIS as vector or raster data structures respectively. The raster model is a representation of the world as a surface that is divided into a regular grid of cells and often has the same functionality available as the vector model, although through different methods. Across the diverse range of GIS applications however, vector data models are predominant and I will therefore focus on the vector model and vector data representations in the following.

3.1 The Vector Data Model

The vector model is feature based, meaning that space is described by its features or geographic objects; in contrast to the raster model, where the world is divided into a sequence of identical, discrete entities.[105] A geographic object consists of a description (or attribute) and a spatial object corresponding to the shape and location of this object within the embedding space[1]. The geographic object of a city, for example, could be spatially described as a point by its coordinates; with the attributes including its name, identification number and maybe population size.

When we are talking about interpretations of a particular space such as the area of a country, we are referring to collections of a purpose-specific subset of its features. For example, for a particular territory, there can be a traffic control interpretation focusing on road network features or a political interpretation selecting administrative features such as shires, cities and states[88]. In the GIS context, we talk about layers when referring to files storing relevant features for a particular interpretation (or theme), e.g. a transportation layer containing the roads, rail, airports, bridges and tunnels; a population centres layer containing built-up areas and settlements, or a drainage layer containing all the waterways and other inland water bodies. But how exactly are these roads or inland water bodies actually represented in the GIS database? Let us first examine the spatial object representation which is quite standardised across different GIS applications; while the attributes of course do differ between the geographical spaces that they describe and the agencies that encode them.

[1] An identity is assigned to each object to make it distinguishable, this identity together with the spatial object and the description forms the geographic object as stored and referrenced in the GIS.

3.1.1 The representation of spatial objects

Technically speaking, a spatial object is the set of all the points of the embedding space that have the same description. "Points are the basis for representation of spatial entities in GIS. Lines link points, and areas are based on lines. Surfaces are built from areas." ([105], p. 34) Point-based models of space are therefore highly relevant for GIS implementations utilising the vector mode.

In the vector model, spatial objects are constructed from the primitives of points and lines. A point is represented by a pair (x,y) of coordinates; and lines are sets of coordinates that define a shape. While coordinates are most often pairs (x,y), they can also be triplets (x,y,z) where z could for example represent a value of elevation. Polygons are sets of coordinates that define boundaries enclosing areas.[39] More precisely, we talk about three types of spatial objects in the context of practical usage within GIS: Zero-dimensional, One-dimensional and Two-dimensional objects.[88]

Zero-dimensional objects or Points

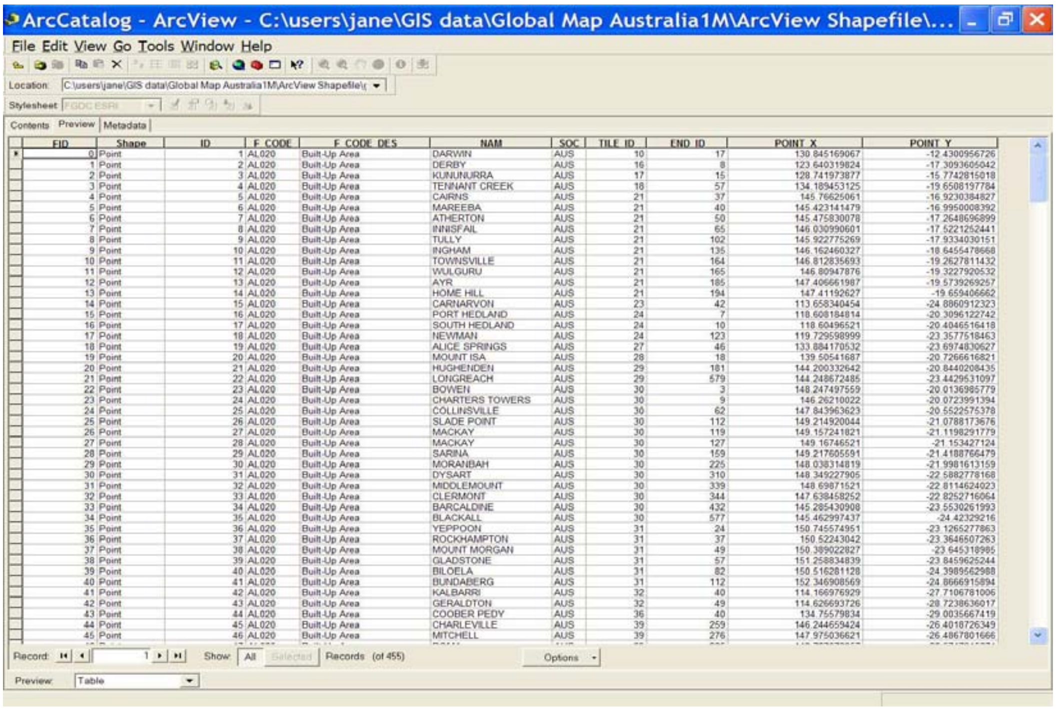
If the shape of a feature is not considered to be useful or its size is very small w.r.t. the embedding space size (i.e. map scale), it is generally represented by a point. In the vector model, points are primitives represented by pairs of coordinates.[88]

One-dimensional objects or Polylines

Networks such as roads are commonly represented by linear objects. In the GIS context, these linear objects are often referred to as polylines defined as sets of line segments where each segment end point is shared by two segements, except the two extreme points which only belong to one segment.[88]

Two-dimensional objects or Polygons

Entities with large areas such as a lake are represented by surfacic objects, commonly polygons. These are defined as a region of the plane that is bounded by a closed



FID	Shape	ID	F_CODE	F_CODE_DES	NAM	SOC	TILE_ID	END_ID	POINT_X	POINT_Y
0	Point	1	AL020	Built-Up Area	DARWIN	AUS	10	17	130.845169067	-12.4300956726
1	Point	2	AL020	Built-Up Area	DERBY	AUS	16	8	123.640319824	-17.3093605042
2	Point	3	AL020	Built-Up Area	KUNUNURRA	AUS	17	15	128.741973877	-15.7742815018
3	Point	4	AL020	Built-Up Area	TENNANT CREEK	AUS	18	57	134.189453125	-19.6508197784
4	Point	5	AL020	Built-Up Area	CAIRNS	AUS	21	37	145.76625061	-16.9230384827
5	Point	6	AL020	Built-Up Area	MAREEBA	AUS	21	40	145.423141479	-16.9950008392
6	Point	7	AL020	Built-Up Area	ATHERTON	AUS	21	50	145.475830078	-17.2648696899
7	Point	8	AL020	Built-Up Area	INNISFAIL	AUS	21	65	146.030990601	-17.5221252441
8	Point	9	AL020	Built-Up Area	TULLY	AUS	21	102	145.922775269	-17.9334030151
9	Point	10	AL020	Built-Up Area	INGHAM	AUS	21	135	146.162460327	-18.6455478668
10	Point	11	AL020	Built-Up Area	TOWNSVILLE	AUS	21	164	146.812835693	-19.2627811432
11	Point	12	AL020	Built-Up Area	WULGURU	AUS	21	165	146.80947876	-19.3227920532
12	Point	13	AL020	Built-Up Area	AYR	AUS	21	185	147.406661987	-19.5739269257
13	Point	14	AL020	Built-Up Area	HOME HILL	AUS	21	194	147.41192627	-19.659406662
14	Point	15	AL020	Built-Up Area	CARNARVON	AUS	23	42	113.658340454	-24.8860912323
15	Point	16	AL020	Built-Up Area	PORT HEDLAND	AUS	24	7	118.608184814	-20.3096122742
16	Point	17	AL020	Built-Up Area	SOUTH HEDLAND	AUS	24	10	118.60496521	-20.4046516418
17	Point	18	AL020	Built-Up Area	NEWMAN	AUS	24	123	119.729598999	-23.3577518463
18	Point	19	AL020	Built-Up Area	ALICE SPRINGS	AUS	27	46	133.884170532	-23.6974830627
19	Point	20	AL020	Built-Up Area	MOUNT ISA	AUS	28	18	139.50541687	-20.7266616821
20	Point	21	AL020	Built-Up Area	HUGHENDEN	AUS	29	181	144.200332642	-20.8440208435
21	Point	22	AL020	Built-Up Area	LONGREACH	AUS	29	579	144.248672485	-23.4429531097
22	Point	23	AL020	Built-Up Area	BOWEN	AUS	30	3	148.247497559	-20.0136985779
23	Point	24	AL020	Built-Up Area	CHARTERS TOWERS	AUS	30	9	146.26210022	-20.0723991394
24	Point	25	AL020	Built-Up Area	COLLINSVILLE	AUS	30	62	147.843963623	-20.5522575378
25	Point	26	AL020	Built-Up Area	SLADE POINT	AUS	30	112	149.214920044	-21.0788173676
26	Point	27	AL020	Built-Up Area	MACKAY	AUS	30	119	149.157241821	-21.1198291779
27	Point	28	AL020	Built-Up Area	MACKAY	AUS	30	127	149.16746521	-21.153427124
28	Point	29	AL020	Built-Up Area	SARINA	AUS	30	159	149.217605591	-21.4188766479
29	Point	30	AL020	Built-Up Area	MORANBAH	AUS	30	225	148.038314819	-21.9981613159
30	Point	31	AL020	Built-Up Area	DYSART	AUS	30	310	148.349227905	-22.5882778168
31	Point	32	AL020	Built-Up Area	MIDDLEMOUNT	AUS	30	339	148.69871521	-22.8114624023
32	Point	33	AL020	Built-Up Area	CLERMONT	AUS	30	344	147.638458252	-22.8252716064
33	Point	34	AL020	Built-Up Area	BARCALDINE	AUS	30	432	145.285430908	-23.5530261993
34	Point	35	AL020	Built-Up Area	BLACKALL	AUS	30	577	145.462997437	-24.42329216
35	Point	36	AL020	Built-Up Area	YEPPOON	AUS	31	24	150.745574951	-23.1265277863
36	Point	37	AL020	Built-Up Area	ROCKHAMPTON	AUS	31	37	150.52243042	-23.3646607263
37	Point	38	AL020	Built-Up Area	MOUNT MORGAN	AUS	31	49	150.389022827	-23.645318985
38	Point	39	AL020	Built-Up Area	GLADSTONE	AUS	31	57	151.258834839	-23.8459625244
39	Point	40	AL020	Built-Up Area	BILOELA	AUS	31	82	150.51628128	-24.3989562988
40	Point	41	AL020	Built-Up Area	BUNDABERG	AUS	31	112	152.346908569	-24.8666915894
41	Point	42	AL020	Built-Up Area	KALBARRI	AUS	32	40	114.166976929	-27.7106781006
42	Point	43	AL020	Built-Up Area	GERALDTON	AUS	32	49	114.626693726	-28.7238636017
43	Point	44	AL020	Built-Up Area	COOBER PEDY	AUS	36	40	134.75579834	-29.0035667419
44	Point	45	AL020	Built-Up Area	CHARLEVILLE	AUS	39	259	146.244659424	-26.4018726349
45	Point	46	AL020	Built-Up Area	MITCHELL	AUS	39	276	147.975036621	-26.4867801666

Figure 3.1: The attribute table view of built up population centres of Australia.

polyline (i.e. boundary).[88]

In summary, a point is represented by a pair of coordinates, where the more complex linear and surfacic objects are represented by some structures on the point representations.[88] In the case of the model presented in Chapter 5, this structure will constitute a set. Therefore, polylines and polygons are defined as sets of points, while a region is defined as a set of polygons.

3.1.2 The geographic object

The geographic object (GO) with its components of spatial data that locate the GO and attribute data that describe the GO, is represented within the GIS in an attribute table. “Attributes are described in database tables as values in a column (attribute) for a given row (records of spatial objects). What makes GIS attributes

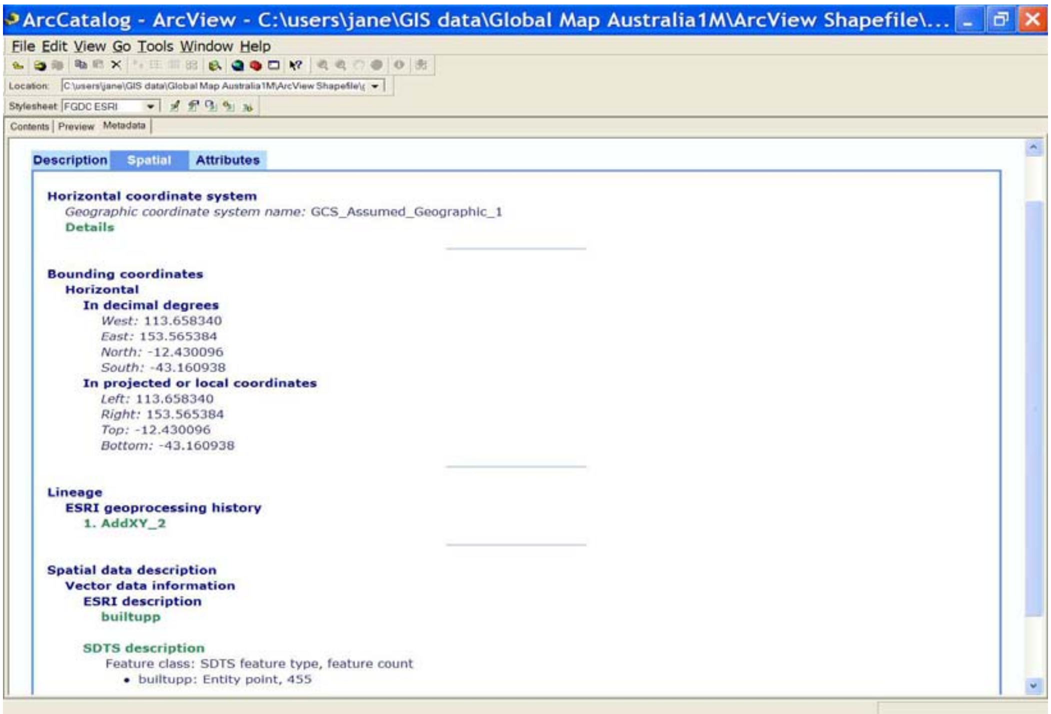


Figure 3.2: Spatial Information of the population centres of Australia objects.

different from that stored in statistical tables is that they are always associated with a spatial location.” ([105], p. 60) Without having this information on the location of objects, the data would be useless for analysis purposes. But what do these attribute tables look like and what information do they give? Let us have a look at a few examples from the data that were used in the experiments reported in Chapter 8. Figure 3.1 shows part of the attribute table, displayed in ArcCatalog®, for the layer of built up population centres of Australia. For each entry, i.e. geographic object, the spatial object’s shape is recorded and the coordinate information which is accessible through the object’s ID was added for the reader’s convinience, but is actually stored in a separate file. The attribute data includes the place name, source country, and so on. However, for successful geoprocessing, additional information about both the spatial and the attribute data might be necessary. The meta-data gives exactly that information about the data, i.e. the geographic object, itself. The spatial meta data

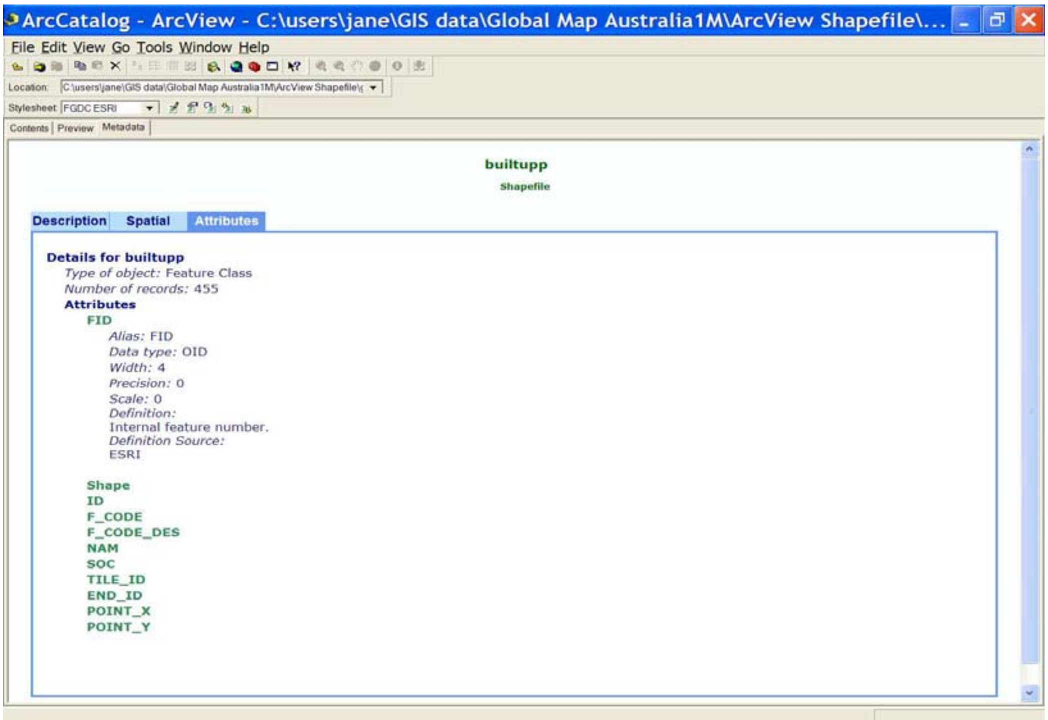


Figure 3.3: Attribute Information of the population centres of Australia objects.

for the built up population centres as seen in Figure 3.2 shows that these particular population features are represented as points and also that the XY coordinates were added as part of the geoprocessing. It does also supply the coordinate system used for the map projection and the coordinates for the boundaries of the represented area. The attribute meta data contains a description of the meaning of each of the attributes used in the table in addition to a record count, as shown in Figure 3.3.

While having the right data is of course essential to perform any useful analysis, GIS also provide a set of analysis tools to enable users to utilise the data that is a available to its fullest. Of special interest here are any tools that contribute to spatial proximity analyses, with the model developed in Chapter 5 aiming to make a contribution to a more comprehensive approach than the ones currently implemented.

3.2 Proximity Analysis in GIS

There are many spatial queries that one can perform on GIS data, according to Aronoff [5] (as cited in Buckely [25]) there are four categories of GIS analysis functions:

1. Retrieval, Reclassification, and Generalisation,
2. Topological Overlay Techniques,
3. Neighbourhood and
4. Connectivity Functions.

Here the neighbourhood operations provide an evaluation of the characteristics of an area that surrounds a specific location, with buffering being one of the most common neighbourhood functions. Amongst the connectivity functions, proximity analysis is decribed as being primarily concerned with the proximity of one feature to another. Proximity itself being “defined as the ability to identify any feature that is near any other feature based on location, attribute value, or a specific distance.”([25], p. 36) This function can answer questions such as *Which house blocks are within 100m of a main road?* to use, for example, in property valuation with respect to road noise levels. In addition to simple buffering however, proximity analysis can incorporate attributes of the selected feature to create different sized buffers for the same type of feature depending on selected attributes. For example, for very large blocks above a certain size, the distance could be decreased to 50m, as the houses on these large blocks tend to be built away from major roads. Another proximity analysis function, according to Buckley [25], is the identification of adjacency defined “as the ability to identify any feature having certain attributes that exhibit adjacency with other selected features having certain attributes.” ([25], p. 36) This could for example be a query to identify all house blocks of a specific size that are adjacent to a major road.

While ArcGIS® 9.2 takes a slighly different view on the categorisation of functions supporting proximity analysis, mainly dividing them into two input type dependent tools: vector and raster; it is still seen as a type of analysis in which geographic features such as points, lines, polygons or rasters are selected based on their distance from other features or cells.[39] Hence, the determiner of proximity used in GIS is distance with the distance occasionally being modified with respect to certain attributes. Taking a closer look at tools that are available for proximity analysis in ArcGIS® 9.2[38][2] will give us a good idea on what is generally available in Geographic Information Systems:

Tool	**Functionality**
Buffer	Creation of new feature data with feature boundaries at a specified distance from input features.
Near	Addition of attribute fields to a point feature class containing distance, feature identifier, angle and coordinates of the nearest point or line feature.
Point Distance	Creation of a new table with distance and feature identifier attributes showing the distance from each point in the input feature class to all points in the Near feature class, within a given search radius.
Select by Location	Selection of features from a target feature class within a given distance of (or using other spatial relationships) the input features.
Create Thiessen Polygons	Creation of polygons of the areas closest to each feature, for a set of input features.
Make Closest Facility Layer	Setting of analysis parameters to find the closest location or set of locations on a network to another location or set of locations.
Make Service Area Layer	Setting of analysis parameters to find polygons that define the area within a given distance along a network in all directions from one or more locations.
Make Route Layer	Setting of analysis parameters to find the shortest path among a set of points.
Make OD Cost Matrix Layer	Setting of analysis parameters to create a matrix of network distances among two sets of points.

Table 3.1: Vector Distance Tools that can be used for Proximity Analysis in ArcGIS® 9.2

[2]This table is taken from the *Proximity Analysis* entry.

Let us have a more detailed look at these functions in the context of a simple example: "A food producer is looking for a new site for their factory somewhere in New South Wales. Property prices in the metropolitan areas are soaring, which is why they are considering regional areas. However, they do require the factory to be within the area of an existing settlement and not further than 10km off a major road to ensure operational road transportation. Additional criteria might be decided on after suitable settlements were identified." We are using the Global Australian Map used in Chapter 8. There are several steps involved in order to identify all the settlements within 10km of major roads:

1. Select by the state attribute the New South Wales area from the state boundary layer.

2. Select by location all the major roads that are contained in the state of New South Wales selection.

We now have several options to arrive at a selection of settlements within 10km of these major roads in New South Wales. We can either use the buffer or the select by location tool.

3.2.1 The Buffer Function

Buffering allows the creation of distance buffers around selected features such as points, lines or polygons; where the buffers themselves are also polygons as they do represent an area.[25] Technically, a specific distance is used to identify or define an area around a particular feature in Euclidean space using a two-dimensional algorithm[3]. For our example, we define a buffer of 10km on either side of the selected

[3]This means that the buffer will have the same width independent of the coordinate system that is used, the curvature or shape of the earth will not be reflected, something to consider for very large buffer distances. As the buffer is generated only by Euclidean distance, differences in terrain, for example are not considered. If there is a cliff on one side of a road, the buffer for possible new roads will therefore also include the unusable cliff side of the area. Here topological overlay techniques can be used with other polygons created in other layers for example.

major roads. This buffer is a feature in itself, which can then be used to select all the settlements that fall within this area. Creating this buffer would particularly be useful, if the company needs to identify any other feature or facilities within this area. The buffer, being a feature itself, can be displayed in a map and allow visual checking, or can be used with overlay functions.

Another way to select the settlements within 10km of the major roads, is the "Select by Location" Function.

3.2.2 The Select by Location Function

The Select by Location tool in ArcGIS, will allow the user to select features from one feature class if they:

- intersect
- are within a distance of
- completely contain
- are completely within
- have their centre in
- share a line segment with
- touch the boundary of
- are identical to
- are crossed by the outline of
- are contained by

the features of another feature class. The choice of operation will obvioulsy depend on the purpose of the selection. In our case, we want to identify all the settlements

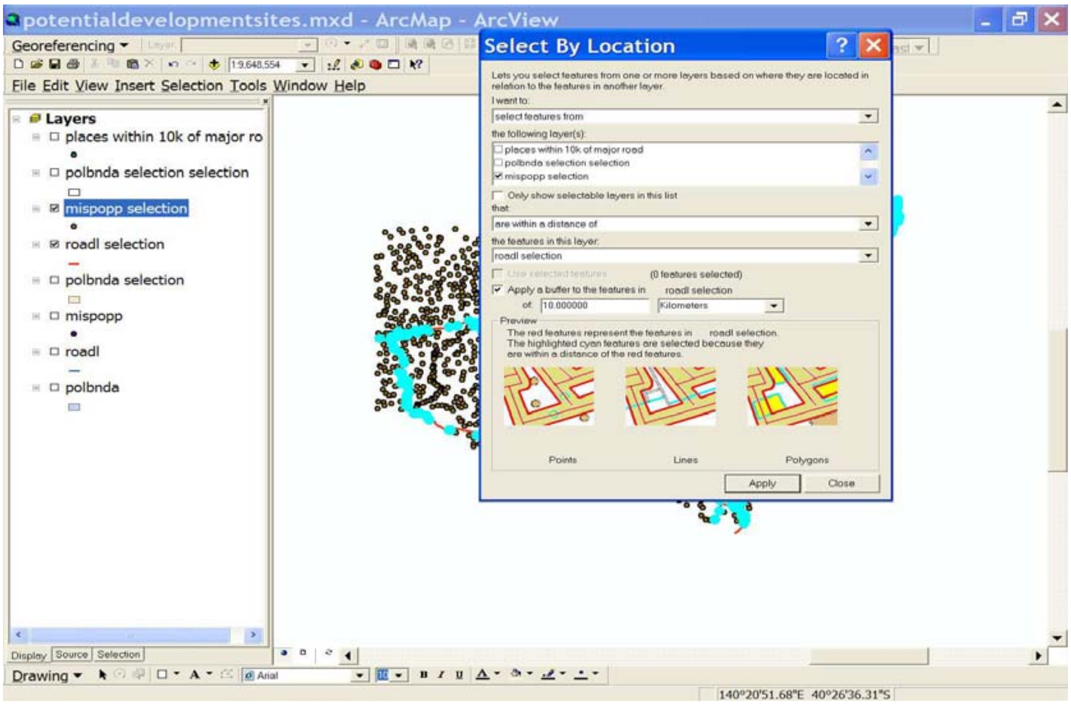


Figure 3.4: The select by location tool with using a 10km buffer around the roads.

that are within 10km of major roads. Therefore, we will use the select by location function on the previously selected major roads in New South Wales and settlements in New South Wales feature classes. Figure 3.4 shows the selection interface for this operation.

The final selection of features is shown in Figure 3.5, showing all settlements in New South Wales that are within 10km of major roads graphically and as an attribute table.

However, as there is still 682 suitable settlements that are within 10km of a major road, additional criteria would be useful to make an informed decision. We would probably be looking for a settlement that is located within a cluster of settlements to ensure a large enough pool of potential employees.

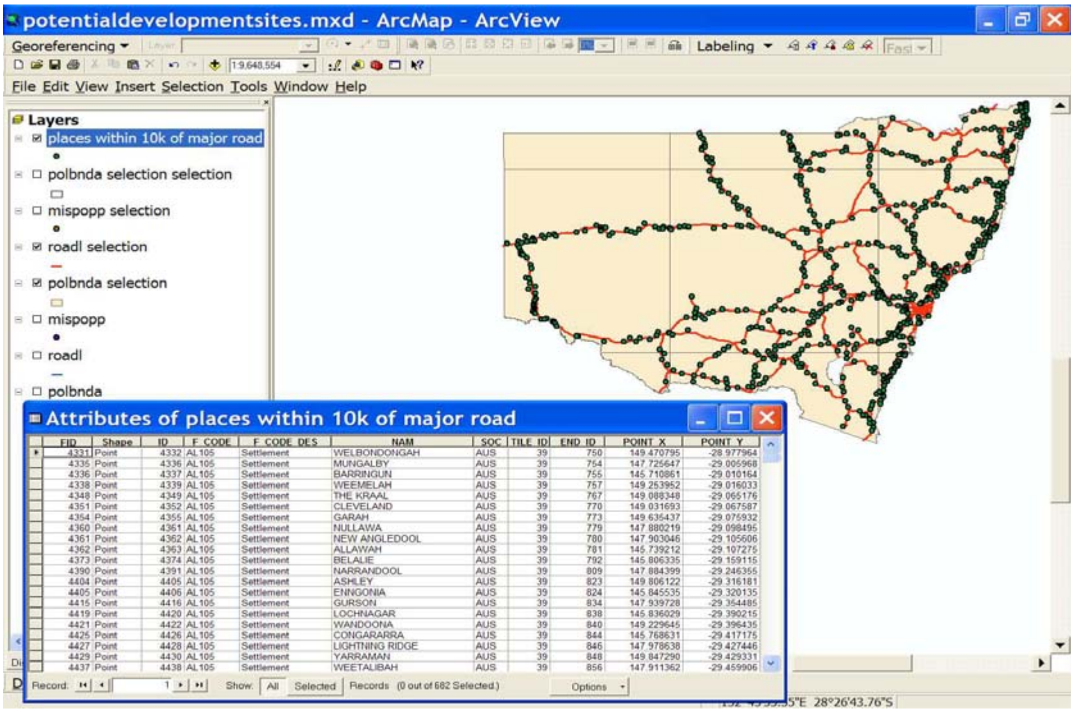


Figure 3.5: All settlements in New South Wales that are within 10km of major roads in map format and as attribute table.

3.2.3 The Point Distance Function

The point distance function can supply us with exactly this information. It calculates the distance between point features in an input feature class to all points in the same or another feature (Near) class within a given search radius. The distances are then recorded within an output table containing the input and near feature ID and the distance between them. If, for example, we wanted to identify settlement clusters for all of the selected features within 10km of the major roads as Near features within a 20km search radius; we would calculate the point distance for each of Near features and then analyse them by both the number of and distance to all the settlements to identify the most suitable places. Of course, one has to keep in mind that the point distance calculated is Euclidean distance and does not reflect the actual distance prospective employees might have to travel along the road to get to work.

3.2.4 The Near Function

The near function calculates the distance from each point in an input feature class to the nearest point or polyline in another feature (near) class within a certain search radius, and records the near feature ID and the distance for each feature in the input feature class' attribute table. In our example, we might want to determine for each settlement what the nearest larger population centre such as a city is. The updated results in the attribute table can then be used for further analysis.

Of course, in this function also, we are using Euclidean distance, which does not necessarily reflect the actual distance travelled along a road. ArcGIS does however supply network analysis functions that can calculate the actual road distance between places available. Network analysis functions allow to calculate distances along networks.

3.2.5 Network Analysis Functions

In ArcGIS, there are four types of network analyses[4] : Finding the best route, finding the closest facility, finding service areas and creating an OD (Origin-Destination) cost matrix.

Finding the best route (Make Route Layer)

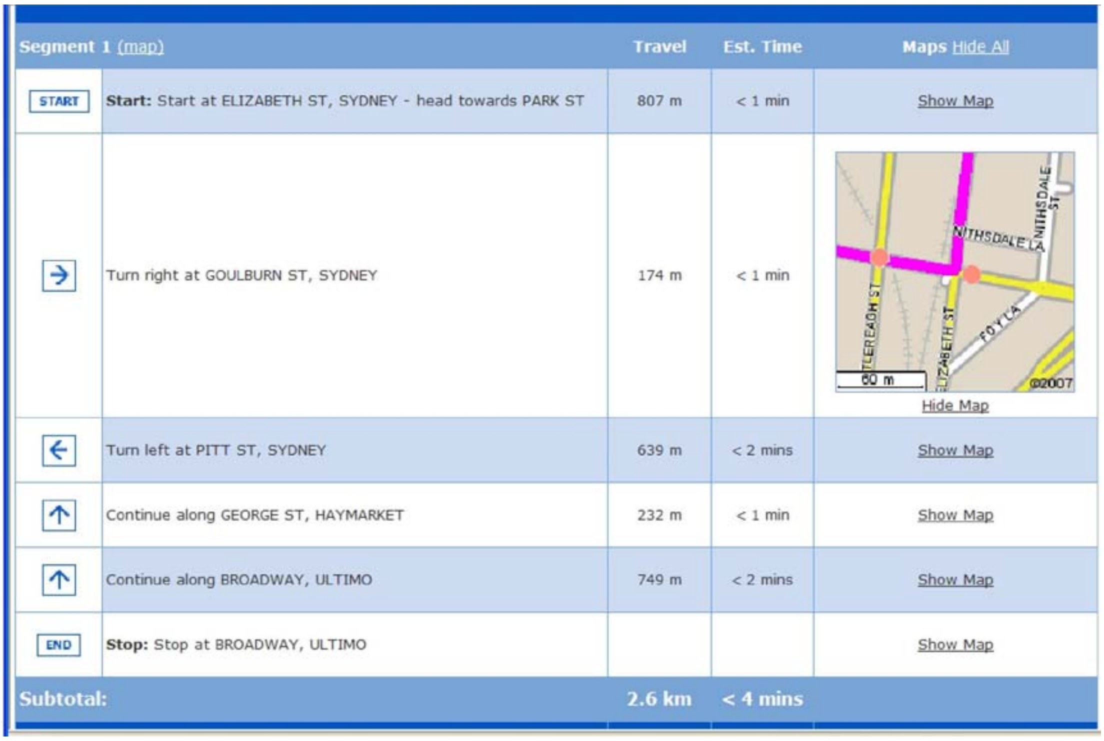
The ArcGIS Network Analyst has a function available that will find the best way to get from one location to another, or the best way to visit several locations. The order of the best route can either be specified by the user or the Network Analyst determines the sequence if no user options are given. The locations themselves be

[4] The following explanations are derived from ESRI webhelp on Network Analysis within ArcGIS: http://webhelp.esri.com/arcgisdesktop/9.2/index.cfm?TopicName=Types_of_network_analyses [viewed on 19.01.2008].

interactively placed on the screen, entered by address or by points in existing feature classes or layers. While it is common for people to attempt taking the best route between two locations or one that visits several locations, "best route" has different interpretations for different situations; it can be the quickest, shortest, or most scenic route. This depends entirely on the impedance that was chosen. If impedance is time, the best route is the quickest one for example. Within ArcGIS, the best route is therefore defined as the route that has the lowest impedance, which is chosen by the user. Impedance here can be any valid network cost attribute.

For example, if time is used as an impedance, the quickest path is generated, while the shortest path is generated for distance as impedance. ArcGIS displays the best routes graphically and also provides directions. There are now also free online tools available that provide some of this functionality, for example whereis.com allows for directions generation between two places with a choice of either time or distance as an impedance. There is also the option of adding up to two stops on the way. Figure 3.6 shows the best path by shortest distance between Elizabeth Street, Sydney and Broadway, Ultimo. The distance here is 2.6km, while the distance for the fastes route was 2.67km.

The ArcGIS network analyst tool is of course, more complex than this, in addition to impedance, restrictions can be included in the path generation such as one-way streets or any other restriction attributes that are available in the dataset. In order to incorporate time-dependent restrictions such as speed limit reductions during school travel times, which might obviouosly have an impact on the travel time, the start time option can be changed from its default 8am. The time windows property allows users to specify such times of limited access to certain features. Another tool is the use hierachy, which is either the default hierarchy of a given network such as an order of highways, major and minor roads; or it is defined by the user who might be prefer roads other than toll ways. If use hierarchy is not enabled, a path will be generated disregarding even the default hierarchy.



Segment 1 (map)		Travel	Est. Time	Maps Hide All
START	**Start:** Start at ELIZABETH ST, SYDNEY - head towards PARK ST	807 m	< 1 min	Show Map
	Turn right at GOULBURN ST, SYDNEY	174 m	< 1 min	Hide Map
	Turn left at PITT ST, SYDNEY	639 m	< 2 mins	Show Map
	Continue along GEORGE ST, HAYMARKET	232 m	< 1 min	Show Map
	Continue along BROADWAY, ULTIMO	749 m	< 2 mins	Show Map
END	**Stop:** Stop at BROADWAY, ULTIMO			Show Map
Subtotal:		**2.6 km**	**< 4 mins**	

Figure 3.6: Whereis.com directions result for the shortest path between Elizabeth Street and Broadway.

We can see that for finding the best path, many parameters are possible to be considered, but this always assumes that the user is very clear about what factors do actually influence his or her choice of best path, and that all these parameters are available as attributes.

Finding the closest facility (Make closest facility layer)

The finding the closest facility function allows the user to identify for example the closest hospital to an accident or the closest repair centre to a customer's address. The maximum number of facilities to be searched for and the travel direction with respect to the facility can be specified as well. A cutoff cost beyond which no search should be carried out, can also be incorporated into the search. For example, a closest facility search for a hospital could specify a cutoff cost of 20 minutes from an accident incidence. Only hospitals that can be reached within 20 minutes would be included in the search results. In addition, the CurbApproach property will restict approach to a network location from only the specified side of the vehicle.

Finding Service Area (Make Service Area Layer)

A Service areas around any location on a network can be found by the Network Analysis function of finding service areas. A network service area is defined as a region which encompasses all streets that lie within a specified impedance. For example, a 30 minute service area of our food producer (i.e. location point) would include all the streets that are reachable within 30 minutes from the factory location. These service areas can be used to evaluate how accessible a certain location is. Accessibility here refers to the ease with which a certain site can be travelled to. One way of evaluating accessibility could be by buffering a point by a certain distance or time value. Coming back to our food producer example, we could try to find out how many potential employees live within a 20km radius of any potential factory location. But considering that the employees would travel by road ("not as the crow flies") doing it this way does quite likely also yield us settlements that are not really accessible within 20km driving distance. The ArcGIS Network Analyst can identify the accessible streets within 20km of the potential factory sites via the given road network. These service networks, i.e. a feature layer that includes all the street within a certain road distance from a particular site or facility, can be used for example to examine relevant features next to accessible streets such as medical facilities for any accidents that might occur during the production process.

Creating an OD cost matrix (Make OD cost matrix layer)

An origin-destination (OD) cost matrix from multiple origins to destinations is a table containing the total impedance from each origin to each destination. It also ranks the destinations for each origin with respect to the travel time from the origin to each destination. The OD cost matrix does provide much of the impedance attributes required within the other network analysis functions.

3.2.6 Thiessen Polygons or Voronoi Diagrams

The Network Analyst function of Create Thiessen Polygons converts points from an input feature class into an output of Thiessen proximal polygons (also referred to as Voronoi polygons). Each polygon contains exactly one point from the input features, and any location within the polygon is closer to this input point than to any of the other input points. The only points that have the same distance to two input points are the points forming the edge between two polygons. Chapter 5 will discuss the notion of Voronoi diagrams in more detail. Thiessen polygons can be used to identify which facilities are the closest to a certain location in the map. If we, for example, generate Thiessen Polygons for all the major population centres (i.e. bigger towns and cities), we can then select all previously selected settlements within 10km of major roads according to the major population centres they are closest to. However, as this is not a network analysis function, only Euclidean distance is used and this is not necessarily representative to distances that will need to be travelled.

3.2.7 Limits of GIS Proximity Analysis functions

In summary, the proximity analysis functions that are now commonly available in Geographic Information Systems, do allow an evaluation based on distance or any other cost measure both within Euclidean space and along (road) networks. Attributes in general can be used to as modifiers to proximity functions. However, there is always complex multi-levelled analysis involved, it is not possible to just enquire about "near" locations to a particular landmark beyond stating a specific distance without first defining all the parameters that do impact on the "near" perception.

For example, if one was to travel through New South Wales, wanting to go from place A to B and including as many interesting sights along the way within one days travel, we would have several ways of options of using available functions for this. We assume that we have an OD matrix available which includes the travel time for each of the roads, a matrix that realistically would be very hard to generate beyond the approximation of speed/distance calculation. Simple buffering or any of the other functions that are based on Euclidean space calculations would not be sufficient as travel is along the road. Hence, we would need to use a network analysis function. For the best path calculations, we would create a stop layer containing all of the sights we might be interested in. The impedance used would be time. There is no way of combining several attributes as impedance. However, we can not ask for a route actually choosing from these stops, the user has to state which stops should be included in the route. Maybe not exactly what we are looking for!

This means that we will have to do some other analysis beforehand to identify the sights that we want to visit, we could define a service area of lets say 10 minutes drive time for each sight that we might be interested in and then select all those sight whose service areas intersect with a previously generated path between A and B, as stops. But, we do always need to really know what stops to include before generating a path or just look for stops along or nearby a given path.

A more intelligent path generation where the path will be generated together with potential stops is to my knowledge not possible with any of the available functions. In addition, to this issue, by giving a specific value to distance for example, we could miss out on potential places of interest, because the drive time might be 11 instead of 10 minutes. This complete reliance on quantitative values could be overcome by introducing more qualitative notions into GIS. The next chapter will have a closer look at approaches in qualitative spatial reasoning to distances and proximity relations before introducing my own approaches to a qualitative dealing with spatial proximity in geographic space.

Chapter 4

Methodology

The work presented in this thesis is hard to place into one specific scientific field of enquiry. My investigation of the concept of spatial proximity is concerned with all its implications to spatial cognition and the development of computational models, with a particular interest in their application to spatial data processing. Consequently, this thesis spans across disciplines as diverse as cognitive science including Artificial Intelligence and spatial information theory. The aim is to examine spatial proximity with a focus on how it is perceived and reasoned about by humans and to find a representation which mimicks this human mental process, at least to some extent, and is implementable to support the development of more intuitive tools for spatial proximity analysis in spatial data processing. While a data model is computationally quite tangible, the first step to arriving at such a model is a thorough understanding of all the different aspects of spatial proximity within this human cognition context. In order to arrive at this thorough understanding, it is necessary to study the broad range of disciplines that concern themselves with physical space, human interaction with this space and models thereof provided by disciplines such as physics, geography and psychology to name just a few. As I would like to place my theoretical findings into a Geographic Information Systems (GIS) context, these systems also need to be subject to further investigation. It is a real challenge to integrate such a diverse body of knowledge and investigation into one comprehesive contribution. I therefore adapted the scientific method to suit this interdisciplinary body of work.

Recall the scientific method at whose centre lies the definition of a hypothesis. As mentioned in the previous chapters, spatial proximity is acknowledged as one of the qualitative spatial relations among topological and directional ones. However while the former two are well defined, nearness is much harder to formalise due to its proven context-dependency and consequently there are currently no formalisms available yet that can describe nearness sufficiently.

> ***Key Hypothesis:*** **There is a suitable nearness notion based on context that goes beyond fixed buffer zones, fuzzy membership functions and stipulated natural language expressions.**

I will introduce the idea of *impact areas* and their interrelated *notions of nearness* that resulted from the study of the current spatially motivated state of the art in diverse disciplines with a focus on spatial proximity and GIS application. It is asserted that this approach is valid and useful in the spatial information science context, and experimental results with GIS data will show this to be true or not.

Let me address the different methodical steps in a little more detail, before moving on to the actual framework development.

4.1 Reduction of Complexity Through Analysis

The knowledge problem faced here is that of an appropriate qualitative representation of and reasoning about spatial proximity that goes beyond the existing approaches in spatial reasoning and methods for proximinity analysis used in GIS. This new approach is to be, while being a data model, human centred to address the complexity of data analysis that GIS users see themselves faced with. Chapter 3 surveys existing GIS data models and proximity analysis functions, and throughout the development of the framework I will continue examining spatial reasoning approaches to proximity where appropriate, thereby clearly identifying the knowledge gap that is to be addressed by the work in this thesis.

Formally, the complexity of Physical Space will be reduced to a universe of objects and relations amongst them. I choose a formal, symbolic approach to represent this reduced view of physical space. Further, human cognition is reduced to a data model in order to make it easily analysable and also applicable to Geographic Data Processing.

4.2 Development of Hypotheses

The main hypothesis drawn from this is that such a reductionist view of physical space can be used to derive a useful representation of spatial proximity as perceived and reasoned about by humans. In particular, the introduction of a *context* variable to the model is asserted to provide a suitable notion of nearness. Combining both a cognitive and a formal approach into a framework can be very useful for geographic data processing applications.

4.3 Design and Replication of Experiments

The hypothesis will be validated for the specific *context* of touristic road travel using geographic data and "cognitive spatial proximity data" as represented in travel guides to examine and validate the concepts of *impact areas* and *nearness notions*.

4.4 Deduction of Results and Rejection of Hypotheses

The results of the experiments will either lead to a confirmation of the usefulness of impact areas and their associated nearness notions or lead to a revision of the approach to account for the findings. This will yield a framework particularly useful to Spatial Information Science, but potentially of benefit to any problems requiring proximity analysis.

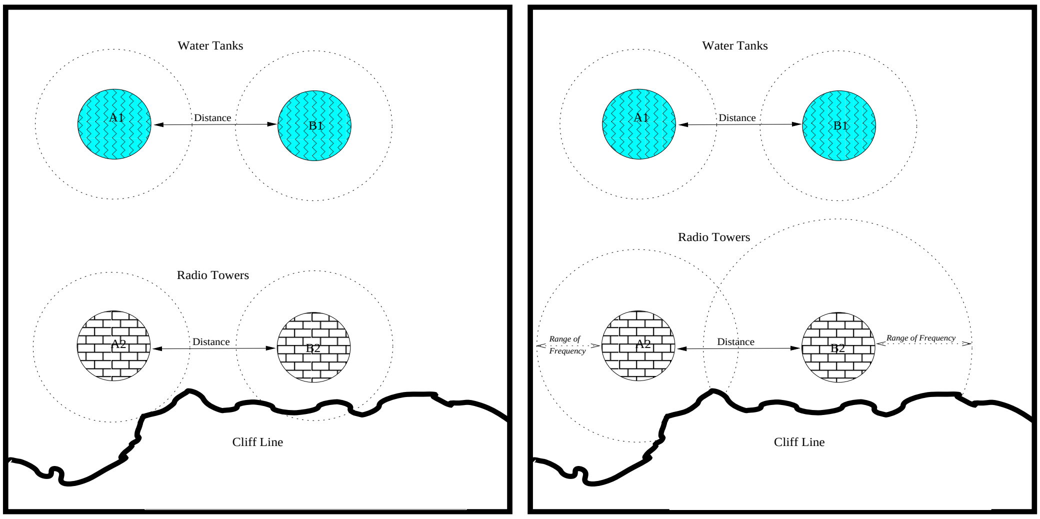
Chapter 5

A Cognitively Motivated Data Model of Physical Space and Proximity Relations

The concept of proximity or nearness is an important aspect of human reasoning in general. It plays a role in areas such as concept categorisation ([102, 101, 51]), data-mining and machine learning, case based reasoning [107] and of course spatial reasoning, just to name a few. Despite the diversity of applications that require nearness or proximity measures, the most intuitive notion is that of spatial nearness. Due to its omnipresent nature in human cognition, it is in many ways the precursor for many of the more abstract nearness concepts. My aim is to propose a suitable notion of nearness. However, this is not as trivial as it might appear at first sight. Questions such as *How far is too far?* or *How close is too close?* seem to be answered easily enough in most contexts. I know that if I need to get from A to B in 30 minutes and all I have got to get there is a bicycle, then B is too far from A if I cannot make it in the specified time. Likewise, anything that can potentially hurt me is **too** close if I am within its area of impact. Why then is it so hard to find a generalism that envelops spatial proximity in all its entirety? One reason is that spatial proximity on one hand can lie very much within the "mind of the beholder", but on the other hand can also work on a subconscious level as reflected for example in the "flight and fight" response. Thus, finding a generalism that covers both this basic perception and the much higher level cognitive evaluation of spatial proximity, has understandibly proven to be very difficult.

Many of the existing spatial reasoning formalisms do not account for proximity at all while others stipulate the notion of nearness by using natural language expressions, such as *close to* or *near*, as symbolic values. Guesgen and Albrecht [57] suggest to associate spatial binary relations such as *far from* or *close to*, or unary relations such as *downtown* with fuzzy membership grades, which could be calculated for locations in a map using Euclidean distance. However, distance is not the only factor that influcences nearness perception; and Euclidean distance alone does not reflect factors such as steep uphill climbs, other relevant terrain characteristics or simply the actual travel distance along road networks. While this information is usually available in GIS data, how and what to include in the evaluation of spatial proximity is the bottleneck question of a comprehensive abstraction.

The question of a suitable notion of nearness remains. How could it be solved? Previous work suggests that it should be defined from a more basic notion of influence area. I will argue that this approach is flawed, and that nearness should rather be defined from a different basic notion, namely, impact area. Let me first illustrate the difference between influence area and impact area, with an example involving water tanks and radio towers, depicted in Figure 5.1. The key influence area of an object o is totally determined by o's spatial boundaries, and determines an area that includes o, with no consideration whatsoever for what o actually is, and o's surrounding environment. With this example, the influence area of a radio tower would be the same as the influence area of a water tank of similar shape and size. Clearly, we would prefer the influence area to be the range R of the radio waves (where a suitable device would detect them). This area should be determined not



(a) Influence areas of water tanks and radio towers are calculated from their spatial boundaries, resulting in the same degree of nearness between tanks and towers of the same size and shape, located at the same distance from one another.

(b) Impact areas of water tanks and radio towers differ when taking the functionality of the towers, in form of the range of frequency, and the surrounding terrain into account. This results in different degrees of nearness between the pairs of tanks and towers.

Figure 5.1: Contrasting Influence areas and Impact areas

only by the tower itself, but also by the surrounding terrain. If the tower is close to the bottom of a cliff then R stops at this natural barrier, and the area's shape is uneven, with the cliff line on one side. If the tower is on a plain with no obstructing natural formation or building, then R is a perfect circle. Rather than redefining the usual notion of influence area, I prefer to introduce a new, richer notion, that of *impact area*, that takes into account both the nature of an object and the surrounding environment. Why is that important? Assume that we base the notion of nearness on influence areas. So assume that the degree of nearness between two objects A and B is totally determined by the influence areas of both A and B. Then given two pairs of objects (A_1, B_1) and (A_2, B_2) such that A_1 and A_2 have the same shape and size, B_1 and B_2 have the same shape and size, and the distance between A_1 and B_1 is equal to the distance between A_2 and B_2, then the degree of nearness between A_1 and B_1 is equal to the degree of nearness between A_2 and B_2. Take for A_1 and B_1 two water tanks and for A_2 and B_2 two radio towers all with the same shape and size, and you will realise that this notion of nearness is much too crude. Basing the notion of nearness on impact areas rather than influence areas allows one to take functionality of objects and context into account, and promises not to suffer the limitations and counterintuitive properties of the latter.

However, switching from a notion of influence area to a more fine-grained notion of impact area still leaves the door open to a number of notions of nearness. Traditionally, nearness is conceived of as an asymmetric relation: what is assessed is whether an object B is near an object A, with A playing the role of reference object. It should come as no surprise that only the influence area of the reference object is then taken into account in the definition. Now let me argue why this is too restrictive, even by letting impact areas play the role of influence areas. Assume that B is outside the impact area of A. If only the impact area of A is taken into account in order to determine whether B is close to A, then the degree of nearness between A and B is independent of where B actually lies in the complement of A's impact area. Consider now three radio towers A, B_1 and B_2, such that the impact areas of A and B_1 intersect, whereas the impact areas of A and B_2 don't. There are contexts where A and B_1 should be considered close to each other, whereas A and B_2 shouldn't. Indeed, assume that two receiver stations R_1 and R_2 are located between A and B_1 and between A and B_2, respectively. Obviously, R_2 can receive signals from at most one radio tower. On the other hand, if R_1 happens to be within the intersection of the impact areas of A and B_1, then its working is going to be affected by the fact that the radio wave ranges of A and B_1 interfere! Hence we would expect that A and B_1 should be considered close to each other. Figure 5.2 illustrates this.

To summarize, a suitable notion of nearness requires that it be based on a notion of impact area, richer than the notion of influence area, and that it takes into account

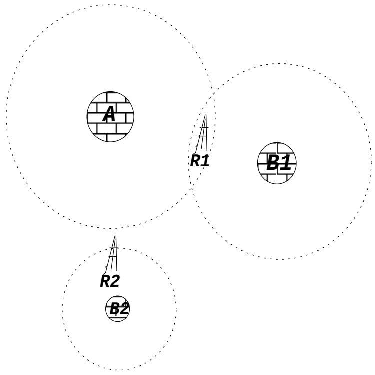


Figure 5.2: Two radio towers A and $B1$ can be too close if a receiver station $R1$ is located in the intersection of their radio wave ranges

the impact areas of both objects whose degree of nearness is assessed, as opposed to the impact or influence area of only one of both objects, seen as a reference to assess the nearness of the other to it. The motivation for the work presented in this thesis is to provide a framework for spatial proximity that supports the development of intuitive tools for users of geographic data processing applications. While this does strongly imply a data focus, which is why a data model approach is taken, cognitive findings are also incorporated to make the framework more relevant to the users of GIS with respect to their own spatial cognition. GIS users bring a wealth of knowledge about physical and particularly geographic space into the processing of the GIS data. The following cognitively motivated data model of physical space gives credit to the fact that GIS data can really only be useful through the analysis of the GIS users themselves. Hence, before we delve into formal details of a spatial proximity framework let us first step back and reflect on the cognitive background. This will make sure that we do not lose sight of where my research does actually fit into this broader field of cognitive science. In the big picture, my proposal has been inspired by this body of research.

5.1 A Cognitively Motivated Data Model of Physical Space

Physical space is not just what surrounds humans, but humans are also integral part of this space. While the concept of embodiment is not new, it is often not taken appropriately into account in computational model approaches to spatial knowledge representation and reasoning. Implementations often rely on existing abstractions of physical space in the form of maps or geometrical models. In the field of robotics, robots do have some form of embodiment and are equipped with sensory receptors. However, even with this sensory input robots are usually limited to only a few of the senses available to humans. In addition, the interpretation of the signals received does often prove difficult and does not necessarily give the same wealth of information that humans would retrieve from the same sensory input. For the purpose of interpretation and to ground the input into the surrounding environment, robots have to rely heavily on representations of the "real world" that are supplied to them by the programmer. Comprehensive representations however are very hard to arrive at, which is reflected in the large body of research in numerous disciplines investigating spatial knowledge and seeking useful representations. The model of physical space that is developed here it not claimed to completely solve this common void of comprehensiveness. But it is cognitively motivated in an effort to incorporate the human experience with physical space, with respect to spatial proximity, to a larger extent than what has previously been done. It thus provides a framework for spatial proximity that supports the development of intuitive tools for users of geographic data processing applications. Keeping this data processing context in mind, the following discussion incorporates a purposive selection rather than a comprehensive coverage of all the, often inconsistent, research results related to human cognition of physical space.

Physical space is directly experienced by the information that is relayed through our senses. The stimuli received from these senses are, so to speak, the "raw material" that is meaningless to the human mind unless interpreted appropriatedly. According to Coren et al. ([104], p. 9), an information processing approach can be "used to emphasize the whole process that finally leads to identification and interpretation of stimuli." And within the context of information processing, a common framework can integrate the different aspects of the human interaction with the external world by defining the three phases of **sensation**, **perception** and **cognition**. Different schools of thought define each of these phases very differently and often the phases themselves are not clearly distinct. There is a general consensus however that our senses are what "connects" us with the outside world, i.e., physical space. And these "raw data" that we receive from our senses are believed to be extensively filtered and interpreted by the brain. This interpretation phase is generally referred to as perception, however the actual process boundaries are not quite clear. The notion of cognition is also very varied across different expositions and studies. While some see it as a process that "comes after" perception and is the way we handle and use knowledge, others believe cognition to be part of the process that IS perception, helping to interpret and use sensual information. I would like to emphasise that this thesis it not meant to try and establish a clear distinction between these phases; instead I would like to provide a consistent data model that can be applied in the context of geographic data processing and selectively draws from research results from investigations into cognition and perception.

5.1.1 Sensation

Coren et al. [104] see sensation as the first contact between humans[1] and their environment. Sensory processes establish relationships between sensory experiences and physical stimulation and physiological functioning based on the physical structure of sensory organs. Sensory experiences are often referred to as "senses" such as

[1]Coren et al. [104] used the more general term of organism.

"touch, smell, taste, sight, hearing and the sense of balance" ([100], p. 5). They do however not only probe the external world, but also monitor positions of the limbs and balance of the body and the sensation of pain as a means of understanding the "self" [55].

> **Sensation** is a process that creates sensory experiences, i.e., senses, from physical stimuli to the sensory organs, where the physiological functioning of the sense organs varies from person to person.

The process of perception is believed to interpret these sensations, making them meaningful and useful, beyond just plain reflexes.

5.1.2 Perception

Perception encompasses the "conscious experience of objects and object relations" ([104], p. 8). The perceptual process forms "a conscious representation of the outside world" ([104], p. 8) by acquiring, interpreting, selecting and organising sensory information. Perception supplies the human organism with the knowledge of "sources of sensations -such as the states of our bodies and objects in the environment—rather than of the sensations themselves" ([55], p. 599). However, perceptions are quite separate from our conceptual understanding of the world, because the process of perception has a very limited timeframe in order to be useful. This contrasts to concept formation, i.e., formation of knowledge and ideas, that has no such urgency attached to it, and that can draw upon large amounts of the knowledge available if necessary. Perception has no such luxury, as it has to work fast, and therefore has to utilise a more shallow, but rapid intelligence with a small knowledge base [55]. It is also believed to take place in the more "ancient" parts of the brain in the cerebellum, which allows swift responses to common stimuli related to movement of the body. It is these routine movements and reactions that are believed to be controlled by the cerebellum at a subconscious level; we do not think about walking around and we can even learn certain sequences of movements such as driving a car or even walking a certain path everyday [35].

> **Perception** is a process that interprets sensations using very basic, often referred to as routine, knowledge.

In the context of the data processing approach taken here, percepts are simply an interpretation of sensory information with the bias of routine knowledge. A useful way of looking at percepts is that they do comprise a qualitative interpretation in contrast to the quantitative nature of sensor data. Concepts that trigger routine reactions are also percepts. For example, the task of walking around a corridor is of no great difficulty to most people. They can subconsciously judge the distance to the wall and adjust any "too close" positioning. There is no evidence that suggests that any precise distance calculations take place in the human mind; instead approximations within certain ranges are utilised, and that at a subconscious level. These "ranges" have been learnt through experience and act as a filter for anything unimportant to the current task at hand. For a task such as walking around a corridor without bumping into the walls, it is not essential to know how far exactly one is away from the wall or what pictures decorate it.

Research generally investigates perception with respect to specific sensory organs such as visual perception or auditory perception; within the former, distance perception has received particular attention. According to Gregory [55], it is even thought of as the precursor of all intelligence, having enabled organisms to move beyond their reliance on just reflexes. Interpreting visual stimuli in terms of depth and distance is more than just "picking up" and selecting sensory information from the eyes. Gregory [55] talks about "vast and still largely mysterious jumps-intelligent leaps of the mind [...] between the sensation and the perception of an object" (p. 599) that are obviously not fully explained yet. Researchers in fields such as vision and image analysis have been working very hard to fill this gap. The results are mixed, as they more often than not neglect the human component and focus on algorithmic improvements. It is not subject of this thesis however to address these issues. But I would like to emphasise here that distance appears to be perceived, through a perceptual process that is quite "basic" in terms of its usage of any existing knowledge and also largly unconscious to the human mind. This is to be contrasted to the much more sophisticated process of cognition which takes place at several levels of proximity evaluation.

5.1.3 Cognition

Cognition is often defined as "the use or handling of knowledge" [55]. While there is also a school of thought that sees cognition as part of perception in terms of its knowledge-based processes enabling the mind to make "sense of the 'neurally-coded' signals from the eye and other sensory organs." ([55], p. 149), I would like to define cognition as a more or less separate process taking the results of perception as granted. Cognition refers to more abstract knowledge and encompasses memory, association, concept formation, language and problem solving [104].

> **Cognition** is a reasoning process that is based on existing conceptual knowledge and allows for the creation of *new* knowledge taking into account the outside world through any percepts available.

In the context of a data processing approach, qualitative higher level concepts are built during the cognition phase through reasoning. The reasoning process incorporates both existing concepts and the qualitative interpretations of sensations previously defined as percepts. One could ask where these existing concepts do originally come from. It will be assumed here that in the early stages of child development, a set of concepts is developed from percepts alone. In the experimental settings of this thesis, important concepts will be derived from appropriate data collections. There is of course also a danger in trying to clearly distinguish between the processes of perception and cognition, as they both utilise knowledge and it is believed that knowledge at the cognitive level can influence perception as well. However, as the reader will see, such a distinction can be quite useful with respect to a data-based approach.

5.1.4 Proximity is more than just a distance measure

It is this distinction that can give one possible explanation for *why* clearly defining spatial proximity in terms of invariants is so hard. We know that distance is one of the main factors for deciding on spatial proximity, but that there are various other factors, a few of them completely non-spatial, that impact on spatial proximity as well. The information processing model of the whole process of internalising and utilising representations of the external world as described above, makes clear that distance measures are actually results of a perceptual process while most of the other factors work at the conceptual level. This obviously has implications when one tries to combine them into one model. Interestingly enough though, while the proximity measure is mostly a conceptual formation[2], it *is* inversely proportional to any distance measure used. For example, if we consider a toxic waste dump, our proximity measure largely depends on our knowledge of the toxic waste, its effects on its immediate environment and the range of spread of the toxins etc. Once this is established however, increasing distance will still decrease the degree of proximity.

Any model of spatial proximity for GIS data should be based on the conceptual context, i.e., the purpose of establishing any degree of proximity such as my positioning with respect to another object for the purpose of vision or for the purpose of actually reaching this other object. Such a model should also incorporate the existing conceptual and perceptual knowledge about the objects in question such as their functionality or their spatial extent. Within such a framework, distance becomes

[2]Conceptual formation here refers to concepts or a structure of concepts acquired through cognition or thinking as opposed to a perceptual formation that comes into being through direct stimulus from the environment. It is a commonly used term in cognitive science, not to be confused with the term formation as a process.

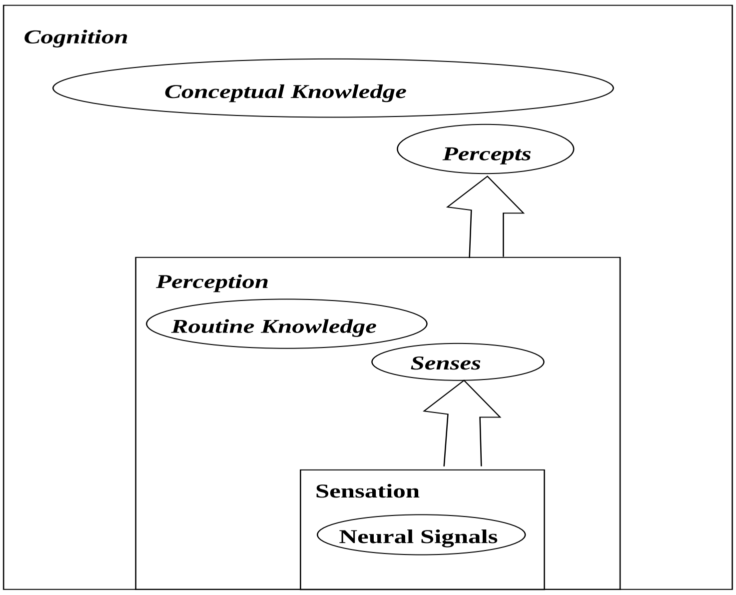


Figure 5.3: Cognitively Motivated Data Model

a modifying factor instead of being the measure for proximity. Proximity is really more than just a distance measure. In the area of spatial reasoning, this is often portrayed in a slightly misleading way, when qualitative distances are described in terms of proximity descriptions, i.e., natural language descriptions of proximity such as *near* or *far*. I will now introduce a model that will hopefully clarify this issue, in addition to the stated aim of providing a framework for more intuitive interfaces for spatial data processing. There are two views that can be taken here, one is the data flow view, where one phase happens clearly after the other using the output of the previous phase as input. The other is one of an encapsulated overall cognitive process, which contains and relies on the other two phases. The latter is the view I will take.

The cognitively motivated data model as shown in Figure 5.3 can easily be specialised into a cognitively motivated data model of physical space. Physical space *is* after all what our senses connect us to.

5.2 A Geographic Data Model

Let me now explain how the cognitively motivated data model of the previous section can be applied to geographic data. I am seeking a natural correspondence that supports intuition. Examining GIS data with the three human mental processes of sensation, perception and cognition in mind, I categorise into sense, perceptual and cognitive data. GIS data in vector format consists, as we know, of geographic objects whose spatial object's characteristics are available in attribute tables. Each column represents the attribute while the rows represent the records of spatial data. One way to interpret this within the context of the cognitively motivated data model is to define attributes as basic concepts or percepts and records as values or sense data. However, some attribute table values can in themselves also be categorised. For example for the attribute *Settlement* there could be three possible values such as {*City, Town, Village*}. In this case, the values represent an interpretation of information such as the population size of a settlement and therefore are basic concepts or perceptual data. The results of analysis functions which are brought about by a reasoning process that the GIS user applied to the data set, can be interpreted as cognitive data. Let us look at some examples to clarify this particular data categorisation approach.

5.2.1 Sense Data

In the cognitively motivated data model context, sense data is anything that can be measured with suitable devices, and is represented in the attribute tables by quantitative values. In addition, I will also consider qualitative values that are associated with a particular spatial object such as place names as sense data, because they do not require any interpretation by the GIS user who records them. The attribute table displayed in Figure 5.4 shows entries for Australian settlements. The spatial object and internal database reference information such as IDs, coordinates

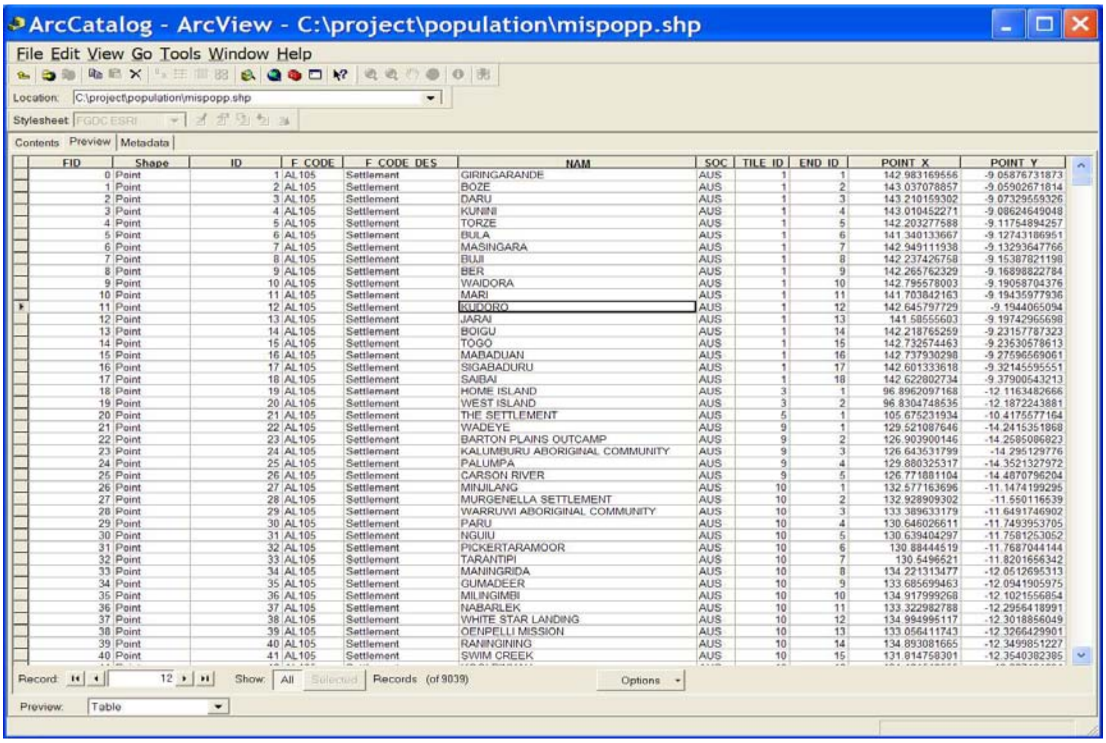


Figure 5.4: Attribute Table for Australian Settlements

or shape is obviously sense data. However "real-world" characteristics of the spatial object as recorded in attributes such as feature code description (F_CODE_DES), name (NAM) and source country (SOC) are not necessarily so. Let me explain why. The attribute values for settlement name and source country are associated with one particular spatial object, no matter what interpretation the GIS user prescribes to. These values can therefore be likened with sensations. In contrast, the entries for feature code description can take two values, *settlement* or *built-up area*, which are not bound to a particular spatial object. Instead, for each of the spatial objects, one of these values is assigned according to certain parameters associated with this object. For example, the population size of a place could be used to categorise it into either *settlements* with less than a certain amount of inhabitants or *built-up areas* with more inhabitants than that. Therefore, these values represent basic concepts or perceptual data rather than just sense data.

5.2.2 Perceptual Data

As we have seen, attribute values can be either sense or perceptual data. In addition to perceptual data represented as attribute values, attributes themselves do also represent categories used to structure the data. They had to be derived by the GIS user who recorded the data in order to store it in a useable way. For example, *Feature Code Description* is a category of all the values a spatial object can take for a particular characteristics or parameter of a geographic object.

5.2.3 Cognitive Data

Where the original data set is not sufficient and analysis functions are applied, we practically add a further level of interpretation of both sense and perceptual data. In order to arrive at a particular output data set, the GIS user has to derive appropriate analysis functions. This derivation process is strongly reasoning focused, and because reasoning is a cognitive process, the result of such analysis functions can be considered cognitive data. For example, when applying the buffer function to road features as we did in Chapter 3, the resulting attribute table of features located within this buffer zone is in fact the higher level concept of a particular region with certain characteristics. In addition to analysis functions, the GIS user does also contribute indirectly to analysis results. Knowledge possessed by the user, in particular tacit knowledge which cannot be codified and is therefore not available as GIS data, will impact on the way analysis is conducted. For example, if a travel path is required that is supposed to include places with interesting sights, path generation functions can be applied with some attribute values as modifiers. While a GIS user unfamiliar with the area to be traversed will need to rely solely on the data recorded, users familiar with the area can use their local knowledge to make place selections. Sometimes this kind of "place" knowledge does not go far beyond experiences or intuition, and is therefore impossible to extract and record in GIS. Travel guides for example are a condensation of the experience of someone who has travelled the places covered by the book. Usually the writer knows the area very well, and knows what places are worth visiting on a particular path, not necessarily only for particular sight, but maybe also for the "atmosphere" of a certain location, something that is impossible to put into words and therefore hard to record. This kind of tacit knowledge is sometimes dealt with in Knowledge Management Systems (KMS) by including "stories" which encapsulate "the message" that is to be brought across. The KMS user can learn from this story without having to be aware of particular parameters or attributes. This is a very useful tool in knowledge extensive processes. While not suggesting to include stories about geographic locations, I would like to take a similar approach here, by supplying additional proximity information taken from travel guides in an encapsulated form rather than trying to extract particular parameters for database storage. For example, using proximiy analysis functions for generating road network distances and then using additional knowledge for more sophisticated queries, could greatly enhance proximity analysis and make it more intuitive. In combination with the concepts of impact areas and their related nearness notions, this will support developers of geographic data processing tools in providing more user-friendly, intuitive interfaces.

The reader should keep in mind that spatial proximity is the main focus of this thesis. Therefore in order to develop a framework that can cater, at least to some extent, for these cogitive processes of the GIS user; it would be helpful to clarify what factors do actually influence proximity perception. The next section takes a closer look at spatial proximity and its place in human perception and cognition, leading us to these influential factors.

5.3 Distance and Proximity Relations

It has often been argued (e.g., Frank [41]) that distance is sufficient to describe proximity concepts such as the ones represented by linguistic symbols, e.g., *near*, *close* or *far*. However, if distance alone is sufficient, how can it be explained that an ant being situated 20 meters from a high rise building is considered far away from it, while another high rise building at the same distance is considered close? Distance by itself is obviously not adequate to explain this kind of phenomenon. The notion of proximity seems more context dependent than the other notions discussed in Chapter 2. However, before we examine other factors that influence proximity, let us first look at spatial distance as it is one of the main determiners.

5.3.1 Spatial Distance

Berendt [9] describes distance as the extent of the space between two spatial entities. While her studies deal with the distortions of memories of distance resulting in what Berendt calls subjective distance, she also examines what she calls objective distances, i.e., distances that we can measure. In the context of this thesis, we will differentiate between qualitative and quantitative distances, with Berendt's objective distances directly corresponding to quantitative distances and subjective distances encompassing both quantitative and qualitative representations.

Quantitative distance does essentially represent any distance between two entities that can be measured in a conventional way, e.g., using tape measures. Or as Berendt puts it: "Quantitative representations are characterised by increasingly constraining information or increasing information content when compared to qualitative representations (p.31)." Qualitative distance is the distance as it is perceived by a human or any other cognitive agent. It is therefore not represented by numeric but by symbolic values that represent a whole range of possible numerical values. The next subsection will review some approaches to representing and reasoning about qualitative distance relations.

Qualitative Approaches to Spatial Distance

Crangle and Suppes [24], in their studies of the geometrical semantics for spatial prepositions, described the semantics of $near(x, y)$ as $d < \epsilon$ where d is the distance between x and y, and ϵ a threshold that would at least be a function of the size of x and y. This function is however not discussed further, but Crangle and Suppes suggest that a probabilistic metric for d, using a probabilistic distribution for the threshold, might be needed to define a semantic for the preposition *near*.

Mukerjee and Joe [84] devised a calculus that can be used to reason about two-dimensional scene descriptions with movable extended objects. Similar to Guesgen's [56] approach, they use tuples of relations between intervals that represent the sides of the rectangular objects, along the axes of the coordinate system.

Frank [41] defined distance categories, which are symbolic values representing proximity relations. He constructs composition tables for the addition of paths and distances utilising axioms, e.g., metric distance properties, concerning path and distance composition. For table cells that are not uniquely described by the axioms, all possible choices are stated. As an example for the compositions that Frank produced, the composition of the symbolic values *near* and *far* would result in the symbolic value *far* in Frank's composition approach.

Zimmermann's [125] Δ-calculus defines the relationship between two one-dimensional measures, e.g., intervals or vectors, by utilising the difference in their length, determining which one of the measures is the greater one. These representations of the spatial objects in terms of the difference relations between them form the basis of reasoning techniques such as compositions and addition of the relations. This calculus is also extendable to 2- and 3-dimensional spatial entities.

Hernández, Clementi and Di Felice [64] developed a framework for representing qualitative distance, which is based on the concept of "distance systems." Distance

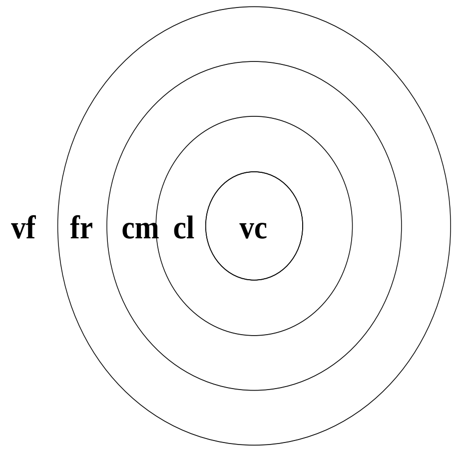


Figure 5.5: Fine grained distance distinction where **vc** is *very close*, **cl** is *close*, **cm** is *commensurate*, **fr** is *far* and **vf** is *very far* ([64]

systems are lists of distance relations[3] in combination with structure relations[4] that define possible relations between the distance relations. Their framework does not only deal with equally sized distance intervals like Frank's [41] approach, but also with regions of different sizes. They distinguish between comparing the magnitudes of distances and naming the distances. For comparison, the usual relations *smaller than*, *greater than* and *equal* are used. In terms of naming the relations, a set of relations is established for each situation considered. The names are given arbitrarily and range from *very close* to *very far*; the granularity can also vary depending on the application considered. The relations are represented by circular regions; see Figure 5.5 for a fine grained distinction. If a decision cannot be made at a finer level, the framework requires a coarser level to be chosen. Distance relations are described by $Q = \{q_0, q_1, ..., q_n\}$ with q_0 being the distance closest to the reference object. Composition tables are defined on these general distance relations considering the orientation of the distances, i.e., compositions for distances for the same orientation, compositions of distances for opposite orientation and so on. This was done in a

[3] i.e. a set of qualitative distinctions with their implied increasing order
[4] i.e. "order-of-magnitude" relations between the named distances

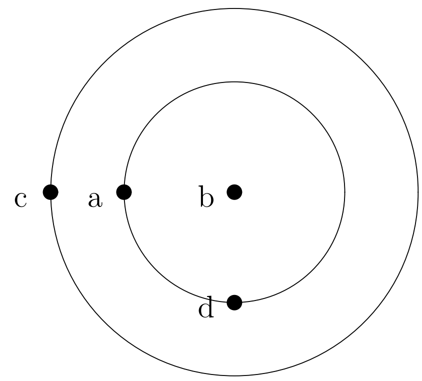


Figure 5.6: Ternary Nearness Relations [112]

similar way to Frank [41], who had devised compositions of distances with specific distance values such as *near* and *far*.

As we will see further on in the discussion, in the presence of additional objects in the scene, humans often reason about proximity using relative distance metrics instead of these binary distance relations. A logic employing comparative, i.e., relative, distances was developed by van Benthem [112].

Logic of Space

Van Benthem [112] suggested, as an extension to his logic of time, a logic of space that uses comparative distances to describe a first order notion of proximity. These comparative distances are represented as ternary relations. For example, using van Benthem's logic, the nearness relation between some of the objects shown in Figure 5.6 can be described as "b is nearer to a than to c" and "b is as near to a as to d." This idea of van Benthem logic of space was taken further by Aiello and Benthem [2] and formally defined in modal logic. Randell et al. [95] employed van Benthem's relative distance to allow for grading of discreteness within the RCC framework, creating RCC$^+$, which can be employed for robot navigation.

None of these approaches go beyond distance as the sole determiner of proximity

Let us now take a look at other factors that can impact on how we perceive spatial proximity.

5.3.2 Factors that influence Spatial Proximity Perception

In the context of GIS, Gahegan [48] conducted psychometric experiments in order to determine what exactly influences the perception of spatial nearness. The objective of Gahegan's [48] experiments was to examine when or how people decide whether objects are near a chosen reference object on a GIS map. The pseudo-metric tests were conducted on a group of 50 subjects, who have all had some practical exposure to Geographic Information Systems. The subjects were asked to rate objects in diagrams representing geographic features on a map, according to how close they were to a given reference object. While Gahegan [48] pointed out that his tests were not necessarily conclusive, he could obtain some interesting results and make several observations that could be helpful in modelling spatial proximity. A first observation is that if a scene is devoid of additional objects, namely if only the reference object and the object to be located inhabit the scene, geometrical reasoning is applied. However, in the presence of other objects of the same type, proximity is partially defined by relative distance. Another observation is that proximity perception is impacted by the scale of the scene, which directly depends on the size of the area being considered.

On the basis of his observations, Gahegan [48] suggested a contextual model of nearness relations in order to account for different influencing factors. Three kinds of metrics are considered in Gahegan's model: an absolute distance metric, a relative distance metric, and a combination of both. Using the absolute distance metric amounts to assuming that proximity is directly proportional to the Euclidean distance between the reference object and the object to be localised. As the scale of the area viewed by the user of a GIS map also seems to have an impact on the perception of proximity, Gahegan [48] further suggested that the bounding boxes of the area in the GIS can be used as scale indicator, the opposite corners of the bounding boxes providing the maximum distance. If the Euclidean distance is now compared with the maximum possible distance in the scene, an actual fuzzy value can be given to the proximity between the two objects. The maximum possible distance is the maximal distance possible in the GIS display in Gahegan's [48] experimental setting. As an example in a more general geographic space setting, consider the maximal distance in a map of a country (showing cities). Here, the maximal distance could be the greatest distance between any two cities in this country. Fuzzy membership functions resulting from Gahegan's work will be examined in more detail in Section 5.6.

In addition to the absolute distance metrics, Gahegan [48] also proposes a treatment of proximity in terms of a relative distant metrics for several reasons. Absolute distance metrics result in continuous proximity with, for example, *very close* > *close* > *far*, but relations such as *closest* or *farthest* cannot be represented. The advantage of absolute distance metrics is that proximity is a fixed relationship between a pair of objects; their proximity is not impacted by the addition or deletion of other objects. Gahegan [48] does however believe that this is counter-intuitive and a more relative approach, considering other objects in a scene as the scene's context, would be more useful.

He proposes an ordinal approach, i.e., a ranking of the objects in the scene with respect to their distance from the reference object in order to represent relative distance. Relative distance representation of proximity could in part also be accomplished by Voronoi Diagrams which Gahegan [49] suggests as tools for an interactive spatial analysis. Voronoi Diagrams are discussed in more detail in Section 5.5.2. Another approach to represent relative distance is the previously discussed logic of space by van Benthem [112] that uses this kind of distance as its basis. Relative distance has been quite extensively used in spatial reasoning, because its comparing nature makes it a convenient mechanism for qualitative spatial reasoning. As previously mentioned, Randell et al. [95] added comparative distance to the Region Connection Calculus to create RCC^{+}. A treatment of binary spatial proximity relations has however not been given a very extensive treatment. The framework of nearness introduced in this thesis addresses this shortcoming.

In addition to the metric factor of proximity, Gahegan [48] also found that a dynamic notion of proximity is required due to the dynamic nature of spatial data. This makes predefined proximity notions, i.e., notions assigned to certain distances, insufficient. The distance, reachability and also the scale factors considered so far are quite objective and measurable parameters. As we will see later, other measures such as the size of objects have an impact on proximity perception. Size was and could not be considered in Gahegan's [48] experimental setting as the objects in his GIS maps were all of the same size. While size can still be measured to some extent, there is also a mainly subjective component to proximity perception. Gahegan [48] calls it the "attractiveness" of objects. As an example he quotes that closeness, for a shop, might be limited to a distance of 1km from a residence, while closeness for a toxic waste dump would extend about 10km away from a residential area. Gahegan [48] argues that while proximity operators are "surrogates for distance measures" factors such as the scale, the "attractiveness" of objects and the reachability need to be considered in some way to model proximity in a cognitively comprehensive way.

5.4 Influence Areas and Spatial Proximity

Kettani and Moulin [69] suggest a grading of closeness in terms of influence areas. In the context of a model to generate natural language route descriptions, considering topology, orientation and distance between objects, the notion of *influence area* is used to assign qualitative distances, each representing a different notion of proximity, to the individual objects in the existing cognitive map. The term influence area was coined by several cognitive psychologists (e.g., Biederman [11]) to describe an area mentally built around objects perceived in the environment.

Kettani and Moulin [69] formally defined these influence areas as a portion of space surrounding an object such that:

- the influence area has an interior and an exterior border,
- the borders of the influence area have the same shape as the object's border.

Further, when an imaginary perpendicular line crosses the influence area from one point on the interior border to another point on the exterior border, the distance between these points is called the width of the influence area. This width is assumed to be a subjective measure of a person's perception and for the implementation of their navigation system, they used simple Euclidean geometry in order to define the width of the influence area and test their model.

Gapp discusses the prepositions *near* and *at* in his 3-D model for representing the semantics of spatial relations. The model performs a scaling between the object to be localised (LO) and the reference object. "The approximation of the LO by its centre of gravity provides an appropriate evaluation if the two [objects] have different sizes ([50], p.1395)." This scaled distance between the two objects, i.e., scaled by their size, indicates if they are more or less near to each other than to any other object considered.

The use of distance as the main determiner for nearness is supported by the results of Gahegan's [48] experiments conducted to identify influencing factors of proximity. While he observed several influences, distance appeared to be the most dominant one. The other factors however cannot be neglected completely, if one wants to arrive at a cognitively useful theory. The concept of Ordinary Voronoi Diagrams and its derivation of Power Diagrams can come to help here. Factors other than distance can to some extent be incorporated into these diagrams by adding specific weights to each site. These weights can reflect different objects, sizes or even the "attractiveness value" of an object as pointed out by Gahegan and Lee [49], an idea that was however not elaborated formally.

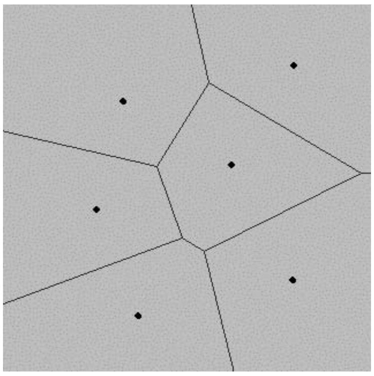


Figure 5.7: Ordinary Voronoi Diagram

5.5 Voronoi Diagrams

Voronoi Diagrams are used to divide a plane of points into Voronoi regions representing all the points closer to the generating point of a particular region than to the generating point of any other region. This principle is often illustrated with what is termed as the post office problem. Given all the post offices in a particular city, a Voronoi Diagram can be generated using the post offices as generating points. If one is now looking for the closest post office to a given query point, it can easily be identified by verifying which post office is the generating point of the region in which the query point is situated. Another example could be a map in which the cities are used as generating points (or sites) while everything else is considered to be the background. The Voronoi region for each city would include all map objects such as roads or smaller settlements other than cities, which are closer to this particular city than to any other city on the map. Objects being as close to one city as to another[5] form the boundary between the Voronoi regions of these cities. Van Benthem's logic of space [112], as previously discussed in Section 5.3.1, very much follows this principle of ternary nearness relations, e.g. by stating that one object is as near to a second as it is to a third object. Power Diagrams add another dimension

[5]This represents a particular ternary nearness relation.

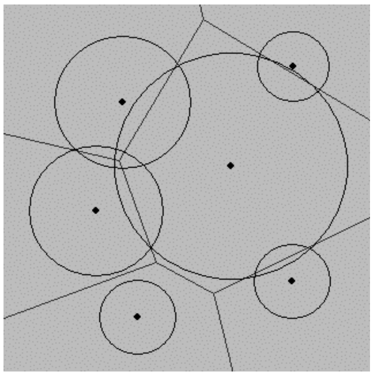


Figure 5.8: Power Diagram

to Voronoi Diagrams by introducing weights to every site, thus defining the area of influence of every site spreading out from the generating point. This can be illustrated by an example. Given several schools in a particular district, an Ordinary Voronoi Diagram can be used to indicate which residential areas are closer to which school. This is shown in Figure 5.7. A school can also have a certain catchment area which might not coincide with its (Ordinary) Voronoi region, e.g., because the school might have a large capacity. Power Diagrams do therefore not only add the areas of influence, i.e., catchment areas in the case of the schools, but they also adjust the Voronoi Edges according to the weight of every site. Therefore, a school with a larger catchment area will also have a larger Voronoi region. Figure 5.8 shows the previous Voronoi Diagram after the weights, represented by circles in the figure, have been added.[6] Let us look at both kinds of diagrams in more detail to explore their capabilities.

5.5.1 Ordinary Voronoi Diagrams

Ordinary Voronoi Diagrams are the special and simpler case of Generalised Voronoi Diagrams (or Power Diagrams). Ordinary Voronoi Diagrams are defined as follows.

[6] Both diagrams were generated using Brendan Lane's Computational Geometry applet http://pages.cpsc.ucalgary.ca/~laneb/Power/index.html.

Choosing a canonical set S of distinct points in the plane (commonly called sites), regions are assigned to every site p by assigning every point to p's region that is not further from p than from any other site q. Regions that share a boundary or edge (i.e., the points of that boundary have the same distance from p and q) are called spatial neighbours. The resulting plane divided into regions as indicated is called a Voronoi diagram. Voronoi diagrams provide very useful tools by transforming distances into a network of topological relations, and by defining neighbours based on relative proximity [31].

Mathematically, a Voronoi region in an Ordinary Voronoi Diagram can be described as:

$$vo(p) = \{x \in \mathbb{R}^2 \mid D(x,p) \leq D(x,q)\ \forall q \in S\}$$

The Voronoi Diagram described above is often also referred to as an Ordinary Voronoi Diagram (OVD).

Voronoi Diagrams have been used in spatial reasoning applications such as Voronoi robots by Choset and Nagatani [18]. In their implementation, Voronoi robots move along Voronoi diagrams that are associated with the spatial environment. Remolina [97] partially uses the concepts of Voronoi robots in the context of the control level of the Semantic Spatial Hierarchy (SSH), see Figure 2.2, in order to keep the robot equidistant from a reference wall. He does however find that the Voronoi approach fails in certain situations. This is not only because even small changes in the spatial constellation can greatly change the Voronoi diagram, and its frequent updating can be computationally very expensive. But Voronoi robots do also work on the assumption that the robot perceives at least two nearby objects in addition to the wall, which cannot always be guaranteed. For the case where the Voronoi approach fails, Remolina employs the control laws of the Semantic Spatial Hierarchy [73] to keep the robot at a uniform distance from the wall. Within the Spatial Semantic Hierarchy, distance is represented by closed intervals of real positive numbers, thus assuming that the spatial information obtained by the navigating robot through its sensory input is always more or less correct.

Edwards and Moulin's [31] suggest a Voronoi model to represent linguistic spatial information. In terms of spatial proximity, the preposition *near*, for example, is interpreted as an n-ary relation (with $n \geq 3$) meaning "nearer than the surrounding points."

The choice of linguistic symbols in many of the spatial reasoning approaches to representing spatial proximity imply distance as the sole determiner, which is not always sufficient. Power Diagrams provide for an incorporation of weights without losing the relative distance information of the Voronoi regions.

5.5.2 Power Diagrams and their Treatment of Nearness

In computational geometry, the notion of nearness is dealt with in an extended way by weighted Voronoi Diagrams where, in a point-based plane, the area of influence of some distinct points or centres stretches out some distance proportional to the weight of the generator points. All points that are covered by the influence of a generator point can be considered to have some nearness relation to this generator point. There might also be points in the plane that do not fall within any of these weighted regions. Ordinary Voronoi Diagrams, as discussed in the previous section, assume that all generator points have the same weight and a Voronoi Region for each of these points is defined, thereby ensuring that every point in the plane falls into the region of one of those centres, i.e., generator points. Power Diagrams combine both types of information. The Voronoi Region notion is very useful in many contexts, because it represents relative distance information. Power Diagrams, by providing a combination, also have potential. The weight of sites in Power Diagrams can be used to represent the factors influencing spatial proximity. It is a generic measure, leaving room for application-dependent factors influencing the perception of nearness. This does require quantitative measures which might not be available for all of the influencing factors. Coming back to Gahegan's [48] example of residential areas, a set of shops might have a very small influence[7] due to its functionality implying *the closer the better*, but a toxic waste dump would have a very big influence[8] due to its potential negative effects on its surroundings, implying *the further away the better*.

Aurenhammer [7] approaches the problem of site weighting by replacing the distance D by $D^2(x,p) - \omega(p)$ with $\omega(p)$ being the weight of p. Note that the above formula is not very well defined, because it also accounts for $D(p,x)$ which would require $\omega(x)$, which in this context is not necessarily available because x is not necessarily a site. When weights are incorporated, the boundaries of a pair of neighbouring sites are shifted depending on the weights of the two sites, without disconnecting any regions that had previously been connected by a Voronoi Edge. It should be noted that connection also includes overlapping and inclusion, e.g., two sites could end up in the same region.

5.5.3 Voronoi Tesselation in Conceptual Spaces

Another interesting approach of Voronoi Tesselation that uses the notion of influence is its application to conceptual spaces. Gärdenfors and Williams [51] suggested the usage of RCC relations and Voronoi Tessellation in conceptual spaces where the influence areas represent the prototype of a category (or concept) and the Voronoi regions represent all the members of the category, including the prototype. RCC relations are used to determine the prototypicality of a member with respect to the category. Members that are inside the prototype's influence area are considered to be better representations of the category than members that are outside the influence area but clearly within the category's Voronoi region. Members that are outside the prototype's influence area and inhabit the Voronoi edge between two categories are considered the worst members of this category. Their suggestion of

[7] i.e., small weight

[8] i.e., very big weight

using both the Voronoi Edges and the weighted site information to reason about the nearness of concepts is very interesting, because it considers both the relative and the absolute distance between concepts. However, it remains unclear how the concepts are actually placed into the metric space, which is a necessity for generating the Voronoi Diagrams.

Each of these approaches has its merits, and both Voronoi Diagrams and Gapp's field theory do attempt to incorporate more than just simple distance measures into their proximity evaluation. But even then, they do not overcome common issues of influence areas such as not taking the nature of objects or the context in which they take places into account in a suitable way. I therefore considered employing fuzzy logic to go beyond these limitations. Various membership functions that had previously been suggested in the literature were examined for their suitability in practical applications.

5.6 Fuzzy Membership Functions to Define Spatial Proximity

Formalising nearness has been the subject of extensive work, resulting in many fuzzy membership functions based on absolute distance metrics, relative distance metrics, and combinations of those. The possible strengths and weaknesses of these functions have been discussed and argued at length, but strangely enough, no experiment seems to have been conducted to assess the merits and shortcomings of competing approaches. Together with Eric Martin, I published a paper [16] about conducting such experiments which not only provided an objective evaluation of the various measures that have been proposed, but also suggested some new measures that outperform all those being analysed. I will provide a brief revision of the work here, to underline the possible usefulness of fuzzy membership functions to represent spatial proximity notions. We [16] proposed and evaluated fuzzy membership functions suitable to implement the notion of spatial proximity, generally represented by linguistic terms such as *near* or *close*, within Geographic Information Systems (GIS). Our studies were conducted to evaluate proximity membership functions against a data set of a distance network and predefined nearness information.

In a similar line with Gahegan [48], Worboys [122] did some interesting studies on the qualitative location of cities and the relative distances between them. He used the road distances between 48 cities in Great Britain, which he called objective distances, and determined their relative distances to each other by first calculating for each centre the mean of the distances to all of the remaining 47 centres. The relative distance between a centre a and a centre b is then determined by dividing the objective distance between a and b by a's mean. This notion of relative distance is actually asymmetric; indeed this method will most likely produce a different relative distance between a and b than between b and a. The relative distance can then be used in calculating fuzzy nearness values using the following definition:

$$nearness(x, y) = (relative\_distance(x, y) + 1)^{-1}$$

Places having high nearness values are therefore very close and low ones are not close. As the greatest nearness is present between a place with itself, the nearness value would be 1. In order to define neighbourhood, Worboys [122] redefines his map space as a topological space where every centre a has a topological neighbourhood which includes every other centre whose nearness to a is above a given threshold or which is near another centre that is also near to a by the same threshold.

Gahegan suggests combining both of his distance metrics approaches, the absolute and the relative one. As both metrics are fuzzy representations, he first defines the membership function for sets of both absolute and relative proximity, and then combines them with the fuzzy union operator. This results in an object being considered *close* if it is geometrically *or* relatively close. The use of fuzzy membership functions had previously been suggested by Dutta [30]. An example mapping from Dutta's results to linguistic variables was suggested by Gahegan in order to illustrate the approach for his own setting. In the example, mapping 0.0 to 0.1 is *very far*, 0.1 to 0.3 is *far*, 0.7 to 0.9 is *near* and 0.9 to 1.0 is *very near*. In a similar fashion, the combined relative and absolute distance membership functions can be mapped to linguistic variables.

Several fuzzy approaches have been devised to represent spatial proximity based on distance. Gahegan's [48] model has already been discussed in Section 5.3.2. Prior to Gahegan, Dutta ([29, 30]) developed a framework to represent approximate spatio-temporal knowledge using fuzzy logic. This framework could then be used to answer queries about relative positions and motion in relation to objects in spatial databases.

Motivated by Gahegan's work, Guesgen and Albrecht [57] suggest to associate spatial binary relations such as *far from* or *close to*; or unary relations such as *downtown* with fuzzy membership grades, which could be calculated for locations in a map using Euclidean distance. Guesgen [58] proposed to define proximity without any distance measure by using the notion of fuzzy sets previously defined in Guesgen and Albrecht [57]. These fuzzy sets were used to reason about the relationship between proximity notions by means of transitive inference on ternary proximity relations such as "If B is closer to A than C is to A, and if C is closer to A than D is to A, then B is closer to A than D is to A."

Robinson [99] shows how human-machine interaction, the machine generating questions and the user answering with yes/no, can be used to acquire fuzzy membership relations for ill-defined spatial relations such as *near* or *far*. This way, the user's subjective knowledge of these relations is explicitly incorporated in the membership functions for specified spatial relations with respect to a particular databases. In contrast to the ILP machine learning approach to learning new spatial relations presented by Nicoletti and Brennan [86] and the approach of Olssen and Powers [87] of evolutionary learning, Robinson's approach does not learn new spatial relations; the spatial relations are already defined and their range is specified by acquiring a membership function.

Similarly to Gahegan [48], but not exclusively, we used the maximal distance between objects on the map of a country or state. This enabled proximity evaluations across several GIS maps if needed. The maximal distance was the largest distance between any two places in the country or state being considered. Absolute distance metrics result in continuous proximity with, for example, *very close* > *close* > *far*, but relations such as *closest* or *farthest* cannot be represented. For this and other reasons, Gahegan [48] proposed to treat proximity in terms of a relative distant metrics, in addition to the absolute distance metrics. More precisely, he suggested an ordinal approach to represent relative distance, by ranking the objects in the scene with respect to their distance to the reference object and the total number of objects. He pointed out that this approach could cause objects to be considered close to a given reference object A, even though such objects might be separated from A by a large distance. As the objects are ranked on the basis of their distance to A, this approach seems to be more absolute than relative in nature. Worboys [122] dealt with this problem in a more efficient way by calculating for each place the mean distance to all other places in the scene.

Gahegan [48] suggested to combine both the absolute and the relative distance. As both metrics offer fuzzy representations, he defined the membership function for absolute distance metrics and assumed a distribution function for nearness based on relative distance, and then combined these functions with the fuzzy union operator. This resulted in an object being considered *close* just in case it is geometrically OR relatively close.

Motivated by Gahegan's work, Guesgen and Albrecht [57] suggested, as previously mentioned, fuzzy membership grades to be associated spatial proximity relations. These grades were calculated from the Euclidean distance between objects on a map. However, they did not test their suggestions against any data and did not provide any membership function for relative distance metrics. Guesgen's [58] further proposal to define proximity without any measure of distance based on these previously defined fuzzy sets has similar issues.

There is no experimental data to give evidence that Gahegan's [48] or Guesgen and Albrecht's [57] fuzyy membership functions can be of practical use. None of their approaches bases fuzzy membership functions on truly relative distances. We therefore found it essential to evaluate Gahegan's [48] absolute distance metrics and Worboys' [122] relative distance metrics before considering whether and how to combine them using fuzzy logic operators. Worboys [122] did some interesting studies on the qualitative location of cities and the relative distances between them. His definition of relative distance is not based on the comparative concept without Euclidean distance, but it does nonetheless incorporate the context of all places under consideration. He used the road distances between 48 cities in Great Britain, which he called objective distances, and determined their relative distances to each other by first calculating for each centre the mean of the distances to all remaining centres. The relative distance between a centre A and a centre B was then determined by dividing the objective distance between A and B by A's mean. This notion of relative distance is actually asymmetric: this method will most likely produce a different relative distance between A and B than between B and A. The relative distance can then be used to calculate fuzzy nearness values using the following definition: $nearness(x, y) = (relative\_distance(x, y) + 1)^{-1}$.

Places having high nearness values are therefore very close and low ones are not close. The greatest nearness is between a place and itself, with a value of 1. This approach does not suffer from the same restriction as Gahegan's approach. The objects do not need to be fairly evenly distributed. In his more recent work on environmental space, Worboys [123] used the number of subjects and the number of *yes* or *no* votes to calculate fuzzy membership values for nearness. This is a very interesting approach given his experimental data. However it is not practically applicable to do such a kind of data collection for every geographic area that GIS-users

Absolute Distance Metrics:	$\mu_{abs}(A,B) = 1 - \frac{Dist(A,B)}{Max}$
Relative Distance Metrics:	$\mu_{rel}(A,B) = \frac{1}{(reldis(A,B)+1)}$
Fuzzy Union:	$\mu_{comb\_u}(A,B) = \mathrm{MAX}(\mu_{abs}(A,B), \mu_{rel}(A,B))$
Fuzzy Intersection:	$\mu_{comb\_i}(A,B) = \mathrm{MIN}(\mu_{abs}(A,B), \mu_{rel}(A,B))$

Table 5.1: Fuzzy Membership Functions

might need to work with.

A serious shortcoming of all the approaches that have been described is that none of them does actually evaluate the membership functions against any real data, in order to see how useful these functions are.

5.6.1 Various Distance metrics

As previously mentioned, in order to address all of the observations that Gahegan [48] made in the context of GIS users perceiving proximity, we evaluated several spatial proximity functions based on absolute distance, relative distance, and combinations of both. Table 5.1 shows the fuzzy membership functions we evaluated in terms of their usefulness within GIS settings.

The fuzzy membership function based on absolute distance metrics is a derivation of Gahegan's [48] function with the maximum value Max being the maximum distance between all of the places in our data set; and $Dist$ being the distance between places A and B. For the fuzzy membership function based on relative distance metrics, we borrowed Worboy's [122] membership function, as we found that Gahegan's ordinal ranking approach is insufficient. Relative distance is calculated using the mean of each place A in the data set, calculated from the n places OP_i, $1 \leq i \leq n$, distinct from A and available in the set: $mean(A) = \frac{1}{n}\Sigma_{i=1}^{n} Dist(A, OP_i)$. The result of this is then used to calculate the relative distance between each two places: $reldis(A,B) = Dist(A,B) * mean(A)^{-1}$. While Gahegan [48] only suggested to combine the membership functions based on absolute and relative distance by applying the fuzzy union, we also investigated the application of the fuzzy intersection operator, which yielded interesting results. The fuzzy union operator will by definition always return the maximum membership function value for each data entry. While the fuzzy intersection operator will by definition always return the minimum membership function value for each data entry. We applied these functions to a data set of 34 places in the Australian state of New South Wales and the distances between them[9]. For each of the given places, we defined the tourist region, the region and the regional area they are located in. For Sydney, a list of regions that are easily accessible for short trips is also supplied, thereby giving some indication of what is perceived and generally accepted as near to Sydney. This data set was collected from the *Tourism New South Wales* site[10]. We were able to use this information to evaluate our membership functions to see how well they suit the data and "nearness" information for the given places.

The membership function based on absolute distance as illustrated in the left graph in Figure 5.9 shows a linear distribution, as expected from the function used. The maximum distance in the dataset is 1710 km. However, the relative membership function as illustrated in the right graph in Figure 5.9 shows quite a varied distribution, which is very different to Gahegan's more or less linear proposal of ordinal ranking. The issue arising from his kind of approach, that objects could possibly still be considered close to one another even when they are separated by a very large distance, is not a problem for the membership function we used, because ours is a function of the distance between the two places being considered.

The two combined membership functions give quite interesting results. On one hand they do support Gahegan's [48] suggestion that absolute measures are more appropriate for non-clustered objects, and relative measures for objects within clusters of same "kinded" objects. On the other hand, the results do contradict Gahegan's

[9] as given by "The Official Road Directory of New South Wales" by the Land Information Centre in Bathurst, The New South Wales Government

[10] www.visitnsw.com.au

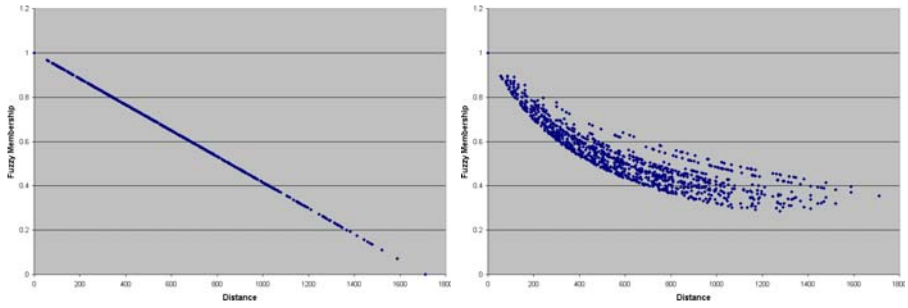


Figure 5.9: Fuzzy Distribution Functions for Absolute and Relative Distance Metrics

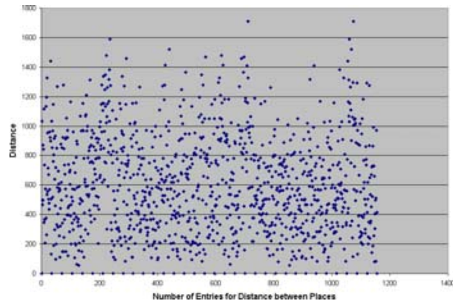


Figure 5.10: Distance Distribution in the Data Set

suggestion to use the union fuzzy operator for an efficient combined function. Indeed, when combining absolute and relative distance metrics functions by union we do get a linear distribution for distances until about 800km, where it changes into a more clustered distribution (see left graph in Figure 5.11).

This is even contradicting Gahegan's own terms that absolute distance metrics, i.e., linear distributions in his case, are more suited for proximity assignments between objects that are located in virtually devoid areas. Figure 5.10 shows that the greater the distances between the places, the fewer places are within the area; this can be explained by the fairly isolated character of the Australian non-metropolitan areas. In order to comply with Gahegan's suggestion to use absolute distance metrics for only lightly and relative distance metrics for heavily populated areas, the membership function distribution should be the reverse of the result we obtained for the combined function using the fuzzy union operator.

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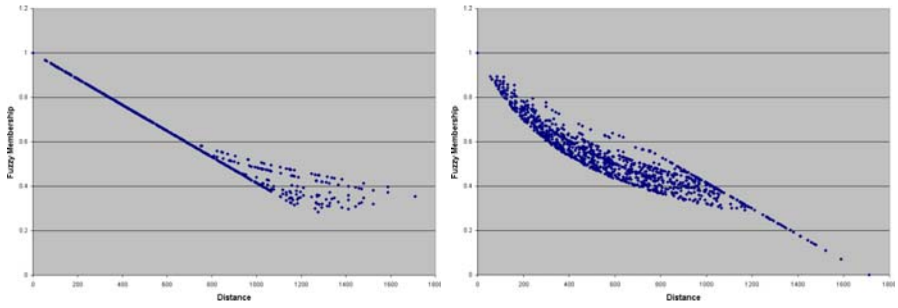


Figure 5.11: Combined Fuzzy Distribution Functions using Union and Intersection Operator

the Australian non-metropolitan areas. In order to comply with Gahegan's suggestion to use absolute distance metrics for only lightly and relative distance metrics for heavily populated areas, the membership function distribution should be the reverse of the result we obtained for the combined function using the fuzzy union operator.

When we applied the fuzzy intersection operator to our data set, we attained precisely such a distribution. The fuzzy intersection changes from a clustered to a linear distribution between 1000 and 1200 km. The right graph in Figure 5.11 shows this clearly. The clustered distribution is more appropriate for smaller distances when there are more places within a smaller area, and the linear distribution will suit areas with fewer objects, which are to be found at greater distances in the given data set. This is perfectly consistent with Gahegan's [48] observations, although it is a different combination operator that gives the desired result.

We evaluated our membership distribution function values against the proximity information, namely *Sydney Surrounds* and regions, to appraise the usefulness of the functions and their combinations in the context of reachability within a road network. For all the places that are within regions which are generally accepted to be in the Sydney surrounding area, all membership function values were not only well above the usual crossover point of 0.5, but also above 0.7. We tested the distances between all places in our dataset that are in the same region using this value as the crossover point. As geographic regions are generally defined with the perception of "everything" within a region being close to "everything" within this region. Out of 94 matches, 14 had two membership values that were below 0.7. These membership values were always the result of the membership function based on relative distance metrics and the combined function that returned the former one. When the threshold was lowered to the normal crossover point (0.5), all matches complied. This is a good indication that the investigated membership functions are useful in the context of a road distance network and the associated reachability of the places within it. Incorporating them into an existing GIS in order to allow for "near" queries could be quite useful. However, these functions are still based on purely spatial measures, any non-spatial factors cannot be incorporated within this fuzzy membership function approach. This is why we will now return from our little excursion into fuzzy logic, to a model of spatial proximity that will incorporiate these findings where necessary or suitable, but leave enough space to address any further factors as well.

When placing both Gahegan's and Worboys' models into the cognitive geographic data model of the previous section, it becomes quite clear that their approaches are based on perceptual processing only. Higher-level concepts are not utilised in their models. The distances that are used are perceptual; and also the relative distance, which is comparative, does not go beyond this level. While Gahegan introduces the notion of "attractiveness" of an object, he does not bring forward any suggestions on how to practically incorporate such a factor into his model. Spatial proximity, particularly in GIS proximity analysis planning as conducted by the GIS user, is largely the result of a cognitive process. Therefore, for a comprehensive evaluation of proximity, the cognitive phase should not be ignored, as it essentially is in these two approaches. Nevertheless, the findings of Gahegan's psycho-metric tests with respect to factors that influence spatial proximity perception are also interesting to a model that seeks to include higher-level concepts. The following chapter will explore a more comprehensive cognitively motivated data model of spatial proximity.

Chapter 6

A Nearness Framework based on Impact Areas

In the previous chapter, I introduced the concept of impact area and a generalised notion of nearness. Let us now place this into the context of spatial proximity queries on GIS data. In the quest for a more intuitive user interaction with the data, I would like to enable qualitative queries such *Is place A near place B?* Considering that we still need a means to do calculations to incorporate quantitative measures that do impact on nearness evaluations, how can such qualitative queries be instantiated? I propose as one solution to this problem a nearness framework that incorporates the previously suggested notions of impact area and generalised nearness into a model of topological space. This allows both qualitative functionality and the option of imposing metrics to perform necessary calculations. In GIS proximity analysis, the use of topological relations is restricted to connectivity-based ones. These relations offer a very efficient way of representing many spatial relations qualitatively, as demonstrated in calculi such as the Region Connection Calculus [93]. However, as Kuipers [73] points out, a metric is needed to represent certain aspects of spatial knowledge. Nearness, for example, cannot be accounted for solely by connectivity-based topological relations. Given two objects that are topologically separated, it is very likely that there will be another pair of objects that are topologically separated but that satisfy the same spatial proximity relations as the former pair. Depending on several factors including the actual distance between them, some of these objects might be considered near to each other while others might be considered far. This distinction cannot be achieved by discreteness alone. Grading of discreteness is therefore necessary and this makes some distance measure an essential part of the equation. However, what interpretation of topological space would be a sufficient representation for spatial nearness? Let us look at some metrics and generalisations thereof, before we place them into the context of GIS data.

We all have a concept of distance, which is generally the metric notion. There are however situations in which this concept is not general enough, as we will discuss later in this chapter. I argue for the notion of quasi-pseudometric space as the most general interpretation of topological space into which the framework of nearness is situated.

Definition 1 (Quasi-pseudometric Space) *We define a quasi-pseudometric space to be a pair* (S, D) *where* S *is a set of points and* D*, the quasi-pseudo distance, is a function from* $S \times S$ *into the set of real numbers, with the following properties:*

(P1) $\forall x, y \in S,\ D(x, y) \geq 0$

(P2) $\forall x \in S,\ D(x, x) = 0$

(P3) $\forall x, y, z \in S,\ D(x, z) \leq D(x, y) + D(y, z)$

There are two specialisations of quasi-pseudometric space, each of which adds an additional constraint.

Definition 2 (Pseudo-metric Space) *We define a pseudo-metric space to be a quasi-pseudometric space* (S, D) *with the additional property:*

(P4) $\forall x, y \in S,\ D(x, y) = D(y, x)$

Definition 3 (Quasi-metric Space) *We define a quasi-metric space to be a quasi-pseudometric space* (S, D) *with the additional property:*

(P5) $\forall x, y \in S$, *if* $D(x, y) = 0$ *then* $x = y$

If pseudo-metric space and quasi-metric space are combined, i.e., if we add properties $(P4)$ and $(P5)$ to the quasi-pseudometric space, we arrive at the common metric space interpretation of topological space.

Definition 4 (Metric Space) *A metric space is a quasi-pseudometric space which is both pseudo-metric and quasi-metric.*

Figure 6.1 illustrates the relationship between these spaces. Once we constrain quasi-pseudometric distances to symmetric distance, we have a pseudo-metric space. If we constrain them to distances for which two points are always the same if the distance between them is zero, we have a quasi-metric space. Adding both constraints to quasi-pseudometric distances leaves us with metric spaces.

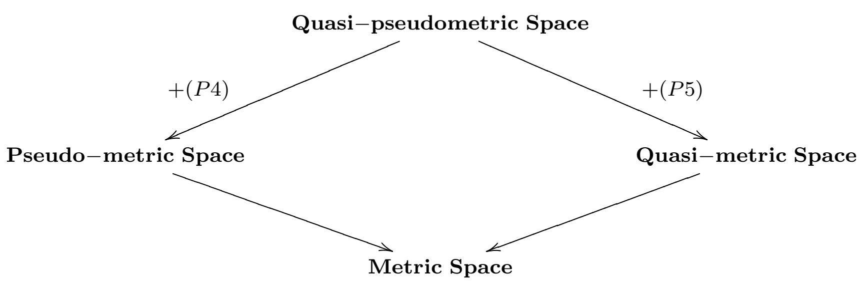


Figure 6.1: Quasi-pseudometric space and its specialisations of pseudo- and quasi-metric spaces, specialising in metric space

How could this be instantiated on the basis of GIS data? Let me first provide an alternative representation for the relationships between Definitions 1-4, that we can then easily populate with concrete GIS data. Figure 6.2 shows a quadrant structure of quasi-pseudometric, quasi-metric, pseudo-metric and metric spaces and their relationships.

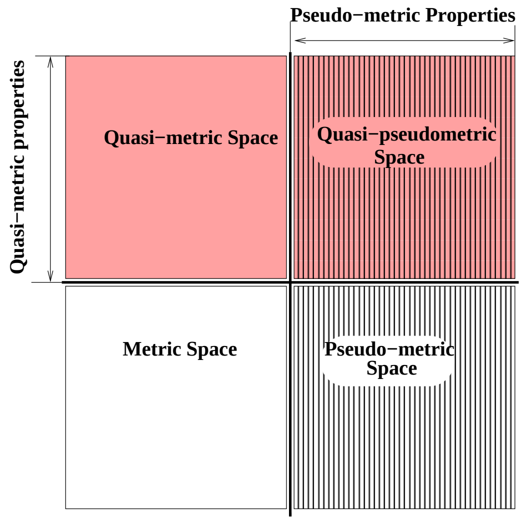
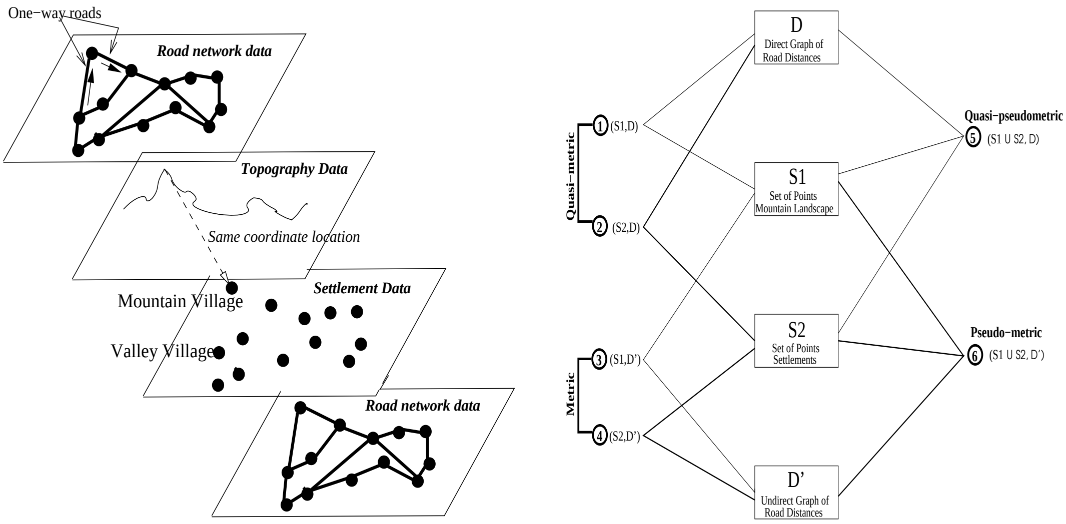


Figure 6.2: Quadrant-structure of quasi-pseudometric spaces and its specialisations

Let us now place GIS data into this quadrant structure, Figure 6.3(a) shows an example. A mountain village located on the mountain peak, both point objects, are located at the same coordinate point. The roads leading to and from the mountain peak down to the first village in the valley are one way roads resulting in different distances between the two places depending on the direction of travel. Figure 6.3(a) shows four different sets of data:

- One road network data set that has been generated for all the roads between settlements as represented by their coordinate location, taking into account one way roads. This data set can be abstracted into a directed graph of distances referred to as D for asymmetric distance.
- One topography data set of points representing the mountain landscape referred to as $S1$.
- One settlement data set of points representing all the settlements of the area referred to as $S2$.
- One road network data set that has been generated for all the roads between

settlements as represented by their coordinate location, without taking into account one way roads. This data set can be abstracted into a non-directed graph of distances referred to as D' for asymmetric distance.



(a) Example for Data

(b) Abstracted

Figure 6.3: Examples for quasi-pseudometric, quasi-metric and pseudo-metric space interpretations of GIS data

Figure 6.3(b) shows sets of points and distances corresponding to each of the data layers and the possible topological spaces for each of the possible combinations. For the pairs $(S1, D)$ and $(S2, D)$ we model a quasi-metric space due to the inclusion of one-way roads. Pairs $(S1, D')$ and $(S2, D')$ represent metric spaces. Once we include both $S1$ and $S2$ into one space, we will have pseudo-metric properties due to the mountain peak and mountain village occupying the same coordinate location. When we look at the union of $S1$ and $S2$, in combination with D we get a quasi-pseudometric space and in combination with D' we get a pseudo-metric space.

Occurrence of pseudo-metrics in geographic data is due to the two-dimensional projection of three-dimensional physical space. In map making this often needs to be adjusted by generalisation, which refers to the dislocation of one of the pseudo-distant objects to allow for a distinct representation on the map. Asymmetric distance as modelled by quasi-metrics however is relatively common in both two- and three-dimensional spaces. Let us therefore take a look at a more everyday situation naturally modelled by quasi-metrics to emphasise this important concept of asymmetric distance. We will find that non-symmetric distance occurs frequently in common physical space, in particular when the distance of the path taken from one point to another is considered instead of Euclidean distance. Figure 6.4 illustrates an example of this showing a railway station with a turnstile at one of its ends. In order to get from B to A, we will have to proceed through the exit of the station and cover a far greater distance than was needed to get from A to B. This results in a quasi-metric interpretation. Berendt [9] differentiates Euclidean distance from route distance when considering the properties of subjective distance, which is distance as it is perceived and memorised by humans. Distance can thus be divided into straight-line distance and distances along the route or path. While the former exhibits the same symmetric properties as metric distance described by ($P4$), the latter would require an additional restriction to this property such that: $\forall x, y \in \mathcal{U}$, $D(x, y) = D(y, x)$ iff $path(x, y) = path(y, x)$. In addition to the path distance, Egenhofer and Mark [32] argue that in the context of naive geographic space, distance is often also seen as a measure of other units such as the time it takes to get from A to B [70], road tolls that have to be paid or petrol consumption. Golledge [54] found that even when the same path is travelled in the opposite direction, the distance perceived might be different for each direction. This difference might result from the terrain of the path (e.g., uphill versus downhill), which can influence the speed of travel or the travel time, for example during rush hour.

The data set used in the experiments reported in Chapter 8 does not require any of these special distance interpretations. However, as we have amply demonstrated, they are very useful concepts in the processing of geographic data. This is why I will base the following spatial proximity framework on quasipseudo-metric space.

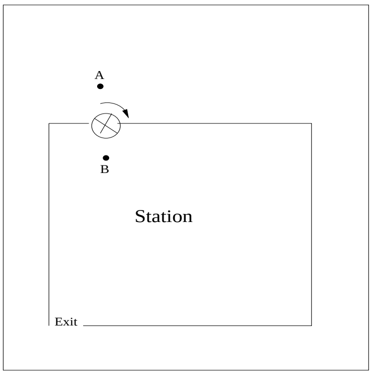


Figure 6.4: Asymmetric Distance Example - Turnstile at a Station

6.1 A Spatial Proximity Framework

As we have already learnt, the notion of nearness is influenced by many factors, distance being only one of them. The concept of Impact Area will take care of this in the framework proposed. Once we have defined the Impact Areas of the two query points or objects, the relations between their Impact Areas can be used to determine the nearness between them. For the purpose of this evaluation, the framework proposed here draws upon and adapts features of the theory of proximity spaces as discussed in the following subsection. This theory is based on sets and their proximity relationships to each other. For a detailed discussion on the mathematical implications of applying proximity space properties to region-based theories of space, see Varkarelov et al. [111]. In the following subsection, we fix a pseudo-metric space (S, D). The reason using it and not any of the other three spaces that we talked about before, will become clear in due course.

6.1.1 Proximity Spaces

As seen in Section 2.5, the concept of point adherence to an arbitrary set is one of the most important concepts in general topology. Proximity spaces deal with the notion of nearness in a very formal way, accounting for its pure mathematics origin.

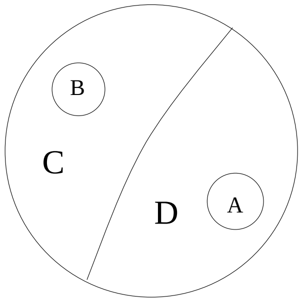


Figure 6.5: An Example of Property 4: For any two sets A and B which are far from each other there exist sets C and D, $C \cup D = P$, such that A is far from C and B is far from D.

In this theory, which was developed in the 1950s (e.g., Smirnov [108], Naimpally and Warrack [85]), the notion of nearness is defined between points or sets in a topological space. Proximity spaces thoroughly consider the implications of proximity to topological and uniform spaces. The original proximity spaces theory does assume pseudo-metrics, and not all of its properties do also apply to a quasi-pseudometric interpretation of topological space. Let us look at the properties of a proximity space.

Given two sets A and B in $\mathcal{U}$, we say that A is near B iff $D(A, B)$, which is defined as $\inf\{D(a, b) : a \in A, b \in B\}$, is equal to zero. Hence two sets are close if they share a closure point. Moreover, identifying a point p with $\{p\}$, a point and a set are near iff the point belongs to the closure of the set. Extending the above, we can say that a set P is called a proximity space if for any two of its subsets, closeness can be evaluated by the following properties:

1. If set A is close to B, then B is close to A.
2. The union of the sets A and B is close to C iff at least one of the sets A or B is close to C.
3. Each point x in P is close to itself.

4. For any two sets A and B which are far from each other there exist sets C and D, $C \cup D = P$, such that A is far from C and B is far from D.

We can see that Property 1 cannot be guaranteed by quasi-pseudometric spaces, as it does require a symmetric distance. This justifies why we consider pseudo-metric spaces in this subsection. For an example of Property 4, see Figure 6.5. In addition to these properties, a partial order can be imposed on proximities. If $near_1$ and $near_2$ are two proximities on P, then $near_1 > near_2$ iff $A\ near_1\ B$ implies $A\ near_2\ B$.

Proximity spaces have been used in settings such as digital imaging, where Pták and Kropatsch [90] claim that the concept of "nearness" finds one of its rigorous forms in the notion of proximity spaces. In addition, they also believe that the axioms of proximity spaces, as shown above, reflect the same properties that can be observed when common-sense nearness is considered. While Pták and Kropatsch did not elaborate on this point, I will be employing and adapting the basic properties of proximity spaces in the cognitive nearness framework proposed here. This does include their partial ordering property.

6.1.2 Foundations of a Nearness Framework

While for most applications a metric interpretation will be sufficient, the generation of impact areas will sometimes need to take quasi- or pseudo-metric properties into consideration. We have seen some examples for this in the previous discussion. I therefore place the framework into a quasi-pseudometric space[1] As we have seen in previous chapters, a point-based representation of geographic features is a common approach in GIS data models. GIS vector data are the result of an abstraction process creating a point-based universe representing physical space and the objects it contains as points or sets of points. I will refer to this universe as the universe of discourse.

[1] For the interested reader, quasi-pseudometric spaces are discussed in more detail by Moshokoa [80].

Notation 5 (Universe) *We denote by $\mathcal{U}$ a quasipseudo-metric space.*

In GIS data, we have geographic objects whose spatial component is represented by either a point, line or polygon. Each spatial object is therefore a set of points.

Notation 6 (Objects) *We denote by objects($\mathcal{U}$) the collection of objects in the universe $\mathcal{U}$.*

The points belonging to an object are distinct from other points in the space, as they have through the object additional information associated with them, e.g., information about a city such as its name and size. In the context of GIS data, I refer to any point that represents or is part of the spatial object of a feature as a site. Recall that spatial objects can be points, lines (sets of points) or polygons (sets of lines). While polygons are used to represent features covering areas, their spatial representation is still the set of lines or polygon which enclose(s) the area. We do therefore only need to consider the polygonal object itself when generating the impact area for such a feature. Let me explain with an example. In order to identify the impact area of a toxic waste dump, we need to consider the spread of toxins through the surrounding soil, i.e., penetration throughout the area outside the waste dump. Therefore, it would be sufficient to calculate the toxin spread from the boundaries of the waste dump. These boundaries are represented by the waste dump's spatial object, the polygon. Figure 6.6 shows the site-based projection from spatial objects into impact areas.

Notation 7 (Sites) *We denote $\bigcup object(\mathcal{U})$ by $sites(\mathcal{U})$.*

6.2 Impact Areas and Context

We assume one reference object consisting of one or more points as previously defined. Within a certain context, the impact area is generated from each of these

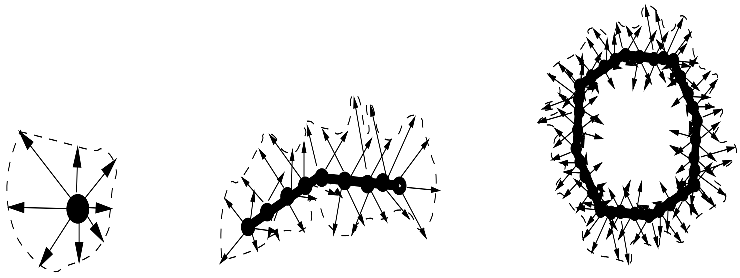


Figure 6.6: Impact areas are calculated by a projection from each site contained in the spatial object of a feature

points. Context represents an expert user, i.e., an expert in context field, or information from the context field as collated by experts and from previous experience. This approach has the advantage that simple queries such as *near(A,B)* can be asked using natural language expressions with no further quantitative input. This assumes that all relevant factors have already been incorporated into the impact area(s). Of course, the question remains how exactly such a context should be defined. I suggest to approach this by asking the following questions:

1. What is the purpose of this investigation?

2. What is the relevant domain, which domain-specific properties need to be identified and what could possible values for these properties be?

The notion of context is meant to be very generic and it is not desirable to impose substantial constraints. We need to understand the domain, its key properties and the values these can take for being able to answer a proximity query. The values of the key properties can take any form such as symbolic, linguistic or numeric. This is why we assume that any possible context can be identified with a set of pairs of the form $(property, value)$. What follows is therefore not a genuine mathematical formalisation, but a way to refer to context easily in the further expositions.

Notation 8 (Context) *We denote by context a parameter which represents a set whose members intuitively capture the values of the domain specific key properties of the proximity query for a particular object.*

The following examples illustrate concretely the various forms that the context can take.

6.2.1 Context - Touristic Road Travel

In the context of touristic road travel, we could answer our seed questions as follows:

1. *What is the purpose of this investigation?*
    - Find the best route for touristic road travel.
    - Identify which places of interest are near other, already fixed, places in a particular trip to decide which places to visit.
2. *What is the relevant domain, which domain specific properties need to be considered and what could possible values for these properties be?*
    - Domain: Road Travel
    - Domain specific properties and possible values:
        - tourist information: e.g. suggested driving tours
        - road network geodata: e.g. places in the road network, road distances between places

6.2.2 Context - Radio Tower Emissions

In the previous chapter, I introduced an example of radio towers whose impact area was determined by the range of the towers and the surrounding terrain that could potentially impact on the radio tower emissions and radio frequency reception.

1. *What is the purpose of this investigation?*

- Determine potential locations of radio towers for optimal performance and minimisation of interferences or other obstructions.

2. *What is the relevant domain, which domain specific properties need to be considered and what could possible values for these properties be?*

   - Domain: Radio Tower Emission and Immission
   - Domain specific properties and possible values:
     - radio tower technical information: e.g. strength of emitter, height of tower
     - knowledge about radio wave transmission and radio frequency reception: e.g. interference values for relevant natural and man made structures
     - terrain geodata: e.g. elevation values for each coordinate point

6.2.3 Context - Toxic Waste Soil Penetration

1. *What is the purpose of this investigation?*

   - Minimise or avoid impact from toxic waste dump (entity)
   - Identify if waste dump is too close to other relevant spatial entities

2. *What is the relevant domain, which domain specific properties need to be considered and what could possible values for these properties be?*

   - Domain: toxin penetration in soil
   - Domain specific properties and possible values:
     - technical details of toxins: e.g. name of toxin and its chemical composition
     - soil type penetration information: e.g. name of soil type and the rate of its penetration by specific toxins

– soil type geodata: e.g. soil type name for each polygonal area

Once the context has been defined in terms of domain specific properties and values, a function can be devised to generate impact areas.

6.2.4 Impact Function ι

Recall that an object o is defined as the union of its *sites*. The area of impact of a site p is a function of $(p, context)$. The impact area of o is therefore the aggregation of the impact areas of all of its sites.

Definition 9 (Impact Area) *Let a quasi-metric space S be given. An* impact function (on S) *is defined as a function that maps every pair of the form (p, context) to a subset of S. Given an object o, the* impact area of o in context c with respect to impact function ι *is defined as the union of* $\{\iota(p, c)|p \in o\}$.

Recall that we are dealing with the primitives of points, lines and polygons representing objects in GIS data. Every point in these objects can be interpreted as a site. Hence, the function ι is to be computed for each point in a line and for a polygonal object, for each point of the polygon.

Identifying, defining and incorporating context into a function ι might be relatively simple for some, but near to impossible for other contexts. We will look at some examples of the simpler, but nevertheless very important cases in the following subsections. Any practical implementation of proximity queries will rely on an operational function ι. One advantage of this approach is that once an expert has defined ι and it is implemented on spatial data, novices can use simple queries to retrieve nearness information without themselves needing to possess any domain specific background knowledge or knowledge about the data itself. This is contrary to the current GIS analysis functions that require in-depth analysis and knowledge by the user.

We have now examined the concepts on which the generation of impact areas should be based. However, the actual implementation of these concepts for GIS data requires a more practical approach, which is provided by the following *Impact Area Generation Model*.

6.2.5 Impact Area Generation Model

Let us summarise what we previously discussed before moving into the workings of the model. For any given GIS data set, proximity queries on two objects are answered by considering the relationship between their respective impact areas. Each of these objects consists of one or more sites p, and the impact area of the object is the union of each of its sites' impact areas. The impact area for each site p is generated using an impact function ι on p and a given *context*. Let us now look at a simple example to illustrate these concepts. A pedestrian navigating around Paris' city centre uses the Eiffel tower as a navigation landmark. Both pedestrian and tower are represented by a single site only. The context is navigation on a vista space level, i.e. navigation based on visibility. The pedestrian's impact area is his or her visual perception range, the tower's impact area is the tower's visibility range in all directions. The tower's height, and the height and width of the surrounding buildings as well as the elevation of the terrain will impact on the visibility of the tower from different observation points. These are the domain specific properties we are after and in this case their values are numeric, representing the height of buildings, their width and the elevation number in each coordinate location. Assuming that for every coordinate point we have this information, we can then compute for any location in Paris city if the Eiffel Tower is visible from there or not.

In general terms, we can say that in the impact area generation process we require some kind of expert. This expert needs to identify all of the domain specific key properties required for the impact area generation. Further, the expert will have to identify where necessary values can be derived from. This can be domain knowledge collated by the expert, knowledge stored in databases, information extracted from GIS data and so on. Together with query point data such as coordinate information, this is fed into the impact function. The model is shown in Figure 6.7. In order to generate an impact area in a GIS map for a query point p, an expert of a given context will use his or her knowledge to devise a suitable impact function and identify the domain specific key properties. This function ι takes as arguments query point data p and the values of the domain specific key properties for p to generate p's impact area.

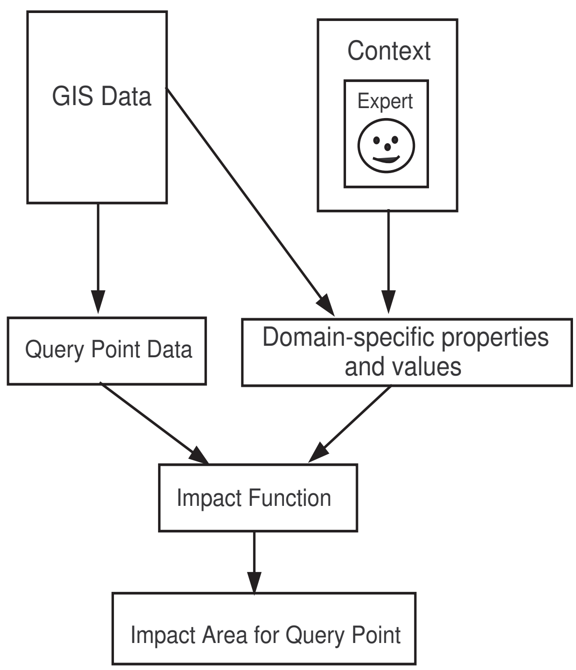


Figure 6.7: Impact Area Generation Model

This model is generally applicable. Let us now look at specific examples of impact functions for the previously examined contexts of *Touristic Road Travel*, *Radio Tower Emission* and *Toxic Waste Soil Penetration*.

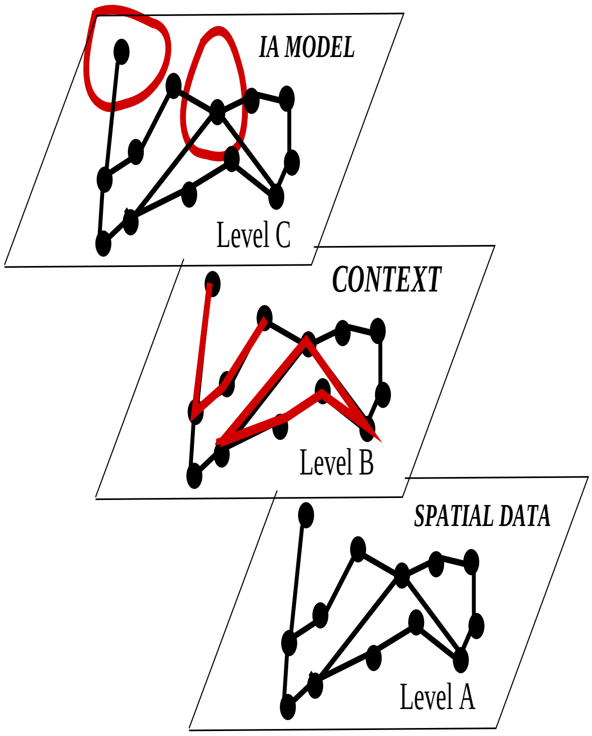


Figure 6.8: Impact Area Generation Model for Touristic Road Travel

6.2.6 Impact Function for Touristic Road Travel

In touristic road travel, the expert is someone who has traveled the relevant region extensively, knows the area, road conditions and sights. We can use this expert's knowledge in the following way. Road travel guides are available in book form, and we can extract expert knowledge from this, by extracting the necessary nearness notions. For example, it is reasonable to assume that anything recorded under day trips is considered close in a tour that spans several days. For any two query points, we can then determine if they are part of the same tour or which tour is closest to both of them. From this, we can for example calculate an average distance or some similar pseudo-distances across all day trip distances within this associated tour. This pseudo-distance can then be used to generate the impact area. The resulting impact area would consist of all the road sections that are within this

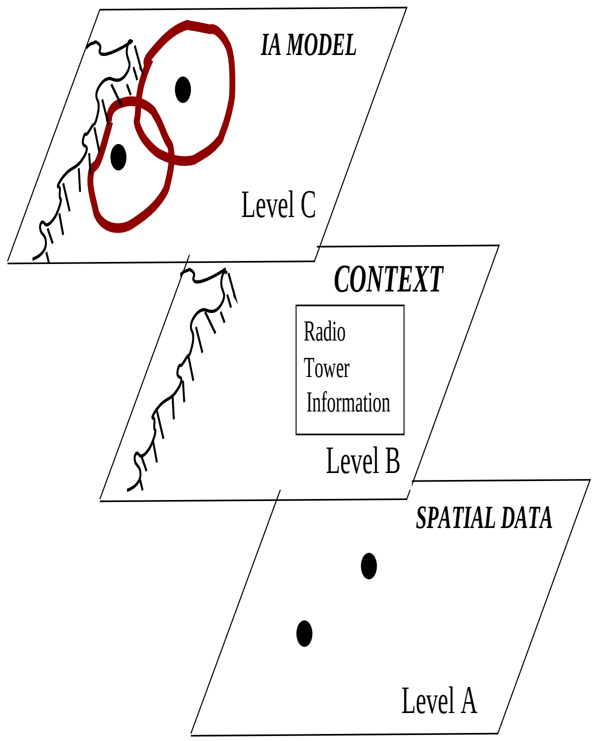


Figure 6.9: Impact Area Generation Model for Radio Tower Emission

given pseudo-distance of the query point.

The impact area generation model could look as shown in Figure 6.8 for this particular context. Here, Level A represents the spatial GIS data such as a road network which is queried for nearness relations. Level B shows the context information such as the touristic road travel information, with different routes of travel. Level C is the result of the impact function ι of spatial data and context, showing the resulting impact areas which can then easily be used to evaluate nearness between the original query points.

6.2.7 Impact Function for Radio Tower Emissions

In the context of radio tower emission, the expert is someone who understands the way the terrain might interfere with the radio tower emissions and also has a sound knowledge of the particular types of radio towers. The impact area generation

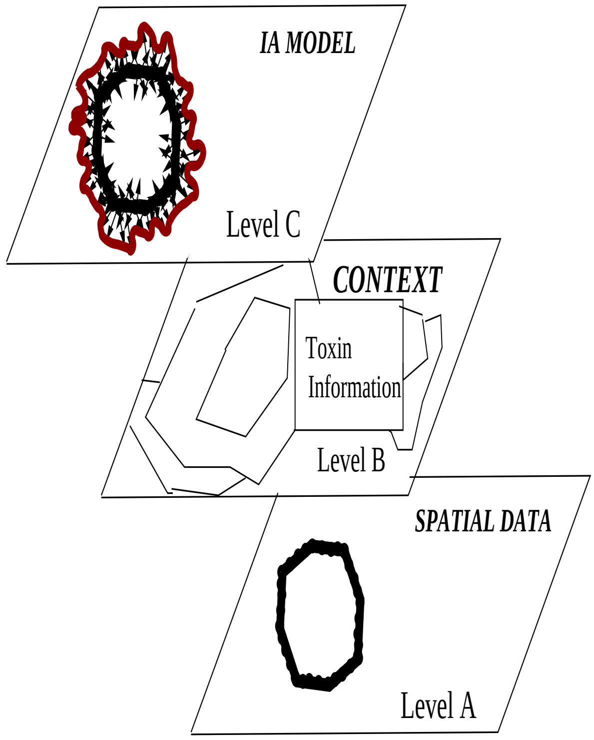


Figure 6.10: Impact Area Generation Model for Toxic Waste Soil Penetration

model for this particular context could look as shown in Figure 6.9. Here, Level A represents the spatial GIS data such as the location of the radio towers. Level B shows context information such as the terrain, i.e., topographic, setup of the area where the towers are located. Additional information about the radio towers and their general workings derived from both the GIS data associated with the spatial object of the towers (probably points) and expert knowledge are also included. Level C again is the result of the impact function ι of spatial data and context, showing the resulting impact areas which can then easily be used to evaluate nearness between the radio towers.

6.2.8 Impact Function for Toxic Waste Soil Penetration

An expert for toxins and the way they penetrate through the different soil types will be able to set the context for the impact of a toxic waste dump on its surroundings.

Figure 6.10 shows the impact area generation model for this particular context. The waste dump is represented as a polygon in Level A, thereby defining its location and spatial extent. Level B provides the context information such as soil type maps and information about the toxins themselves. The result of the impact function ι of spatial data and context is the impact area of the toxic waste dump in Level C. In this particular context, we are mainly concerned with the impact of the waste dump only. Nearness is generally evaluated for the toxic waste dump in relation to geographic objects of different types such as residential areas, where the impact of the other query object is not so crucial. On the other hand, there can of course be cases where the other object's impact is also important. For example, if the toxins in the waste dump are inflammable, a fireworks factory would need to be far enough away that in the case of an explosion none of these inflammable toxins are within reach of the open flames.

6.2.9 Different Types of Impact Areas

Definition 9 provides us with a very general description of impact areas. This is necessary to account for the different types of regions that can result from the impact area generation process. Regions can be convex or not, with significant extra computational complexity for nonconvex regions. Let us look at some examples that are relevant for spatial proximity queries.

Convex Impact Areas

Convex impact areas will usually result when generated for convex shaped query objects in less complex contexts. For example, the impact areas[2] in the navigation setting used in Kettani and Moulin's [69] influence area approach were generated by applying object specific *widths* to the boundaries of common map shapes such as

[2]As previously discussed, in Kettani and Moulin's [69] model, influence areas are one particular kind of impact area and are therefore also referred to as impact areas.

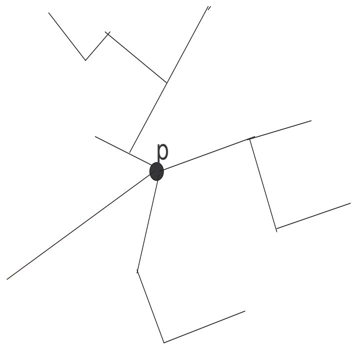


Figure 6.11: Possible Impact Area for Road Travel from a place p: a complex tree-structured region

quadrangles representing buildings. In the case of Kettani and Moulin's GRAAD system implementation, these shapes were convex resulting in convex impact areas.

The simplest case of a convex impact area is that of a disk. For example, when we look at the general principles of radio frequency emissions, the frequencies are emitted equally in all directions, therefore the impact area would be defined by the distance r within which the radio signal can be received, resulting in a disk shaped area of radius r. The impact of waves can generally be described by disks as long as there is no need to take any environmental variables into account and the domain specific background knowledge can be considered empty. We will utilise disk shaped impact areas in one of the nearness notions introduced in the next chapter and in a detailed discussion of the bidimensionality of nearness in Subsection 7.3.2.

Nonconvex Impact Areas

Many of the day-to-day situations in which we need to consider nearness will result in impact areas that resemble regions which cannot be described as convex. Tree-shaped regions, for example, could be the result of generating impact areas for facilities and their reachability along a road network within a certain impedance, for example 30 minutes driving time. The resulting region could look as shown in Figure 6.11. This is a very complex region, however as we will see in the next subsection, it can be simply described. Note that when generating these kind of impact areas within ArcGIS using network analyst functions, as was done in the experimental Chapter 8, the resulting region is a polygon connecting the end points of the final road sections.

Hollowed regions are an interesting example of nonconvex impact areas. They can result when the generation of impact areas for radio frequency emissions needs to take interferring environmental variables such as natural obstructions into account. In this case, holes occur in areas of no reception such as a valley, while further away from the tower on a mountain top reception might be available again, including this elevated area in the impact region. Holes in the Vista Space example used to illustrate the impact area generation model, would represent every point within the furthest possible visibility range where the Eiffel tower cannot be seen. This could occurs behind large buildings for example. The impact area generation for the toxic waste dump context could also result in hollowed regions where the holes could constitute areas of particular sediments (e.g. some rock type) that do not allow penetration of the toxins.

It is clear that the generation of hollowed regions requires the generality of impact function ι as defined in Definition 9. However, there are also numerous cases for which it can be simplified to a function that together with domain-specific background knowledge allows us to define ι in simple terms. For example, in the context of road travel when looking at how far one can travel along the road network, a single number R together with road network knowledge is enough to retrieve the impact area. In this case we will call R the impact area generation distance used to generate an impact area including all road sections that are within distance R from the query point. We use this approach in the experiments in Chapter 8.

6.2.10 Mapping Function

As previously discussed, there are cases where $\iota(site, context)$ can be simplified to return a single number R. This justifies the introduction of a new notion ω, which represents a simplified ι.

Notation 10 (Mapping Function) *We denote by ω a function that maps a pair of the form (site,context) to a positive real number R.*

Here $\iota(site, context)$ is the set of all points at a distance of at most $\omega(site, context)$ from the *site*. R can take any value from zero to very large numbers. Let us illustrate this with examples. In vista spaces not considering the terrain, very large R occur for very tall buildings that can be seen for a long distance away, for example the Eiffel Tower in Paris can be seen for several kilometers. In the context of radioactive contamination, very large R result for objects, e.g. nuclear power stations, that have the potential to emit harmful radioactive rays into the environment for a long distance. Very small R in vista spaces occur for small objects, for example a small fountain that can only be seen for a few meters. A small R could also be the case for a disused power station a few thousands of year after it was switched off. R could take a value of zero in a chess game for a pawn that has no options to move.

Chapter 8 will report on experiments conducted to evaluate the general nearness framework in the touristic road travel context. Impact Areas will be generated on query places in the road network data. Let us take a look at how ω could be defined for this specific example. The impact area will be determined using road network distances. For each query point, we will calculate an impact area, using the concept of the service areas in GIS analysis functions, for a particular distance along the road network. How can we determine this distance? The data that we have available in addition to the road network is information about travel routes, which in turn consists of day tours. For example, $route(A, B, C, D)$ stands for a trip from place A to D, with three day tours such that $daytour(A, B)$, $daytour(B, C)$ and *daytour*(C, D). It is a reasonable assumption that in the context of a vast country such as Australia, places that can be reached within a day can be considered near each other. It is assumed that the road network does not include any one-way roads, and feature overlay is not of concern either. A metric space interpretation is therefore a good choice. We approch the impact function in the following way. First, we are looking for the closest travel route or road trip for each query point or the smallest area that includes both a query and a trip. This will give us a road trip for each query point. Once we have identified a trip, we can then calculate the impact area generation distance, which is a very particular case of ι discussed and explained previously. For all day tours in each road trip, we calculate:

- the maximal distance of all day tours
- the minimal distance of all day tours
- the average distance of all day tours.

These distances, representing a different R each, will ultimately be used as distances to generate different possible impact areas for the relevant query point. It will have to be determined which of these R is the most appropriate in this context. The distance R is calculated using the query point's closest road trip. This ensure that if two query points are situated in quite different road condition areas, the impact areas generated would also be quite different. However, it would also be interesting to see how nearness notions behave if the actual travel distances between two road trips is taken into account. For this purpose, I will evaluate the Hausdorf distance for any two query points that have distinct closest road trips. Here, the generating distance for the impact areas of both query points will be the maximal distance that occurs between any two points each from another set. For example, if $Trip1 = \{a, b, c, d\}$ is the trip identified for query point p and $Trip2 = \{e, f, g, h\}$ the trip identified for query point q, then the Hausdorf distance for the two sets is $Hausdorf\ Distance = max(x \in Trip1, y \in Trip2 \mid D(x, y))$. The distance D used in this equation requires a metric space interpretation which is given by the data set used in the experiments.

When we consider disk shaped impact areas, R simply becomes the radius of the disk, we have previously discussed examples of where such impact areas might be relevant.

6.2.11 Nearness Notions based on Impact Areas

A combination of the previously discussed impact function ι with notions from the theory of proximity spaces forms the basic assumption of the nearness framework presented in this thesis. In Chapter 7, a "family" of notions of nearness is discussed, formalised and justified on the basis of case studies, each of which provides a consistent interpretation of two axioms representing the generic notion of nearness. In Section 7.3.1, the "sub-family" of the symmetric notions of nearness previously introduced is revisited and its properties are discussed. Then its implications are investigated in the context of two models: navigation and natural language. Examples of cross-country navigation are used for the former and a set of spatial expressions for the latter model.

In most cases, the symmetric notion of nearness is adequate. There are however cases where nearness is not symmetric. As we have previously discussed, the topological space interpretation of quasi-metric space accounts for this. However, we will still need to look at how we will deal with such cases. The asymmetric aspect of nearness is discussed in more detail in Section 7.4. One of the classic examples in the linguistic literature, used to show that nearness relations in natural language can be asymmetric, is the nearness relation between a house and a bicycle. Symmetry means that if the bicycle is near the house, then the house would also be regarded as near the bicycle. But according to Talmy [109], this is not necessarily the case. Crangle and Suppes [24] did also investigate nearness in spatial language, however they did not consider the asymmetry of nearness at all. The basic assumption of the formalism is shown to be valid when applied to GIS data and domain specific background knowledge in the context of touristic road travel in Chapter 8.

The following chapter will introduce a “family”’ of nearness notions that can account for these different situations.

Chapter 7

Axiomatising Nearness Notions

In the previous chapter, I introduced definitions for and approaches to generate impact areas based on context. I will now show how these can be used to evaluate nearness between two objects given a pair of impact areas associated with an object each. The discussion in this chapter refers to a given pseudo-metric space (S, D). In the following case studies, several notions of nearness are identified. One of the definitions (a-near2) is limited to an arbitrary space interpretation where impact areas comprise disks. These different notions of nearness belong to the same "family" of nearness relations. A family encompasses a set of binary relations on sites, each of these relations being defined on the basis of D and ι or its specialisation ω. Note that we abuse notation here, ω is used as the image of the function on a particular argument instead of the function itself. Eric Martin and I previously investigated nearness in the context of single site object, an approach resulting in definitions not quite as rich as the following. Most of the following chapter represents this published work [13, 14, 15, 17] from which only what is irrelevant to the thesis has been left out.

I formalise nearness as satisfied by two axioms. Axiom (A1) is straightforward. I assume that every object is near itself. Linguistically, there might be cases where an object is not considered near itself, but formally this is a natural assumption that does not need to be justified. From the case studies I have done, I could conclude that any two objects whose impact areas do not intersect have no nearness relation. Axiom (A2) expresses this property.

$(A1)$ *For all objects* o $Near(o, o)$

$(A2)$ *For all objects* o_1, o_2 $IA(o_1) \cap IA(o_2) = \emptyset \rightarrow \neg Near(o_1, o_2)$

Based on these axioms, which constrain all nearness notions, several nearness notions can be defined as follows. We first introduce all these definitions and comment on them extensively later in the chapter.

Definition 11 *For all objects* o_1 *and* o_2*,* s-near1(o_1, o_2) *holds iff* $IA(o_1) \cap IA(o_2) \neq \emptyset$*.*

Definition 12 *For all objects* o_1 *and* o_2*,* s-near2(o_1, o_2) *holds iff* $(o_1 \cap IA(o_2) \neq \emptyset) \vee (o_2 \cap IA(o_1) \neq \emptyset)$*.*

The following definition requires a specific mapping function that results in disk shaped impact areas and is therefore not generally applicable.

Definition 13 *For all objects* o_1 *and* o_2*,* a-near2(o_1, o_2) *holds iff* $(IA(o_1) \cap IA(o_2) \neq \emptyset)$ *and for all* $p \in o_1$ *there exists* $q \in o_2$ *such that* $\omega(p) \leq \omega(q)$*.*

Definition 14 *For all objects* o_1 *and* o_2*,* a-near3(o_1, o_2) *holds iff* $o_1 \cap IA(o_2) \neq \emptyset$*.*

Definition 15 *For all objects* o_1 *and* o_2*,* s-near4(o_1, o_2) *holds iff* $(o_1 \cap IA(o_2) \neq \emptyset) \wedge (o_2 \cap IA(o_1) \neq \emptyset)$*.*

Definition 16 *For all objects* o_1 *and* o_2*,* a-near4(o_1, o_2) *holds iff* $IA(o_1) \cap IA(o_2) \neq \emptyset$*.*

We will now study various interpretations of one particular abstracted space of four objects, which is shown in Figure 7.1. These different interpretations each follow a particular case study. For each of the interpretations all possible models

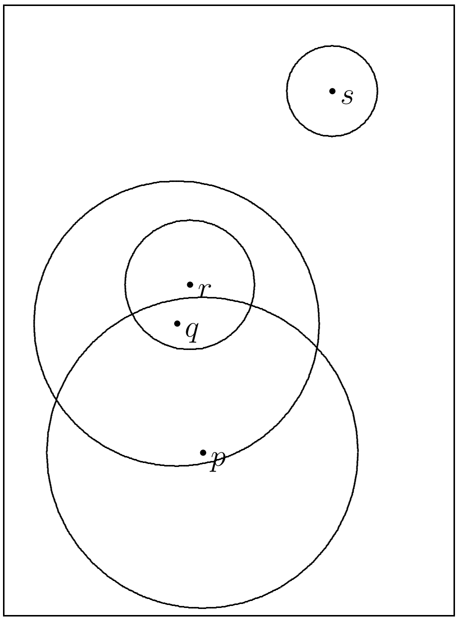


Figure 7.1: Example Space with four Objects, showing impact areas

in terms of nearness are considered in order to show the motivation for all these notions and justify their need.

The case studies are divided into small-scale and large-scale space settings, as these two kinds of space exhibit quite different properties with respect to nearness. The line drawn between these two spaces is not always clear and therefore not always consistent across the literature, which also employs numerous terms in similar contexts. I will try to overcome these discrepancies where possible and aim to provide a clear distinction within the settings. As a rule of thumb, in the English language, we would usually describe the orientation of objects in small-scale spaces by using relative orientation relations such as *left of*, *right of*, *in front of* or *to the back of*.

It should also be noted that every possible model (i.e every possible case) for each interpretation is considered, even if particular cases might be quite unlikely. That means that all possible models, that are not explicitly excluded by a certain interpretation, will be included in the analysis for that interpretation.

Although, small- and large-scale space do exhibit different properties, we will first examine interpretations in small-scale spaces, as they are the basis for large-scale space perception. For example, a newborn will first learn to recognise and deal with space in the small-scale context, before they are able to orient themselves in large-scale ones. We will then move on to see how the nearness notions drawn from small-scale can be adapted to large-scale spaces as they are represented in GIS data.

7.1 Small-Scale Spaces

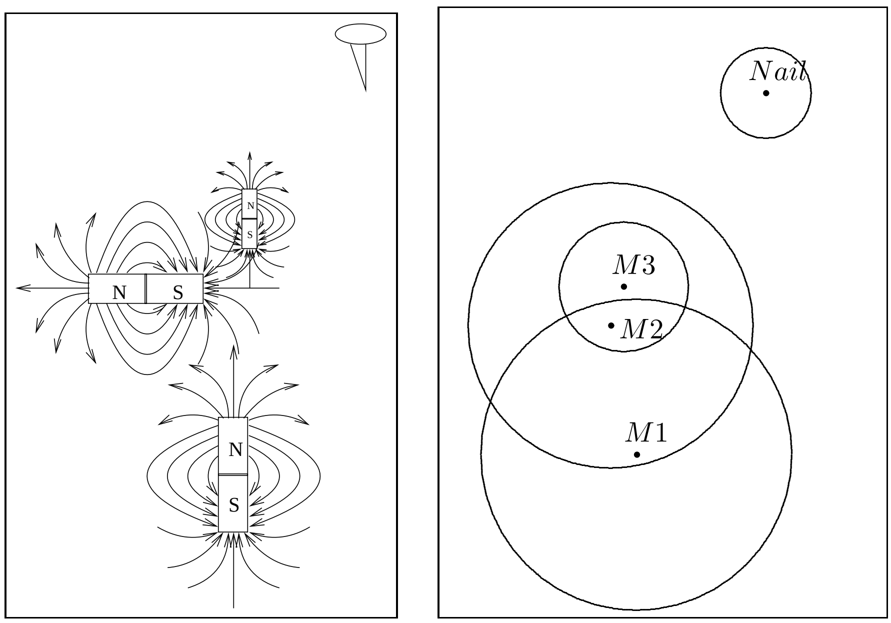
Small-scale spaces are characterised as spaces whose structure is within the sensory horizon of the agent. Manipulable objects in a small-scale space are essentially three-dimensional with all three dimensions being about equally important. When an object is moved, its spatial and non-spatial properties, apart from its positioning, remain practically unchanged [32].

We will first consider a magnetic field example. I discussed previously that contrary to other approaches to representing nearness that consider only the impact area of one of the objects, nearness is determined by the relationship between the impact areas of both objects in this framework. The magnetic field example very clearly shows the significance of the approach. Due to its more general nature, a model such as Kettani and Moulin's influence areas can easily be incorporated as one of its interpretations.

I will then move to the example of a *table-top* scene, meaning by that the manipulable space on top of a table. It should be noted that I do refrain from calling this scene a *table-top* space example to avoid confusion, because the term table-top space is often used synonymously with small-scale spaces. The example following the table-top setting is that of, what I will call, egocentric space. In this space, the agent doing the abstraction is part of the scene itself and he or she considers everything that he or she can reach as near. Finally, an environmental space setting is explored, which is a substantially larger space than the previous one. However, because it can be observed from a single point of view, I still consider it small-scale space.

7.1.1 Magnetic Fields

This particular interpretation shows a space of three permanent two-bar magnets and a nail (i.e. an unmagnetised iron object). The scene is shown in Figure 7.2. It is well known that magnets attract unmagnetised iron objects and attract or repel other magnets depending on their polarity. A bar magnet sets up a magnetic field in the space around it, and a second body responds to it [106]. For example, if a nail happens to be within a magnetic field, it will be drawn towards the magnet. For magnets however, the second magnet does not have to be within the first magnet's field to either be drawn to or repelled from it, it is sufficient when the second magnet's field gets into contact with the first magnet's field.



(a) Magnets and Nail (b) Abstracted Space

Figure 7.2: The Impact of Magnetic Fields

In this interpretation, the term magnetic field describes the area within which the friction with the table top is not enough to stop an object, i.e. the magnets or the nail, from moving. This means that the impact areas depend on the frictional characteristics of the object being attracted or the frictional characteristics in addition to the magnetic properties of a magnet being attracted or repelled. In order to consider the spatial setting of the magnets, I assume that the observing agent is moving the magnets into the positions shown and then holding on to them. This allows their fields to intersect without them being physically moved at first encounter. The nail in the scene is not affected by any of the magnets. The nearness relations between these magnetic objects and even between unmagnetised iron objects and magnets are truly symmetric. This results in exactly one model of the scene shown in Table 7.1, where T stands for a *True* and F stands for a *False* nearness relation.

	M1	M2	M3	Nail
M1	T	T	T	F
M2	T	T	T	F
M3	T	T	T	F
Nail	F	F	F	T

Table 7.1: Model of Nearness in the Scene in Figure 7.2

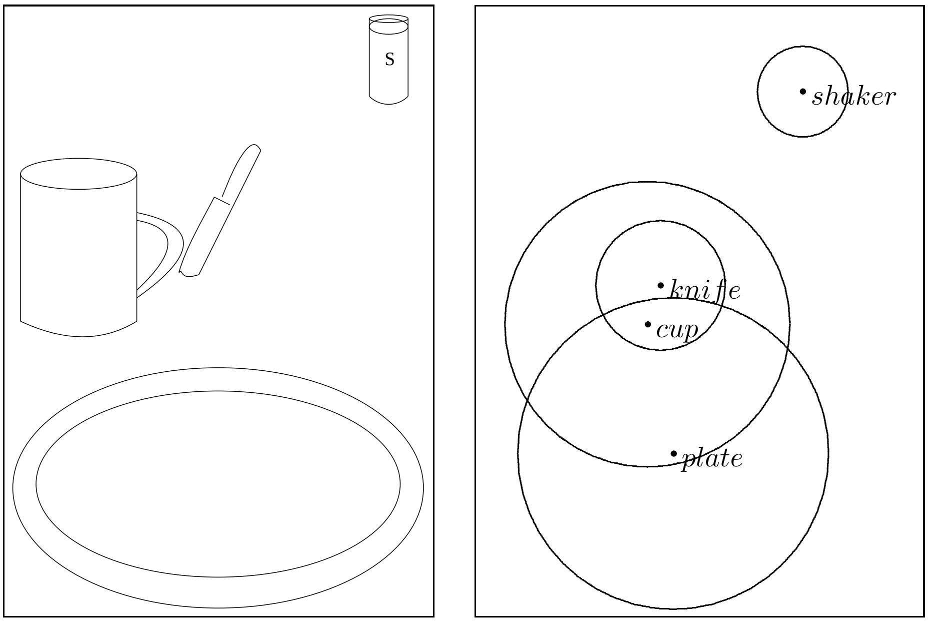
The model clearly satisfies axiom (A1) with every object being near itself. Axiom (A2) is satisfied by the nail, whose impact area does not intersect with the impact area of any of the magnets, being not near any of the magnets. It can be observed that the magnets whose impact areas intersect, are also near. **Definition 11** expresses this symmetric nearness notion s-near1. It is the most general nearness notion in the “family” of nearness relations. This formulation was derived from the context of proximity spaces, in which two sets are near each other if they share at least one closure point. Adopting this to a universe containing distinctive points, i.e. site, their related objects and associated areas of impact, nearness holds for two objects if their impact areas intersect, i.e. share at least one point.

This does not only make sense in the context of proximity spaces, but can also be shown to be a reasonable approach for physical space. Together with Eric Martin, I analysed experimental results obtained from studies conducted by Worboys [123] in the domain of environmental spaces in the context of impact areas and used these results to validate this general nearness notion s-near1. It was found that s-near1 was satisfied by 99.56% of all empirical cases i.e., 230 out of 231 cases recorded by Worboys. A detailed account of analysis can be found in [15]. The experiments in Chapter 8 show this notion can being applied and validated using GIS data in the touristic travel context.

In addition to notion s-near1, it can also be noted that in the model shown in Table 7.1, when objects are included in the impact area of another object, they are always near. For example, magnet M2 is in the impact area of magnet M1 and M1 in the impact of M2. The nearness notion s-near4 expressed in **Definition 15** is a specialisation of s-near1. When query objects are included in each other's impact areas, we arrive at much finer grained nearness relation than when they are not and only the most general notion s-near1 can be satisfied by their impact areas having some overlap. This justifies the introduction of the finer notion of s-near4 to being able to distinguish between these different degrees of proximity. Note that the definition for s-near4 also allows for partial inclusion of an object o_1 in the impact area of o_2 and vice versa. This accounts for area objects such as a lake that could for example be reached by public transport on one of its shores only.

7.1.2 Table-top Scene

The scene in Figure 7.3 describes a table-top with a plate, a cup, a knife and a salt shaker on it. This is a relatively small space and the observing agent can easily reach the objects within that kind of space. It is therefore quite likely that the nearness relations within that space are symmetric. I will however, also consider asymmetric cases.



(a) Table-top Scene (b) Abstracted Space

Figure 7.3: Table-top Scene

This particular interpretation has only two models. The only difference between these two models is that while the knife is clearly near the plate, the plate might not necessarily be considered near the knife due to the difference in size. Both models in Table 7.2 satisfy axiom ($A1$) and also ($A2$). All nearness relations that are *true* also show that the impact areas of these two objects intersect. The nearness relation s-near1 as given in **Definition 11** accounts for this fact. In model 2, the knife is near the plate while the plate is not near the knife. While s-near1 is still valid for this case as well, it is certainly not restrictive enough and needs to be refined resulting in the asymmetric nearness notion a-near2 expressed in **Definition 13**. In this definition, it is taken into account that objects with less impact might be considered near an object with a larger impact, using the latter as landmark for the former for example, but not vice versa.

It can observed in both models that cup and plate have a symmetric nearness relation. Therefore it can be concluded that there is a nearness relation between

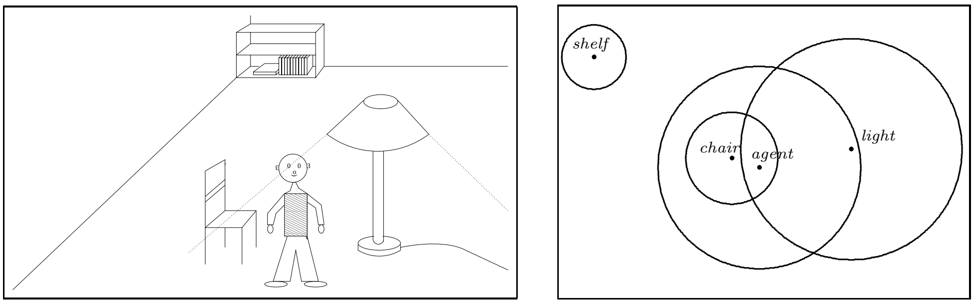
Model 1

	plate	cup	knife	shaker
plate	T	T	T	F
cup	T	T	T	F
knife	F	T	T	F
shaker	F	F	F	T

Model 2

	plate	cup	knife	salt
plate	T	T	F	F
cup	T	T	T	F
knife	T	T	T	F
shaker	F	F	F	T

Table 7.2: Models of Nearness in Table-top Scene



(a) Egocentric Space (b) Abstracted Space

Figure 7.4: Egocentric Space Example

two objects that are situated in the other object's impact area. This is accounted for by nearness notion s-near4 as given in **Definition 15**.

7.1.3 Egocentric Space

In this particular interpretation, the agent is part of the scene and his or her area of impact is determined by how far he or she can reach. This reachability impact area translates into everything within the agent's reach including objects reached by reasonably small forward-backwards or sideways movements such as bending forwards or taking a small step. Everything that is within the reach of the agent is also near the agent, but the reverse is not necessarily the case. For a model of human-arm-reachable workspace see [75].

In addition to the agent, the scene in Figure 7.4 contains a chair, a shining standing light and a book shelf. The impact of the light is the area of its direct light beam. Chair and book shelf exhibit only their own spatial extent.

Model 1

	light	agent	chair	shelf
light	T	T	T	F
agent	T	T	F	F
chair	T	T	T	F
shelf	F	F	F	T

Model 2

	light	agent	chair	shelf
light	T	T	T	F
agent	T	T	T	F
chair	T	T	T	F
shelf	F	F	F	T

Table 7.3: Models 1 and 2 of Nearness in Egocentric Space Scene

There are four possible models of this interpretation shown in Tables 7.3 and 7.4. The chair is always near the light, even though only part of the chair is actually within the light's beam and the agent is between light and chair. This is signified by the nearness relation between chair and light being true in all four models shown in Tables 7.3 and 7.4. The light however is not necessarily near the chair, because the chair does not have much impact on the light and even less so with the agent being situated between light and chair.

Models 1 and 2 in Table 7.3 reflect the symmetric nearness notion, where the light is also considered to be near the chair and the nearness notion s-near1 is sufficient to describe these relations.

Model 3

	light	agent	chair	shelf
light	T	T	F	F
agent	T	T	T	F
chair	T	T	T	F
shelf	F	F	F	T

Model 4

	light	agent	chair	shelf
light	T	T	F	F
agent	T	T	F	F
chair	T	T	T	F
shelf	F	F	F	T

Table 7.4: Models of Nearness in Egocentric Space Scene

Models 3 and 4 in Table 7.4 reflect the cases when light and chair are not considered near. While s-near1 is still valid for this case as well, it is certainly not restrictive enough and needs to be refined, resulting again in the asymmetric nearness notion a-near2.

As can be seen in the previous discussion, the “in-betweenness” of the agent with respect to the light and the chair has only played a small role in the model definition of this interpretation. If this kind of “in-betweenness” of the agent needs to be considered for the nearness relation between light and chair, another mapping functions that does not include the impact area of the chair would have to be assigned to the light resulting in a different interpretation. It is not of concern to this interpretation of egocentric space.

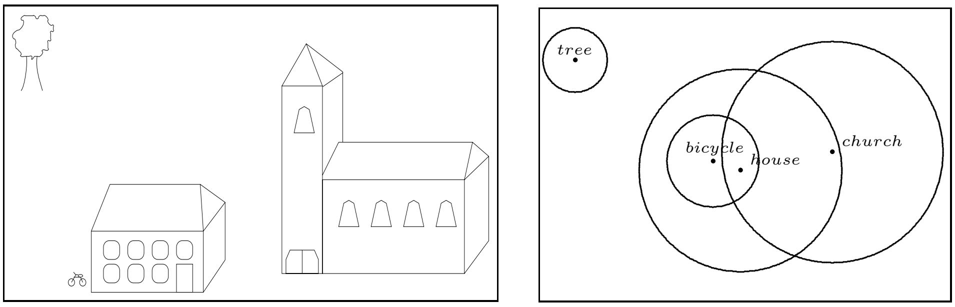
The chair is definitely near the agent due to the reachability, but the agent is not necessarily near the chair, as shown in Model 1 in Table 7.3 and Model 4 in Table 7.4. This is a quite unlikely model, but valid within the framework by Axiom (A2) and this interpretation.

The other relations in Models 1 to 4 in Tables 7.3 and 7.4 can all be described by nearness notion s-near1 given in **Definition 11**.

7.1.4 Environmental Space - A Natural Language Interpretation

Montello [79] described the environmental space as the large-scale space in which we live. I include this particular interpretation in the small-scale space section, because the scene shown in Figure 7.5(a) can be viewed from a single view point by the observing agent. In addition to that, this scene is also interpreted as a natural language representation, thus having natural language restrictions imposed on its possible models. The English language is used in this interpretation.

The scene contains a bicycle next to a house which is in proximity to a church. A tree is shown in the distance. According to Talmy [109], natural language expressions representing spatial relations are quite commonly asymmetric. Among other criteria, this is the case when the objects vary considerably in size. While a small object might be near a large object, the large object is usually not correctly described as being near the small object, in natural language terms. For the scene depicted, the



(a) Environmental Small-scale Space (b) Abstracted Space

Figure 7.5: Environmental Small-scale Space Example

bicycle is definitely near the house, however not vice versa as can be seen in all four models shown in Tables 7.5 and 7.6.

Model 1

	church	house	bicycle	tree
church	T	T	F	F
house	T	T	F	F
bicycle	T	T	T	T
tree	F	F	F	T

Model 2

	church	house	bicycle	tree
church	T	F	F	F
house	T	T	F	F
bicycle	T	T	T	T
tree	F	F	F	T

Table 7.5: Models 1 and 2 of Nearness in the Environmental Small-Scale Space of Figure 7.5

The whole impact area of the bicycle is enclosed in the impact area of the house, but not conversely. This example and similar ones justify the introduction of an asymmetric nearness notion, namely a-near4, given in **Definition 16**.

The bicycle can also be considered near the church in certain contexts as shown in Models 1 and 2 in Table 7.5. For example, if the emphasis is on the bicycle being parked next to the house and near the church, and not, for example, near the station where it is usually parked. The bicycle is therefore considered to be near the church, while in this context, it would not be said that the church is near the bicycle. The asymmetric nearness notion a-near2 given in **Definition 13** accounts for these kind of situations.

Model 3

	church	house	bicycle	tree
church	T	T	F	F
house	T	T	F	F
bicycle	F	T	T	T
tree	F	F	F	T

Model 4

	church	house	bicycle	tree
church	T	F	F	F
house	T	T	F	F
bicycle	F	T	T	T
tree	F	F	F	T

Table 7.6: Models 3 and 4 of Nearness in the Environmental Small-Scale Space of Figure 7.5

The relationship between house and church is symmetric in some contexts, abstracted in Models 1 and 3, but asymmetric in other contexts, abstracted in Models 2 and 4 in Table 7.6. While it would always be considered that the house is near the church, it would not always be considered that the church is near the house, due to the church's greater size and also higher priority as a landmark. The relation a-near2 accounts for the asymmetric case.

7.2 Large-Scale Spaces

Large-scale spaces are defined as spaces whose structure is at a much larger scale than the sensory horizon of the agent [73]. GIS data represent an abstraction of these spaces.

7.2.1 Environmental Space

Within the frame of spatial knowledge representation, Worboys [123] investigated nearness relations in environmental spaces. He considerd nearness as one of the "conceptual" distance relations and conducted experiments in the environment of Keele University Campus, sketched in Figure 7.6a. Worboys investigated possible regularities in the perception of nearness across a variety of individuals. The goal was to find out whether formal theories can be applied to reasoning with vague spatial

24 hour reception	?	Holly Cross	F
Academic Affairs	?	Horwood Hall	?
Barnes Hall	F	Keele Hall	?
Biological Sciences	?	Lakes	F
Chancellors Building	?	Leisure Centre	F
Chapel	T	Library	T
Chemistry	?	Lindsay Hall	?
Clock House	?	Observatory	F
Computer Science	F	Physics	?
Earth Sciences	**T**	Students Union	T
Health Centre	F	Visual Arts	F

Table 7.7: Nearness to Library ([123] Table 2, changes in bold print)

notions such as nearness. Worboy's [123] experiments were structured as follows: a list of significant campus places was provided to the subjects (see Table 7.2.1). The subjects were divided into a truth group and a falsity group. The results of the experiments were analysed by Worboys in several ways, here we are concerned only with the results of his three-valued logic analysis. Worboys [123] used a χ^2 test to evaluate whether his data indicated nearness or not-nearness. At a significance level of 0.001, the nearness relation between places could either be *true* (T), *false* (F) or *indeterminate* (I).

If we consider, for example, the library as reference object, as was reported in Worboys' paper, a three-valued logic can be imposed as shown in Table 7.7. For example, the library was evaluated as near to the chapel by 10 subjects in the truth group and not near by nobody in the falsity group. This is clearly indicating that the chapel is perceived as near the library. For less clear-cut results, he used significance levels to determine if a place is near to the reference place or not, or if it was indeterminate.

Impact areas can be assigned to all the places included in the experimental setting. The impact area of each place, i.e. of each reference, is established by assigning to it every other place that is near the reference or whose nearness relation

1	24 hour reception	12	Holly Cross
2	Academic Affairs	13	Horwood Hall
3	Barnes Hall	14	Keele Hall
4	Biological Sciences	15	Lakes
5	Chancellors Building	16	Leisure Centre
6	Chapel	17	Library
7	Chemistry	18	Lindsay Hall
8	Clock House	19	Observatory
9	Computer Science	20	Physics
10	Earth Sciences	21	Students Union
11	Health Centre	22	Visual Arts

Table 7.8: Significant Places on Keele Campus ([123] Table 1)

to the reference is indeterminate.

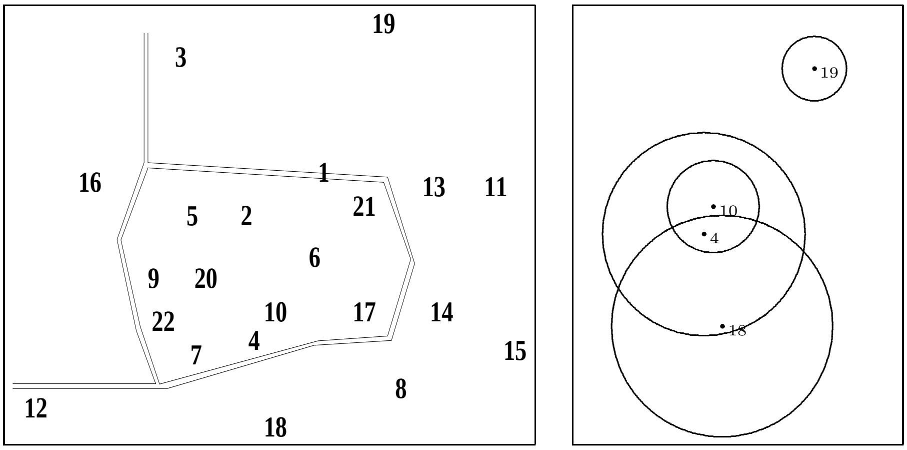
	4	10	18	19
4	T	T	T	F
10	T	T	I	F
18	I	I	T	F
19	F	F	F	T

Table 7.9: Nearness Relations for Scene in Figure 7.6(a)

From the scene in Figure 7.6 and the nearness information available from Worboys' experiments shown in Table 7.9, eight different possible models of the scene can be derived from the different interpretations of the three indeterminate values. Even though Worboys suggested that nearness relations in environmental spaces are weakly symmetric[1], we will still consider asymmetric interpretations. For example, while the nearness relation between 4 and 18 is true, the nearness relation between 18 and 4 is either false or true in different models. If in Table 7.9 we consider only the pair (o_1, o_2) such that $Near(o_1, o_2)$ and $Near(o_2, o_1)$[2], then s-near1 given in

[1]The term *weakly symmetric* is used by Worboys to refer to the fact that his test data exhibit no two objects a and b for which $Near(a, b)$ is true and $Near(b, a)$ is false or vice versa.

[2]Hence consider the following pairs (4,4), (4,10), (4,19), (10,4), (10,10), (10,19), (18,18), (18,19), (19,4), (19,10), (19,18) and (19,19) as symmetric nearness relations.



(a) Environmental Large-scale Space (b) Abstracted Space

Figure 7.6: Environmental Large-Scale Space

Definition 11 adequately describes the *true* nearness relations for these pairs. The *false* nearness relations satisfy axiom (A2).

The following models will be discussed in detail to determine what implications all possible interpretations of the indeterminate values in Table 7.9 have.

Model 1

	4	10	18	19
4	T	T	T	F
10	T	T	F	F
18	F	F	T	F
19	F	F	F	T

Model 2

	4	10	18	19
4	T	T	T	F
10	T	T	T	F
18	F	F	T	F
19	F	F	F	T

Model 3

	4	10	18	19
4	T	T	T	F
10	T	T	F	F
18	F	T	T	F
19	F	F	F	T

Table 7.10: Models 1-3 of Environmental Large-scale Space

Models 1 to 3 in Table 7.10 are quite unlikely models, because objects 18 and 4 are not near in this model, even though the objects are included in each other's impact areas, which should indicate a quite strong nearness relation. In Model 1, object 18 is not near object 10, nor is object 10 near object 18. These models do, however, satisfy axioms (A1) and (A2) and are therefore valid models.

Object 18 is not near object 10 in Model 2, however object 10 is near object 18. As the mapping function of object 18 produces a much greater impact area than the mapping function of object 10, this situation can be described by nearness notion a-near2 given in **Definition 13**. In Model 3, object 18 is considered near object 10, but object 10 not near object 18. This is again a very unlikely situation, but it does satisfy axiom (A2).

Model 4

	4	10	18	19
4	T	T	T	F
10	T	T	T	F
18	F	T	T	F
19	F	F	F	T

Model 5

	4	10	18	19
4	T	T	T	F
10	T	T	F	F
18	T	F	T	F
19	F	F	F	T

Model 6

	4	10	18	19
4	T	T	T	F
10	T	T	T	F
18	T	F	T	F
19	F	F	F	T

Table 7.11: Models 4-6 of Environmental Large-scale Space

As in Models 1 to 3, Model 4 in Table 7.11 assumes that object 18 and object 4 are not near, this being a very unlikely, but valid interpretation. Object 18 and 10 are near each other, describable by nearness notion s-near1. In Model 5 and 6 in Table 7.11, objects 18 and 4 are near, which can be described by nearness notion s-near4 given in **Definition 15** assuming that the objects are located within each other's impact area. Objects 18 and 10 are not near each other in Model 5. This situation does satisfy axiom (A2) and also nearness notion s-near4, because the condition of this notion for being near i.e., that the objects are located within each other's impact area, is not given for objects 18 and 10. Model 6 exhibits the situation where object 18 is not near object 10, but object 10 is near object 18. The impact area of object 10 is much smaller than the one of object 18 and their asymmetric nearness relation can therefore be described by nearness notion a-near2 given in **Definition 13**.

In Model 7 in Table 7.12, objects 18 and 4 are near, which can be described by nearness notion s-near4 given in **Definition 15**, assuming that the objects are

Model 7

	4	10	18	19
4	T	T	T	F
10	T	T	F	F
18	T	T	T	F
19	F	F	F	T

Model 8

	4	10	18	19
4	T	T	T	F
10	T	T	F	F
18	F	F	T	F
19	F	F	F	T

Table 7.12: Models 7 and 8 of Environmental Large-scale Space

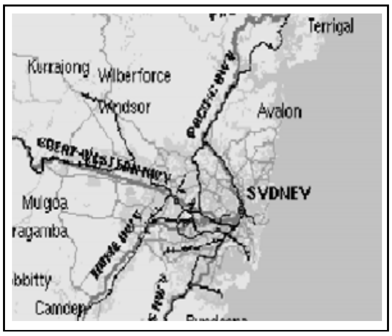
located within each other's impact area. Model 7 also displays the situation where objects 18 and 10 are near each other, describable by nearness notion s-near1 given in **Definition 11**. This nearness notion obviously can not describe the situation in Model 7, where object 18 is near object 10, but object 10 is not near object 18. While it does satisfy axiom (A2), it is a very unlikely interpretation. As in Models 1 to 4, Model 8 in Table 7.12 assumes that object 18 and object 4 are not near, this being a very unlikely, but valid interpretation.

7.2.2 Geographic Space

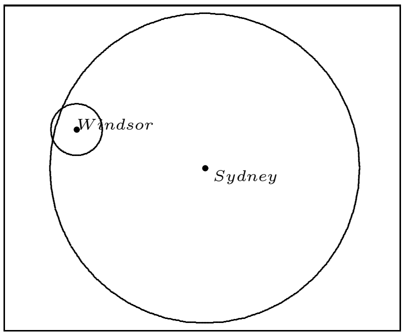
Geographic space[3] is, in contrast to small-scale space, essentially two-dimensional. The following geographic space interpretation is the map shown in Figure 7.7. For this interpretation, the impact area of Windsor does not need to be completely included in the impact area of Sydney.

The perceiving agent focuses on two of the places shown in the map, one being Sydney, a large city in South-Eastern Australia, and the other one being Windsor, a town North-West of Sydney. There are two possible models of this interpreation as shown in Table 7.13. In each of the two models, the town of Windsor is near the city of Sydney. Sydney is also considered near Windsor, when one for example considers the train trip between Sydney and Windsor and vice versa. An agent who considers that this train trip between Sydney and Windsor is short and therefore

[3]according to Naive Geography [32]



(a) Geographic Space



(b) Abstracted Space

Figure 7.7: Geographic Space Example

considers Sydney to be near Windsor, will also conclude that Windsor is near Sydney. Model 1 in Table 7.13 reflects this situation. As the abstracted space is quite different to both previous interpretation examples, a more specific nearness notion is necessary to acurately describe this model of the scene. The object representing Windsor is situated within the impact area of Sydney, however Sydney is not situated within Windsor's impact area. The nearness notion s-near2 given in **Definition 12** captures this situation. This definition again allows for both complete and partial inclusion of a query object in the impact area of the second query object.

In contrast, Model 2 represents contexts where Sydney is not considered to be near Windsor. For an example of such a context, imagine someone describing where Windsor is to people who only know Sydney but not Windsor. One would say that Windsor is near Sydney, however not that Sydney is near Windsor, because Sydney is a far more important landmark.

Model 1

	Sydney	Windsor
Sydney	T	T
Windsor	T	T

Model 2

	Sydney	Windsor
Sydney	T	F
Windsor	T	T

Table 7.13: Models of Nearness in the Scene in Figure 7.7

Impact areas of cities can also be determined by the catchment area of their infrastructures. For example, there are many specialist hospitals and government offices located in the Sydney area that also service Windsor. In that respect, Windsor is near Sydney. Sydney however is not near Windsor, because none of Windsor's infrastructures service Sydney; thus exhibiting the same asymmetric nearness relation as in the previous example. We therefore need a more specific nearness notion, an asymmetric refinement of s-near2. The relation a-near3 in **Definition 14** provides for this. Partial inclusion of o_1 in $IA(o_2)$ can be sufficient in some cases and is therefore allowed by the definition.

7.3 Synopsis of Nearness Notions

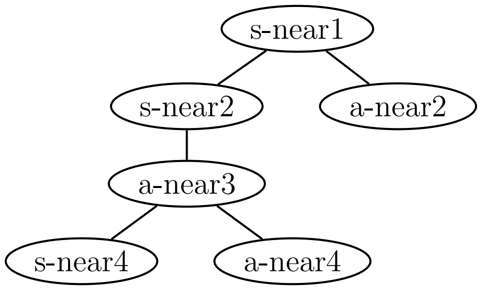


Figure 7.8: A "Family" of Nearness Relations for Specific (D, ω)

The formalism of nearness developed in this section is based on the generic notion of nearness satisfying axioms $(A1)$ and $(A2)$. A "family" of nearness relations for specific distance and mapping function satisfying $(A1)$ and $(A2)$ were defined resulting in a relational tree shown in Figure 7.8, starting with s-near1 as the most general nearness notion of the "family." This nearness notion s-near1 will be justified against GIS data and expert knowledge data in the experiments in the next chapter.

s-near1(o_1,o_2)$=_{Def}$ $IA(o_1) \cap IA(o_2) \neq \emptyset$

s-near2(o_1,o_2)$=_{Def}$ $(o_1 \cap IA(o_2) \neq \emptyset) \vee (o_2 \cap IA(o_1) \neq \emptyset)$

a-near2(o_1,o_2)$=_{Def}$ $(IA(o_1) \cap IA(o_2) \neq \emptyset)$ and

for all $p \in o_1$ there exists $q \in o_2$ such that $\omega(p) \leq \omega(q)$

a-near3(o_1,o_2)$=_{Def}$ $o_1 \cap IA(o_2) \neq \emptyset$

s-near4(o_1,o_2)$=_{Def}$ $(o_1 \cap IA(o_2) \neq \emptyset) \wedge (o_2 \cap IA(o_1) \neq \emptyset)$

a-near4(o_1,o_2)$=_{Def}$ $IA(o_1) \subseteq IA(o_2)$

7.3.1 Symmetric Nearness and its Properties

As previously discussed, Worboys concluded from his test results that nearness was a weakly symmetric relation, because there were no pairs (o_1, o_2) such that o_1 near o_2 and o_2 not near o_1 or vice versa[4]. Recall that the formalism introduced here is based on a two-valued logic.

The following section discusses the properties of symmetric nearness based on nearness notion s-near1. Recall that s-near1$(o_1, o_2) =_{Def} IA(o_1) \cap IA(o_2) \neq \emptyset$. In terms of proximity spaces, this means that the distance between the closest closure points of the two set (i.e. impact areas) is zero.

Axiom (A1) and Axiom (A2) are satisfied by s-near1(o_1, o_2) and we can add a third Axiom (A3) stating the symmetric nature of this nearness notion, which is valid for all symmetric nearness notions.

$$(A3)\ For\ all\ objects\ o_1, o_2\ Near(o_1, o_2) \leftrightarrow Near(o_2, o_1)$$

As discussed in Chapter 3, points, lines and polygons are the spatial object primitives in GIS vector data. The nearness framework presented here adapts this to a more general notion of objects comprising points and sets of points. So far, we have examined nearness with respect to this broader concept of general objects. Let us now look at the specific case where each object is represented by a single point only.

[4]In addition to that, Duckham and Worboys [28] found that for significance levels less than 0.169, if the nearness relation between places o_1 and o_2 is true, the nearness relation between o_2 and o_1 would not be false.

7.3.2 The case of the Singleton Object

Singleton objects are common in GIS vector data, particularly in large scale maps, where many features are abstracted into points. Consider city representations in a national map, for example. The experiments reported in Chapter 8 use towns and settlements as query objects, which are also point representations. In addition to the nearness notions previously introduced, there are some specific implications for singleton objects that I will consider in the following. Note that we only consider disk shaped impact areas in this subsection.

A brief look at the bidimensionality of *Nearness*

With ω and distance being the parameters of nearness, nearness can be considered in two different dimensions. One is a discrete dimension, in which D and ω can have any value with the constraints imposed on their behaviour resulting in different discrete concepts of *Near*. The second dimension considers D and ω as specific and continuous parameters, which can be applied to any concept, therefore allowing "fine-tuning" of the specific concepts of *Near* in the other dimension. Figure 7.9 shows this principle with the *Concepts*-axis representing the first dimension and the *Parameters*-axis representing the second dimension. The dotted line shows that for any given specific distance D and ω, each concept has a certain resticted scope. Note that this scope might cover the entire universe for certain values of D and ω and certain concepts represented by nearness relations. In order to capture whether a nearness relation is finer or coarser than another, we introduce a relation to express this.

As can be seen in Figure 7.9, we are aiming at introducing a partial ordering amongst the given concepts e.g., s-near4 > s-near1. The ordering requires all the concepts to be placed in the same branch of a conceptual lattice and the more general notion is implied by the more specific notions.

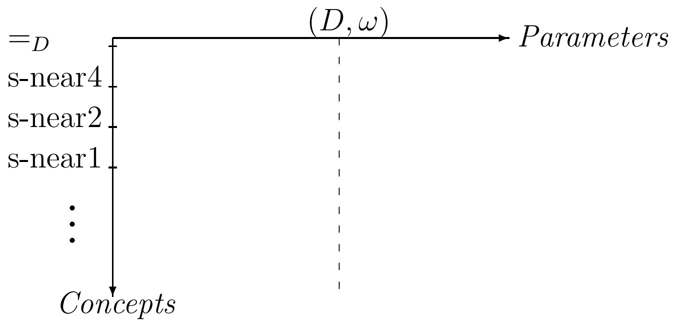


Figure 7.9: The two dimensions of Nearness where D is distance and ω is the result of a specific mapping function

Definition 17 (Partial Ordering) *Let μ and δ be two nearness relations on U then $\mu > \delta$ iff $\forall p, q\ \mu(p, q) \rightarrow \delta(p, q)$.*

Section 7.3.3 will extend on this idea by supplying such a set of concepts in the context of a navigational setting.

I will now consider properties of symmetric nearness that hold for any distance D and weight ω.

Equality of Sites

Equality of sites i.e., the distance between sites being zero, is not very interesting, but is included for completeness.

Property 18 *The equivalence relation defined by $=$ is a refinement*[5] *of the equivalence relation defined by $=_D$.*

Note that this property of symmetric nearness is also a more specific concept of symmetric nearness.

Inclusion of at least one Site

This property covers the case when only one site is included in the other's impact area.

[5] *i.e., a special case*

Proposition 19 *For all* $p, q \in \mathcal{U}$*, if* $D(p,q) \leq sup(\omega(p), \omega(q))$ *then* s-near1(p,q).

Proof. If $D(p,q) \leq \omega(p)$ then by Definition 9, $q \in IA(p)$. q is also an element of $IA(q)$. Therefore $IA(p)$ and $IA(q)$ have at least the point q in common. The case of $D(p,q) \leq \omega(q)$ is analogous.□

From this proposition, I will now derive and discuss two corollaries.

External Connectedness of Sites

In the Region Connection Calculus (RCC) [93] the relation $EC(x,y)$ is defined as applicable to regions R_1, R_2 and holds if R_1 and R_2 are externally connected i.e., have at least one common point in the RCC terminology. This was extended by Asher and Vieu [6] to assume that the regions have only closure points[6] in common when they are externally connected. That way, the relation can also account for real world objects considered to touch each other without sharing any of their matter.

If regions were singletons i.e., points, the RCC definition would not allow for external connectedness. In this formalism, we resort to pseudo-metric space, because it allows us to define points as *near to each other* when the distance between them is zero. They are as close as possible to each other without being identical.

Corollary 20 *For all* $p, q \in \mathcal{U}$*, if* $p =_D q$ *then* s-near1(p,q).

In this case we can also conclude with the definition of s-near4, but in order to keep this discussion straightforward, I will continue to refer to s-near1.

Inclusion of both Sites

This property covers the case when site p and q are included in each other's impact area, including the previous property.

Corollary 21 *Suppose that* $\mathcal{U}$ *is dense. For all* $p, q \in sites(\mathcal{U})$*, if* $D(p,q) \leq inf(\omega(p), \omega(q))$ *then* s-near1(p,q).

[6]See Section 2.5 for an explanation of what a closure point denotes.

I will now discuss different concepts of symmetric nearness in a navigation setting.

7.3.3 Concepts of Symmetric Nearness in Navigation

In this subsection, specific concepts of symmetric nearness as refinements and generalisations of s-near1 are discussed. Chains of intersecting impact areas implying nearness between objects that are otherwise not considered near can have interesting implications to navigation tasks. The following example therefore considers a bushwalker navigation around a forest using trees as landmarks.

Generalisations of s-near1

Let the trees in the forest be query objects. The bushwalker is trying to navigate from one tree to an unknown point in the forest and back to the initial position. In this context, the the impact area assigned to every tree could be defined by the distance the agent can see while standing beside the tree. Another aspect that needs to be added is the reasoning abilities of this agent during navigation. An agent with rather bad navigating skills might only feel comfortable to walk to the next tree that he or she can see and back to the one he or she started from. For a better navigator, he or she might feel comfortable to navigate along a couple of these “near” trees and back. Thus, given that the total distance is not very far nor hard to cover, by considering the first and the last tree actually being near to each other, s-near1 in Definition 11 can be generalised as seen in the following definition.

Definition 22 *Let $i > 0$ given. For any two objects p and q: $Near_i(p, q)$ holds iff there exist objects $r_0, ..., r_i$ with $r_0 = p$, $r_i = q$ and for all $j < i$, $IA(r_j) \cap IA(r_{j+1}) \neq \emptyset$.*

A clear ordering occurs among these generalised nearness relations as expressed in the next property. By Definition 22 we can say that $Near_{i+1} \rightarrow Near_i$, therefore by (partial ordering) Definition 17 we can conclude that $Near_{i+1} > Near_i$.

Property 23 *For all $i > 0$, $Near_{i+1} > Near_i$.*

Note that this partial ordering can actually be total.

Refinements of s-near1

Let us now look at a bushwalker, who might consider trees near each other if at least one of them is in sight of the other. This situation could occur if the agent is, for example, at a smaller tree from which he or she can see a tall tree in the distance but not vice versa. The relation s-near2(p, q) given in Definition 12 accounts for this fact that two trees p and q are near to each other if and only if $p \in IA(q)$ or $q \in IA(p)$.

Another agent might only consider two trees near each other, if he or she can see the second tree being positioned at the first one and vice versa. Relation s-near4(p, q) given in Definition 15 accounts for this fact that two trees p and q are near to each other if and only if $p \in IA(q)$ and $q \in IA(p)$.

A clear ordering occurs among these refined nearness relations as expressed in the following property. By Definitions 15 and 12 we can say that s-near4 $\rightarrow$ s-near2 and therefore we can conclude by (partial ordering) Definition 17 that s-near4 $>$ s-near2.

Property 24 s-near4 $>$ s-near2.

7.3.4 Enriching the Formalism

In order to enrich the formalism to gain more expressive power for reasoning, I will now add the notion of one site being in between two others.

Definition 25 (*Between*(r, p, q)) *Given the distinct points p, q, r in $\mathcal{U}$ and $p \neq r$, if $D(p, q) = D(p, r) + D(r, q)$ then r is said to be between p and q.*

There is the limit case that all three points p, q, r are pairwise pseudo-equal and any of them is between the other two. Another, very interesting, aspect of Definition 25 is that all pseudo-equal points to p, q, r also comply to the *Between*-relation, resulting in a fuzzy notion of *Between*. This is shown in Figure 7.10,

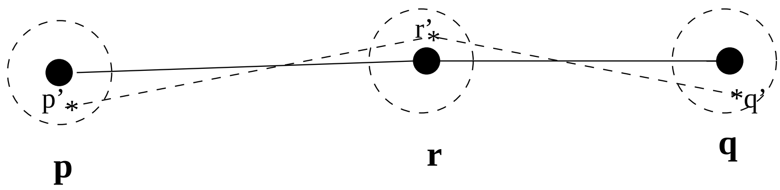


Figure 7.10: Fuzzy Notion of *Between* where p', q', r' are pseudo-equal points to p, q, r respectively

where the points p', q', r' denote the pseudo-equal points to p, q, r respectively and $Between(r, p, q) \rightarrow Between(r', p', q')$.

The *Between* relation could be made more expressive if orientation relations were added as suggested in Frank [41] and Hong et al. [67], but this is not in the scope of this discussion as it would add more parameters to the formalism than desired.

The *Between*-relation could also very effectively be represented using Ordinary Voronoi Diagram information, as has been shown by Edwards and Moulin [31] in their Voronoi model approach. However, the potential user has to weigh up the advantages of a more effective representation against this computationally more expensive approach.

7.4 The Asymmetric Nature of Nearness

In most cases, the symmetric notion of nearness, as discussed in the previous section, is adequate. However, when it comes to the everyday world around us and the way we perceive it, navigate around and talk about it, this symmetric property does not always hold. There are cases, as we have seen in the case study in Section 7, where nearness is not symmetric. Asymmetric nearness does satisfy axioms (A1) and (A2), but obviously not axiom (A3), which only applies to the class of symmetric nearness notions. This asymmetric aspect of nearness is now discussed in more detail in this section.

As previously mentioned in Section 5.3.2, there appear to be several factors that influence the perception of nearness. One such factor is disparity in the size of the spatial entities. This and other causes of perceptual disparity have been extensively researched cross-linguistically and is apparent as the natural language division of objects into reference objects (RO) and objects to be localised (LO).

For example, picture a bicycle near a house. Expressing this spatial situation as "the house is near the bicycle" would be considered as incorrect by most and "the bicycle is near the house" as the only correct description. This is a classic example from the linguistic literature originating with Talmy [109], who conducted cross-linguistic experiments and summarised his findings on spatial language reference in terms of general properties valid across languages. Talmy defines reference objects as objects whose location and sometimes also other properties, referred to as "geometric" properties, are already known. The site, path or orientation of the object to be localised is therefore defined in terms of the distance between the reference objects and the object to be localised or in terms of the relation to geometry of the reference objects.

Talmy identified several properties of an object that might lead to its choice as either the reference object or the object to be localised, with at least one of these properties applying to each of the scene's objects. These properties are shown in Table 7.14.

Object to be localised	Reference Object
spatial variables need to be determined	acts as a reference object with known spatial characteristics
more movable	more permanently located
smaller	larger
conceived as geometrically simpler	taken to have greater geometric complexity
(often point-like)	
more salient	more backgrounded
more recently on the scene/in awareness	earlier on the scene/in memory

Table 7.14: Properties that determine an object's choice as reference object or object to be localised

Some of these criteria are also reflected in the area of influence that is perceived of an object. As we will see in the following subsection, a navigation system has

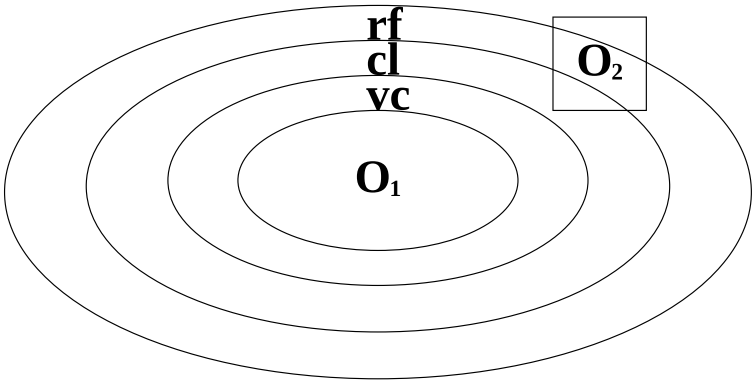


Figure 7.11: Influence Areas according to Kettani and Moulin [69]

succesfully been implemented by using size and shape of objects by Kettani and Moulin [69]. Generally, when objects with smaller ω are perceived as being near objects with much larger ω, the reverse is not always true. The relation a-near2 in the family of nearness notions does reflect this possibility. In the context of natural languages, this is caused by the likely reference object role of the object with the larger impact area, to which the object with the smaller impact area is related, as Talmy points out, in terms of distance.

7.4.1 A Natural Language Example

As part of the GRAAD project, Kettani and Moulin [69] developed a knowledge-based navigation system that incorporated orientation and proximity information to generate routes and also provide natural language descriptions. For the representation of proximity, the GRAAD utilises a model that grades closeness around objects by the means of influence areas. Instead of having only one influence area for each object, several influence areas are assigned each representing a different degree of "closeness".

Kettani and Moulin's notion of influence area describes imaginary areas surrounding objects perceived in the environment in order to grade proximity, in the same way that natural language does, reflected in words such as *very close*, *close* and *relative far*. These influence areas are described as portions of space surrounding an object such that each influence area has an interior and an exterior border having the same shape as the object. The length of an imaginary perpendicular line crossing each influence area from one point on the interior border to another point on the exterior border is called the width of this influence area. While this width is a subjective measure of a person's perception, Kettani and Moulin [69] used simple Euclidean geometry to calculate the width of the influence area of objects in their cognitive maps so as to make practical use of their ideas in the navigating system. An object would then be considered to be *very close* to, *close* to or *relative far* from another if it was situated in the appropriate influence area. For example in Figure 7.11, object o_2 is *close* to object o_1, because part of o_2 is situated within the *close* (i.e. *cl*) influence area of o_1.

The differently graded influence areas for each object were introduced to provide a differentiation between different degrees of proximity. The nearness notions defined in this formalism of nearness can also be used to provide different degrees of proximity between objects and it can possibly also account for gradings finer than natural language, similar to the concept definitions in Section 7.3.3.

Considering the example of Kettani and Moulin's model shown in Figure 7.11 where *vc* stands for *very close*, *cl* stands for *close* and *rf* stands for *relative far*. According to their model, these relations have the degrees of proximity of $dp - 2$, $dp - 1$ and dp respectively. This means that $(O_2 \cap IA_{dp}) = \emptyset$, $(O_2 \cap IA_{dp-1}) \neq \emptyset$ and $(O_2 \cap IA_{dp-2}) \neq \emptyset$, where O_n is the region that represents object o_n.

The question now is, if the nearness notions, as previously defined, would be sufficient to account for these different degrees of proximity without having to resort to grading the impact area of an object itself. We will presume that the impact area of the object to be localised is equal to the object's spatial extent as represented by O_2. The impact area of the reference object is the union of the *very close*, *close* and *relative far* influence areas. Given this interpretation, different nearness notions could be used to describe the three different influence areas shown in Figure 7.11:

- For the *very close* degree of proximity, nearness notion s-near4 could be used, thus assuming that both O_1 and O_2 have to be in each other's impact areas for *very close* to be true. O_2 is within the impact area of O_1, but not vice versa. Therefore O_2 is not *very close* to O_1.

- For the *close* degree of proximity, nearness notion a-near3 could be used, thus assuming that O_2 has to be in O_1's impact area for *close* to be true. O_2 is within the impact area of O_1, therefore O_2 is *close* to O_1.

- For the *relative far* degree of proximity, nearness notion s-near1 could be used, thus assuming that the impact areas of O_1 and O_2 have to intersect for *relative far* to be true. We know that the impact areas of O_1 and O_2 intersect, therefore O_1 is *relative far* to O_2.

We know that the more specialised notion does always imply all of the more general notions. If for example, an object O_1 would be *very close* to an object O_2, the degrees of proximity *close* and *relative far* would always hold, even if O_2 would not be situated in Kettani and Moulin's *relative far* influence area. This is, however, not as much of a problem as it might seem at first sight, as generally the stronger nearness notion would be considered. In the above example, we would reason with the relation *close*, rather than with the *relative far*, as it gives us more specific knowledge.

Therefore, we can add to the above descriptions, that by Definition 17, *very close* $>$ *close* $>$ *relative far* and that always the greatest proximity degree will be chosen for reasoning.

After this excursion into the case of the singleton object, let us now explore how the previously defined nearness notions and their implications for singleton objects fare when applied to GIS data. All the notions defined in this chapter, except a-near2 are based on the fully general notion of impact areas ι. Therefore, they are suitable for use in different spaces such as road networks. Notion a-near2 is specific to disks only and will therefore not be considered in the experiments of the following chapter.

Chapter 8

Experiments

In the previous chapters, I discussed the concept of impact area and a generalised notion of nearness, and argued for its advantage over other methods currently available. This chapter will now examine what these concepts yield when applied to data sets. For the particular context of touristic road travel, I will demonstrate how expert knowledge can be extracted from tourist travel guides and I will introduce a specific mapping function to generate impact areas. It is interesting to note that GIS proximity analysis functions require fixed distance values to be determined and the break values to be specified at the time of function definition. For the mapping function used in these experiments the break values are not fixed, but are generated dynamically for each query point. The values can also change when new domain specific background knowledge is added. The relevance of this can be seen when looking at the way humans make decisions. Decision making, both spatial and non-spatial, is guided by background knowledge and changes to knowledge influences the process and its outcome. The traditional way of "fixed-value" proximity analysis is not flexible enough to account for this. In order to put more emphasis on the advantage of dynamically generated break values, I will also investigate a method using "fixed-values" breaks to evaluate nearness between query points. Let us refer to this method as the "naive approach," because it is naive in terms of not considering the dynamic nature of the spatial environment as perceived by cognitive agents.

The set up of the following experiments might be criticised for being limited to personal evaluation as opposed to an extended user evaluation to demonstrate that the proximity ideas developed actually make intutive sense to people (users). However, it needs to be kept in mind that this thesis comprises a huge body of work and to cover each aspect of evaluation would have been beyond the scope of a PhD. The following experiments were conducted and included to provide some practical evaluation of the theoretical framework developed. Before we proceed with the experiments themselves however, let me introduce the data sets employed, the experimental setup, and describe how the data was collected and prepared for analysis.

8.1 Experimental Setup and Data sets

The general idea of these experiments is to show, within the context of Touristic Road Travel, how the Impact Area approach can benefit proximity analysis in GIS. In addition to a map of Australia in form of a GIS data set, a nearness data set was generated from Tourist Travel Guides and Tourist Websites. This data set consists of pairs of places assumed to be in nearness relation. A road trip data set was generated from a comprehensive Australian holiday guide covering most of Australia's road network. This trip data set constitutes the expert knowledge as described in the *Impact Area Generation Model* introduced in Chapter 6 (see Figure 6.7).

8.1.1 Experimental Setup

I used a two month evaluation version of *ArcGIS* and its *NetworkAnalyst* extension. Initially, I investigated free applications such as QuantumGIS, that have most of the functionality that comes with the complete *ArcGIS*, however they are less user friendly and insufficiently documented. I primarily used *ArcCatalog* and *ArcMap* with extensions enabled to perform the data preparation and the experiments themselves. A complete automation of the mapping function is possible through *ArcGIS Model Builder*, however due to the complexity of this particular tool this would constitute a project on its own, going beyond the objectives of these experiments. Hence, I only partially automated the mapping function and conducted other parts manually. The complete automation is subject to future work.

Prior to conducting experiments, the data sets had to be generated and prepared for analysis. In the following, I will give a detailed account of all data sets involved and their preparation for analysis.

8.1.2 Data sets

In accordance with the *Impact Area Generation Model*, the data sets used can be divided into two classes: *GIS data* and *expert knowledge*. GIS data was obtained from *Geoscience Australia* and the expert knowledge constitutes data extracted from tourist information material. In addition, an evaluation data set was also generated from tourist information material. The latter two sets will be described under the heading of **Additional Datasets**.

GIS Data

The *National Mapping Division, Geoscience Australia* has a wide variety of GIS data available for free download from their website *http://www.ga.gov.au/*. The official distributor of the data is the *Office of Spatial Data Management* (OSDM) representing the Commonwealth of Australia. When downloading any of their data, a licence is granted on a royalty-free, non-exclusive, non-transferable basis allowing the licensee to:

(a) use, reproduce, adapt, modify, commercially exploit and communicate the Data (including by development and distribution of a Derivative Product);

and

(b) sublicense the Licensee's right to use, reproduce, adapt, modify, commercially exploit and communicate the Data, subject to the terms of this Licence.

The particular data set used in these experiments is the **Global Map Australia 1M 2001** under ©*Copyright Commonwealth of Australia (Geoscience Australia) 2001.* It is a digital dataset that covers the Australian landmass and island territories at a scale of 1:1 million. Four vector and four raster layers comprise this map. Of the four vector layers the population centres and transportation information is of concern to these experiments, and were used in shape format. The population centres layer includes built-up population centres and settlements. The built-up centres are stored as both points for point map representation and areas to represent the spatial extent of cities. The transportations layer includes roads, rail, airports, bridges and tunnels. Of interest here are only the point-map representations of the population centres and the roads. The feature *builtup* describes "an area containing a concentration of buildings and other structures" ([8], p. 17); it can be represented by the spatial object of point or polygon. In the following experiments, I used the point representation as stored in the *builtupp* layer. As distance is one of the main parameters in the experiments and is usually calculated between places, using some kind of centroid (or point) is the most appropriate representation. The feature of miscellaneous population centres as stored in the *mispopp* layer describes "a concentration of small dwellings" ([8], p.17) and its spatial object is also a point representation or a node/entity in another spatial feature such as a road. The feature class in layer *roadl* is described as "an open way maintained for vehicular use" ([8], p.14); its spatial object is a chain or line.

Additional Data sets

In order to provide data for verification purposes, I have derived a data set from Tourist Travel Guides comprising nearness information between places in Australia.

I made the assumption that places mentioned as possible side trips or day trips for a particular tourist destination are commonly agreed upon as being near this destination, with respect to the tourist's travel needs. All places found under *day trip*, *side trip*, *nearby* and similar entries in the travel guides were recorded in a nearness data set. This data set was then validated against and modified to match the availability of places in the **Global Map Australia 1M 2001** data set. I will discuss this process of validation and modification in more detail in the data preparation section. Two tourist guides, "Frommer's Australia 2001" [71] and "Let's Go Australia," [110] were scanned and a list of pairs (A, B) where place B is considered near place A was produced. It is important to keep in mind that symmetry is not implied in the nearness relations between these places and will therefore also not be tested for. Several additional tourist guides such as the Lonely Planet's "Australia: a travel survival kit" [114] were considered, but did not possess any notably different nearness information. This supports the claim that there is a general consensus on which places are near a particular tourist destination. Let us look at some examples to illustrate the data collection process. The Frommer's tourist guide [71] for example recommends Phillip Island as *side trip* when staying in Melbourne. Consequently the pair *(Melbourne, Phillip Island)* was recorded in the nearness data set. In the "Let's Go Australia" guide [110], the term *day trip* indicates some degree of nearness between places that are suggested for day trips from a particular reference place. For example, *Kiama* was recommended as a day trip when staying in *Sydney.* Consequently the pair *Sydney* - *Kiama* was recorded in the nearness data set.

57 nearness pairs were recorded from *side trip* references in "Let's go Australia" [110]. In "Frommer's Australia 2001" [71], both *road trip* and *side trip* references indicated a good degree of nearness. 25 such nearness pairs were recorded. The overall collection of 82 nearness pairs was used to derive the final evaluation data set which was used in the experiments.

The second data set that was recorded from tourist travel information comprised

35 two to ten day long road trips across Australia. These road trips constitute the expert knowledge as referenced by the *Impact Area Generation Model*. The assumption is that someone with knowledge of a particular area designed these trips with factors such as road conditions, availability of facilities or points of touristic interest implicitly taken into account. The knowledge of the person who designed these trips could be said to be encapsulated in the resulting road trips. From "Australian Road Trips - The Complete Holiday Guide" [96] 35 road trips were recorded. The trips are divided into day tours along the trip path. A road trip example is:

```
%Road Trip 2, The Great Inland Way
roadtrip(2,gilgandra,mackay,qld,qld).
daytours(2,gilgandra,lightningridge,[gulargambone,coonamble,walgett],nsw,nsw).
daytours(2,lightningridge,roma,[hebel,dirranbandi,stgeorge,surat],nsw,qld).
daytours(2,roma,rolleston,[injune,carnarvongorge],qld,qld).
daytours(2,rolleston,clermont,[springsure,emerald,capella],qld,qld).
daytours(2,clermont,mackay,[moranbah,coppabella,nebo,epsom,eron,walkerston],qld,qld).
```

8.2 Data Preparation

A large part of the efforts of any spatial data analyst is devoted to preparing data for upcoming analysis. The following describes how the relevant data were prepared and different data sets sufficiently integrated to enable nearness analysis in the Touristic Road Travel context.

8.2.1 Verification and Modification of the Additional Data Sets

When generating attribute tables for both the nearness and road trip data sets it became apparent that several places from the originally collected data were not recorded in the **Global Map Australia 1M**. Some places were not in the map at all; where possible I replaced them by places within their vincinity as verified in other maps such as *whereis.com* or *maps.google.com.au*. This was obviously not an option with many remote towns or settlements that could not be found in the **Global Map Australia 1M** and therefore had to be removed from the nearness or road trip data set. This was the case for locations such as *Burke and Wills Road House*, *Cape Crawford* or *Barkly Roadhouse*, which consequently resulted in road trips 12 and 24 being removed from the road trip data set. Several places in the nearness data collection were stated as day trips from a particular city such as *Austinmere* from *Wollongong*, but were administratively suburbs of these cities and therefore not recorded in the **Global Map Australia 1M**. Again, replacing them with another place was not an option as the closest location was their associated city. Other places were recorded under differing names between the nearness and road trip data sets, and the **Global Map Australia 1M**. These names were changed to the **Global Map Australia 1M** entries, if a verification was possible through online and paper maps, in combination with tourist information sites. Some places represented larger entities, such as the *Royal National Park* or *Lake Macquarie*. In such cases, I researched entry points or places that allow access to those entities. All places that could be unambigiously identified were added to the nearness data set if they were recorded in the **Global Map Australia 1M**. This sometimes resulted in additional nearness pairs. For example, the original nearness pair (*Adelaide*, *Adelaide Hills*) resulted in four nearness pairs after verification and modifications: (*Adelaide*, *Hahndorf*), (*Adelaide*, *Callington*), (*Adelaide*, *Lobethal*), and (*Adelaide*, *Echunga*). The resulting nearness data set consistent with the **Global Map Australia 1M** contains 55 nearness pairs. The resulting road trip data set, consistent with the **Global Map Australia 1M**, contains 32 road trips.

8.2.2 Creating Network Data

All places that are used in the nearness and road trip data sets were selected into *AustralianPlacesSelect*, consisting of 488 places. In order to conduct the experiments, a road network graph with best route distances between all *AustralianPlacesSelect* places needed to be generated. For this purpose, all relevant shape files were projected into *the North American Datum 1927 (Clarke 1866)* coordinate system through the shape file's properties option in *ArcMap*. A road network data set was then generated from the *roadl* shape file. This was done in *ArcMap* with the *Network Analysts* extension enabled. The following options were chosen throughout the network set up using the network dataset wizard:

- Connectivity with end-point default and one connectivity class only with no elevation modifications.
- Turns were included for potential future requirements.
- The cost attribute for *Distance* in kilometers was added to be used as impedance in the relevant network analysis functions. Its type is a *field* with the value of *shape*. Having this added attribute allows the addition of distances calculated from *shape lines* during the cost analysis to be added to the attribute table.

For all *AustralianPlacesSelect* places, I generated an *OD Cost Matrix* (Origin-Destination Cost Matrix) as follows.

8.2.3 Generating a Road Distance Graph

In the *ArcGIS Network Analyst*, I used *New ODCostMatrix* to create a Road Distance Graph, displaying the road distances between all places from this data set. In *ArcMap*, after enabling the Network Analyst under the Tools menu, *New OD Cost Matrix* is selected. *AustralianPlacesSelect* are added as both *Origins* and *Destinations* to generate an exhaustive matrix of best route distances between all places. Then, in the *Properties Window* under the *Analysis Settings* tab, distance in kilometers was chosen as impedance and U-turns not allowed. Distance was also checked as an accumulation attribute. The cost matrix for the distances between all 488 places resulted in 214024 distance pairs. In order to perform the naive approach,

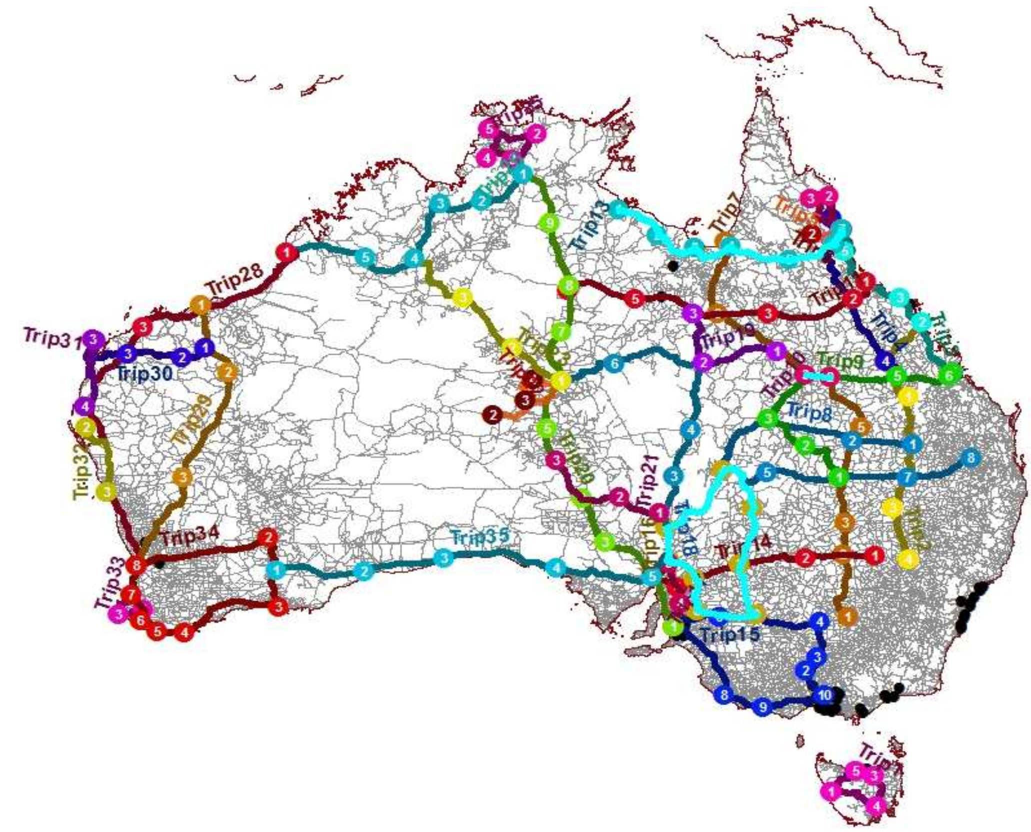


Figure 8.1: The road trips recorded give a good coverage for all query places from the nearness data set, which are shown as black point objects.

all distance pairs from the nearness data set were selected from this road distance graph and stored in *NearPlaceDistances*.

8.2.4 Adding Road Trip Information

In *ArcMap*, after enabling *Network Analyst* under the Tools menu, *New Route* is selected. For each road trip, a new route needs to be generated. The start and end points for all day tours contained in the trip are selected from *AustralianPlacesSelect* and added as *Stops* with U-turns *not allowed anywhere* in the analysis settings tab of the *New Route* properties window. The sequence of stops can be modified accordingly to reflect the original road trip design before solving the function. Figure 8.1 shows all 32 road trips and as can be seen, they are fairly evenly distributed across Australia.

8.3 Naive Approach

As previously mentioned, the distances between all nearness pairs was selected from the ODMatrix that was generated for all places in *AustralianPlacesSelect*, and consequently recorded in *NearPlaceDistances*. When looking at the distribution of distance values for this data set, as displayed in Figure 8.2, we can see that the majority of nearness pairs exhibit a distance below approximately 50km, with the next largest cluster being below approximately 96km and so on.

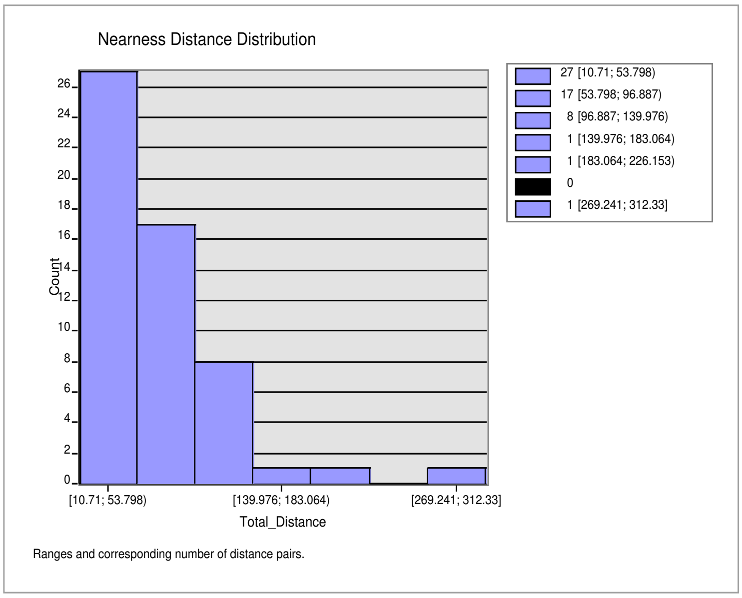
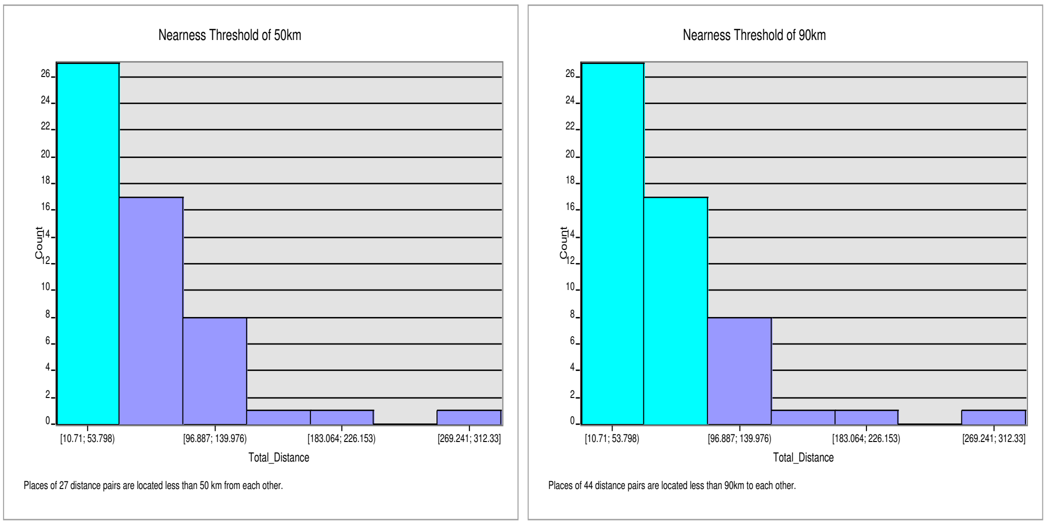


Figure 8.2: Statistical Information on the Distribution of Distances between all nearness pairs as recorded in the *NearPlaceDistances* attribute table

If we use "fixed-value" breaks, where we assume nearness for any pair of query points below a particular threshold, an obvious choice would be the end distances of the ranges displayed in Figure 8.2. If we choose a threshold of 50km, 27 distance pairs would evaluate as near pairs (see Figure 8.3(a)). If we increase the threshold to 96km,



(a) Under 50km there are 27 near pairs

(b) Under 96km there are already 44 near pairs

Figure 8.3: Naive Approach: Nearness Pairs determined by Thresholds

the amount of near pairs has already increased to 44 (see Figure 8.3(b)). Obviously, the more we increase the threshold the more inclusive we become. However, the purpose of nearness in human spatial cognition is to arrive at more information about the spatial environment. If a nearness notion becomes too inclusive, it also becomes less useful. If we were to increase the threshold for example to 300km, we would include almost the entire nearness data set AND a large amount of place pairs that we would not want to consider near. Near larger cities, we might consider travel within excess of 150km as far. In the remote regions of Australia's Outback, even 300km might be considered near, due to a lack of coverage of facilities. The threshold approach is obviously not flexible enough to deal with these kinds of outliers without becoming too inclusive. We would need to increase the threshold value to a point where places which should not be considered near would bear the nearness label. Let us see how the impact area approach fares with nearness evaluation across the nearness data set.

1. Identify closest road trip to A:
   (a) Find closest place in a road trip through *Closest Facility* function where A is incident and all places in road trips are facilities.
   (b) Select road trip(s) that contain(s) the "closest facility"
      i. If one road trip only, choose this road trip RT_A .
      ii. If more than one road trip, generate polygon for each road trip containing road trip and A, choose road trip RT_A that generates smallest polygon.
2. Identify closest road trip to B:
   (a) Find closest place in a road trip through *Closest Facility* function where B is incident and all places in road trips are facilities.
   (b) Select road trip(s) that contain(s) the "closest facility"
      i. If one road trip only, choose this road trip RT_B.
      ii. If more than one road trip, generate polygon for each road trip containing road trip and B, choose road trip RT_B that generates smallest polygon.
3. For all day tour stops S in road trips $RT_A = S_{A1}, ..., S_{Ai}$ and $RT_B = S_{B1}, ..., S_{Bj}$ calculate distance values D:
   - Minimum distance: $D_{min}(A) = \min\{D(S_{A1}, S_{A2}), ..., D(S_{Ai-1}, S_{Ai})\}$ and $D_{min}(B) = \min\{D(S_{B1}, S_{B2}), ..., D(S_{Bj-1}, S_{Bj})\}$
   - Average distance: $D_{av}(A) = \frac{\sum_{i=1}^{n} D(S_{Ai}, S_{Ai+1})}{n}$ and $D_{av}(B) = \frac{\sum_{j=1}^{n} D(S_{Bj}, S_{Bj+1})}{n}$
   - Maximum distance: $D_{max}(A) = \max\{D(S_{A1}, S_{A2}), ..., D(S_{Ai-1}, S_{Ai})\}$ and $D_{max}(B) = \max\{D(S_{B1}, S_{B2}), ..., D(S_{Bj-1}, S_{Bj})\}$
   - Hausdorf distance: $D_{hausdorf} = \max\{D(S_{Ai}, S_{Bj}) | 1 \leq i \leq n, 1 \leq j \leq m\}$
4. Calculate road network impact areas for A and B through using the *Service Area* function with break values of D.

Figure 8.4: Mapping Function for Touristic Road Travel

8.4 Impact Area Approach

8.4.1 Mapping Touristic Road Travel

Recall the *Impact Area Generation Model*, where we assumed that context can be supplied by an expert. The context we are looking at now is Touristic Road Travel where a travel guide or a frequent traveler figures as the expert. The expert knowledge is the previously discussed road trip information. We use this in conjunction with the prepared GIS data to arrive at a distance value used to generate the impact areas of query objects through a mapping function. In this particular case, we extract the distance value from the closest road trip to the query point. In contrast to other "fixed-value" approaches applied across the whole data set, this approach represents a flexible distance value as it depends on the closest road trip, which changes with location. The mapping function used in the experiments will generate impact areas for every query points A and B following the steps outlined in Figure 8.4. While the steps show four different impact area generation distances, it should be kept in mind that for each impact area being generated only one of these distances is chosen. The function that will return the impact area generation distance corresponds to the impact function ι discussed in Chapter 6, in this particular case ι can be refined as ω, because it returns one single number R. A detailed discussion on this specific ω can be found in 6.2.10. The domain specific key properties are given by the road network and the touristic road travel information; the values for these properties are the road trip and road network data. The query points are the start and destination locations. Note that the *Closest Facility* and *Service Area* functions are discussed in more detail in 3.2.5 and 3.2.5 respectively.

8.4.2 Results

Obvious Cases of Spatial Proximity

Let us look at the query example for *Adelaide* - *Williamstown*. We first locate the closest road trip for each query point by identifying the closest place contained in a road trip. A list of places contained in all road trips is loaded as *facilities* and the query place as *incident*. For *Adelaide*, the closest place contained in a road trip is *Adelaide* itself, which is contained in *Trip15*, *Trip17* and *Trip 20*. We choose the road trip that generates the smallest polygon including both *Adelaide* and the trip, which is *Trip17*. This will ensure that the road trip reflects the conditions likely to being encountered when traveling from Adelaide. For each of the day tours contained in this trip, we can now calculate the maximum, minimum and average distance to be used as default polygon breaks, i.e., the road distance that can be covered from the incident place within these given impedances. Day tours can also be considered to give some kind of nearness indication between their start

Query Place	Closest Trip	Trip Stops	Day Tours	D	D_{av}	D_{Max}	D_{Min}
Adelaide	17 (closest facility Adelaide)	ADELAIDE BURRA PORT AUGUSTA HAWKER ADELAIDE	ADELAIDE - BURRA BURRA - PORT AUGUSTA PORT AUGUSTA - HAWKER HAWKER - ADELAIDE	127 195 107 342	193	342	107
Williamstown	17 (closest facility Adelaide)	ADELAIDE BURRA PORT AUGUSTA HAWKER ADELAIDE	ADELAIDE - BURRA BURRA - PORT AUGUSTA PORT AUGUSTA - HAWKER HAWKER - ADELAIDE	127 195 107 342	193	342	107

Table 8.1: Distances between day tour places along the closest road trip *Trip 17* for *Adelaide* and *Williamstown*, and their associated break values for the impact area generation.

and destination places, a reason why I use day tour distances to derive break values for impact areas. For *Williamstown*, the closest place contained in a road trip is also Adelaide. We therefore choose *Trip17* for Williamstown. Table 8.1 summarises the data for these two query points. For this particular query pair, we cannot consider the *Hausdorf Distance* as one Road Trip is the closest for both query points.

We can now use the different distance measures to generate the impact areas for both query points. *Network Analysts* provides the *New Service Area* function through which polygons are generated that, in this particular touristic road travel context, play the role of impact areas. A new service area is generated for each of the query points. The two query places *Adelaide* and *Williamstown* are selected from the *NearnessPlacesDataSet* as the *facilities* from which the service area polygons are to be generated. The distances identified as D_{av}, D_{Max} and D_{Min} are entered as default breaks and U-turns are *not allowed anywhere*.

Figure 8.5 shows the resulting impact areas for both query places; the areas for Adelaide are pattern filled to differentiate them better. These two places are very close to each other with their impact areas not only intersecting, but the query points being located in each other's impact area. Thus, for this query pair we can conclude that all but one of the nearness relations defined in the previous chapter hold true. The relation a-near4(*Adelaide*, *Williamstown*) does not hold because none of the corresponding impact areas, i.e., with the default polygon break based on the same distance type, are actually contained in the other query object's impact area. Similar results were yielded for the queries: *Adelaide - Lyndoch*, *Adelaide - Lobethal*,

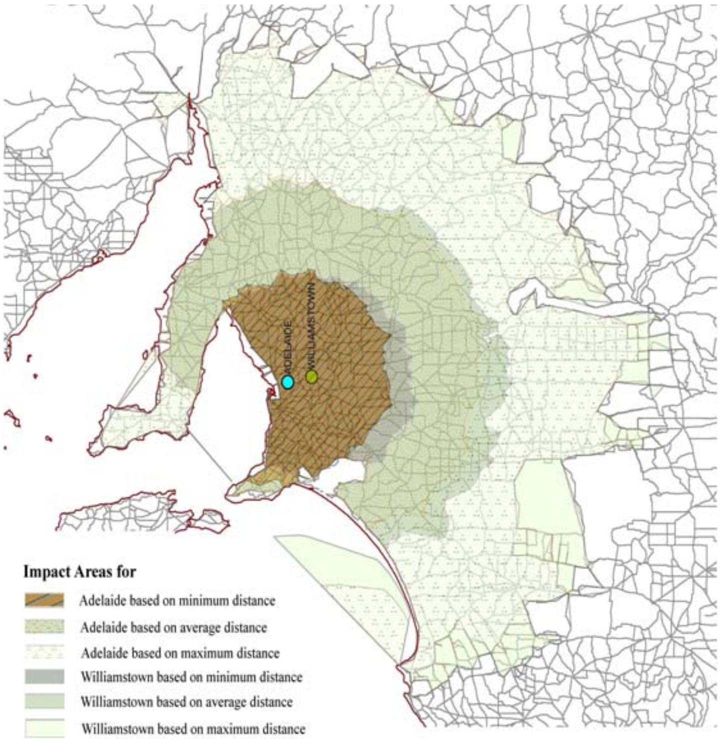


Figure 8.5: Three impact areas each based on average, maximum and minimum distance of day tours were generated for the query points *Adelaide* and *Williamstown*. The areas for *Adelaide* display a patterned fill to allow better differentiation.

Adelaide - *Tanunda*, *Adelaide* - *Springton*, *Adelaide* - *Mylor*, *Adelaide* - *Hahndorf*, *Adelaide* - *Angaston*, *Adelaide* - *Eden Valley*, *Adelaide* - *Echunga* and *Adelaide* - *Callington*. All these pairs exhibit distances in the range of 27km to 76km between the two query points. *Trip 17* is the closest road trip for places contained in these pair, resulting in impact areas with the same break values. Both query points are always located in each other's impact areas indicating very strong nearness.

Less Obvious Cases of Spatial Proximity

Let us now explore an example of two query places that are situated at a larger road distance than the previous two in order to evaluate how well the impact area approach works for less obvious cases. The road distance between *Mount Isa* and *Camooweal* is approximately 190km and should be an interesting point in case for

Query Place	Trip	Trip Stops	Day Tours	D	D_{av}	D_{Max}	D_{Min}
Mount Isa	19	WINTON BOULIA MOUNT ISA	WINTON - BOULIA BOULIA - MOUNT ISA	361 286	324	361	286
Camooweal	11	TOWNSVILLE CHARTERS TOWERS MAXWELTON MOUNT ISA SOUDAN TENNANT CREEK	TOWNSVILLE - CHARTERS TOWERS CHARTERS TOWERS - MAXWELTON MAXWELTON - MOUNT ISA MOUNT ISA - SOUDAN SOUDAN - TENNANT CREEK	133 412 353 310 352	312	412	133

Table 8.2: Distances between day tours places along the closest road tour *Trip 19* and *Trip 11* for *Mount Isa* and *Camooweal* respectively, and their associated break values for the impact area generation.

FROM (Trip 19)	TO (Trip 11)	DISTANCE
WINTON	TOWNSVILLE	593
	CHARTERS TOWERS	461
	MAXWELTON	223
	MOUNT ISA	463
	SOUDAN	774
	TENNANT CREEK	1126
BOULIA	TOWNSVILLE	955
	CHARTERS TOWERS	823
	MAXWELTON	449
	MOUNT ISA	286
	SOUDAN	575
	TENNANT CREEK	927
MOUNT ISA	TOWNSVILLE	896
	CHARTERS TOWERS	764
	MAXWELTON	353
	MOUNT ISA	0
	SOUDAN	310
	TENNANT CREEK	662
	HAUSDORF DISTANCE:	**1126**

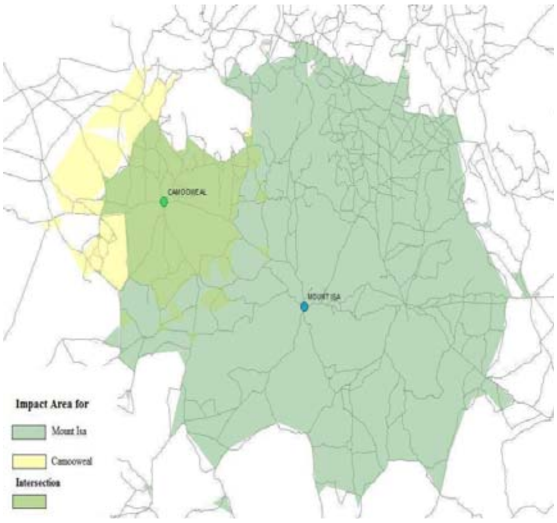
Table 8.3: Distances between places of *Trip 19* and places of *Trip 11* are used to determine the Hausdorf distance between these two trip, which is the maximum of these inter-set distances.

the impact area approach.

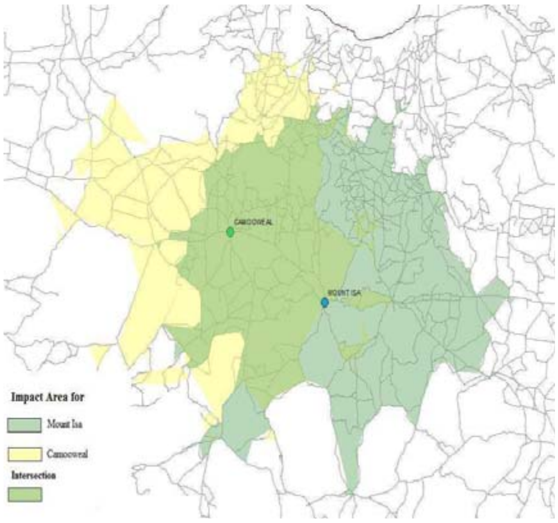
At first, we determine the closest road trip for *Mount Isa* and *Camooweal*, which are trips *Trip19* and *Trip11* respectively. Table 8.2 summarises the data for each of the identified road trips and the related distances within them. The Hausdorf distance was calculated for the two road trips *Trip 11* and *Trips 19* by determining the maximum distance that occurs between any two places each from another road trip. Table 8.3 shows the distance pairs relevant for finding the Hausdorf distance between the two trips. The maximum distance, i.e., Hausdorf distance, is 1126km. Figure 8.6 shows the resulting impact areas. We can see that for all four distance values, the most general of all nearness notions s-near1(*Camooweal*, *Mount Isa*) holds true. When applying D_{min} and D_{av} as break values, there appears to be an asymmetric nearness notion, as *Camooweal* is situated inside the impact area generated for *Mount Isa*, but not vice versa. The nearness notion *Mount Isa*) and a-near3($Camooweal, Mount\ Isa$) holds true as seen in Figure 8.6(a) and (b). When applying D_{Max} and $D_{hausdorf}$ as break values as seen in Figure 8.6(c) and (d), both query points are located in each other's impact areas, making s-near2($Camooweal$, $Mount\ Isa$) true, and changing it to a symmetric notion. It would be expected that this kind of grading becomes more difficult the larger the actual distance between query places becomes. In the "fixed-value" distances (or naive) approach, outliers such as this one would often not be included in the nearness category. Hence, let us consider another example from our *NearnessPlacesDataSet*, where the distance between the query points is even larger. It will be interesting to see if the impact area approach can still detect any nearness between such query points and if any grading is still apparent.

The largest distance between any of the nearness pairs collected is 320km for *Lawn Hill - Mount Isa.* The closest road trip identified for *Lawn Hill* is *Trip 13* and the closest road trip for *Mount Isa* is as previously stated *Trip 19.* The minimum, average and maximum distances for *Trip 13* are 111, 234 and 299km, respectively. The Hausdorf distance between *Trip 13* and *Trip 19* is 1167km. For the break values of D_{Min}, D_{av} and D_{Max} as seen in Figure 8.7(a), (b) and (c), respectively, nearness notion s-near1($MountIsa, LawnHill$) holds true, but none of the stronger correlations can be found. This is a very good case in point for the more general notion of nearness s-near1 that does consider objects near as long as their impact areas intersect. As shown in Figure 8.7(d), when applying $D_{hausdorf}$ as break value, *Mount Isa* and *Lawn Hill* do suddenly display the very strong nearness notion of s-near4.

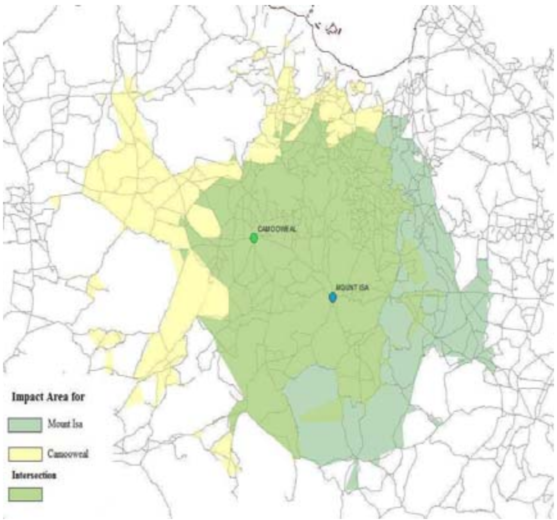
The fact that the Hausdorf distance appears to cause a shift in nearness notions is worth some further investigation. Let us consider obvious negative examples such as *Melbourne - Mount Isa* that would not be considered near in our context of Touristic Road Travel being separated by 2377km. The closest road trip to



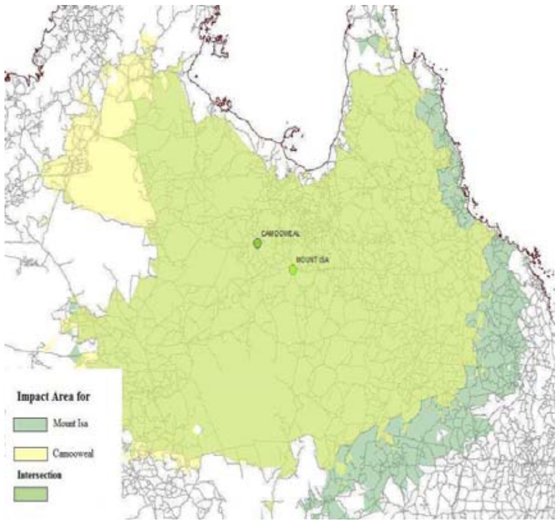
(a) Impact Areas for Mount Isa and Camooweal using the minimum distance of the day tours



(b) Impact Areas for Mount Isa and Camooweal using the average distance of the day tours

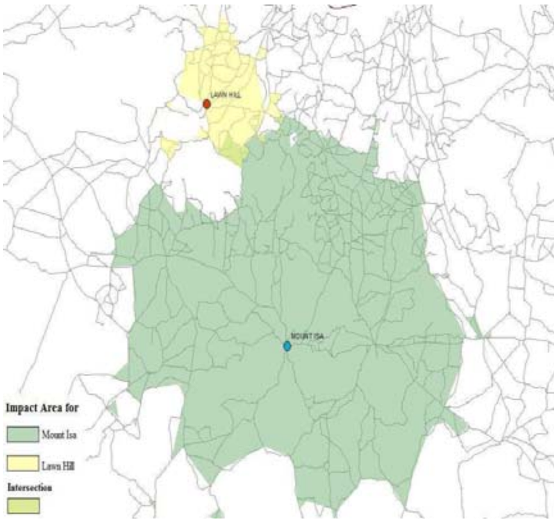


(c) Impact Areas for Mount Isa and Camooweal using the maximum distance of the day tours

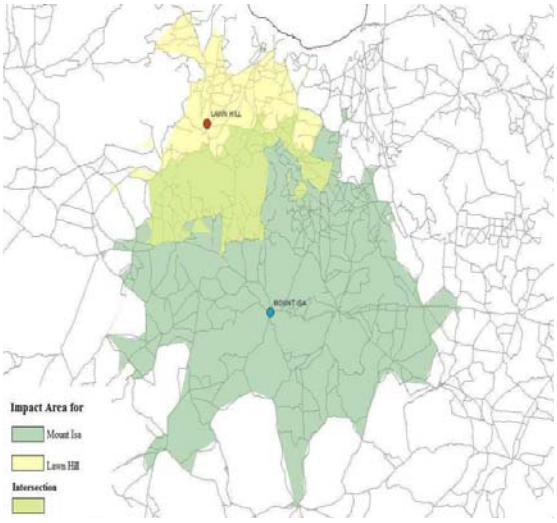


(d) Impact Areas for Mount Isa and Camooweal using the Hausdorf distance between road trips

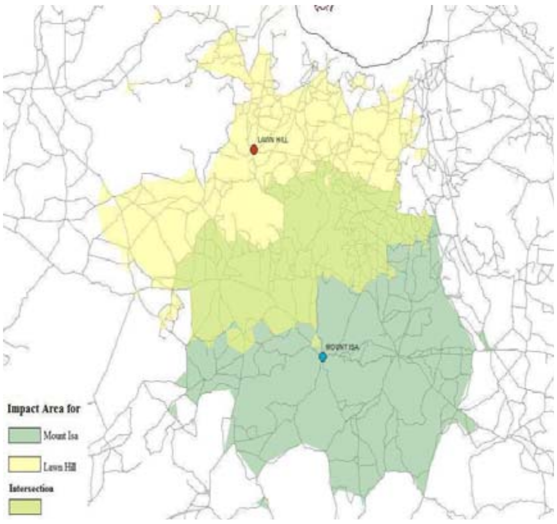
Figure 8.6: Impact Areas for Mount Isa and Camooweal generated using day tour distances from their respective closest road trips (*Trip 19* and *Trip 11*)



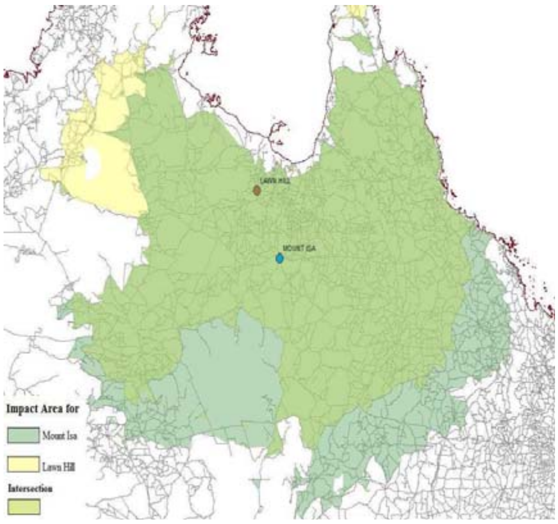
(a) Impact Areas for Mount Isa and Lawn Hill using the minimum distance of the day tours



(b) Impact Areas for Mount Isa and Lawn Hill using the average distance of the day tours



(c) Impact Areas for Mount Isa and Lawn Hill using the maximum distance of the day tours

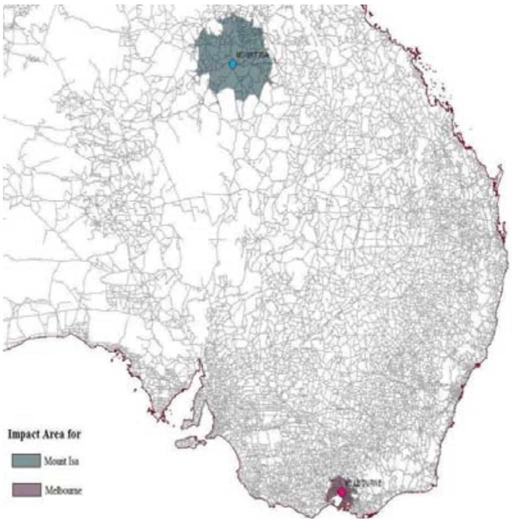


(d) Impact Areas for Mount Isa and Lawn Hill using the Hausdorf between road trips

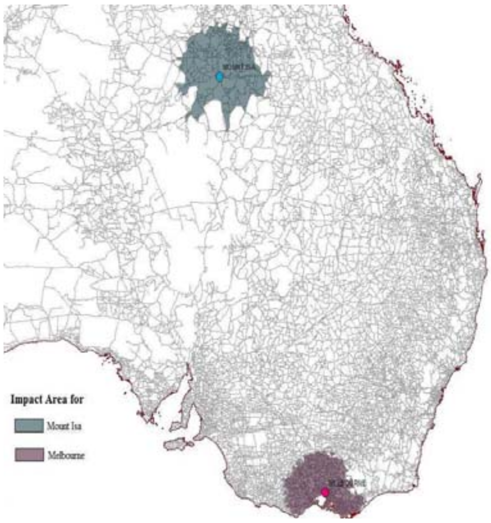
Figure 8.7: Impact Areas for Mount Isa and Lawn Hill generated using day tour distances from their respective closest road trips (*Trip 19* and *Trip 13*)

Melbourne is *Trip 15* and the closest road trip to Mount Isa, as previously identified, is *Trip 19*. For *Trip 15*, the minimum, average and maximum distances are 95, 224 and 454km, respectively. The Hausdorf distance between *Trip 15* and *Trip 19* is 2377km. Figure 8.8 shows what was expected for break values of D_{Min}, D_{av} and D_{Max}, namely that none of the nearness notions hold. The impact areas do not share a single point. However, when the Hausdorf distance is applied, there is a large area of overlap between both impact areas. This curious result raises the question whether the Hausdorf distance is suitable for calculating break values. Let us consider another negative example to investigate the behaviour of Hausdorf distance break values a little further.

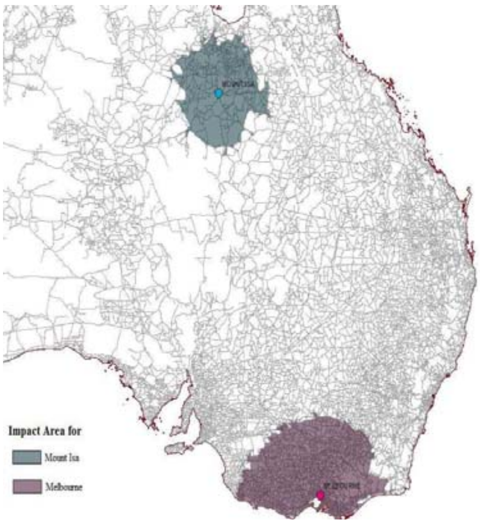
Another pair of query points that are under most circumstances not considered to be near is *Mount Isa* - *Denham* being separated by 3385km. The closest road trip to *Denham* is *Trip 32* from *Geraldton* to *Monkey Mia* return. Minimum, average and maximum distances all have the same value of 424km. The Hausdorf distance between *Trip 32* and *Trip 15* is 3726km. When examining the impact areas generated by the usual mapping function as seen in Figure 8.9, it can be clearly seen that there is no nearness relation between these two places; at least this is the case for break values of D_{Min}, D_{av} and D_{Max}. However, when using the Hausdorf distance again we have intersecting impact areas and this time even the strongest of all nearness relations a-near4(*Mount Isa*, *Denham*) holds true, because the entire impact area of query point *Denham* is included in the impact area of *Mount Isa* indicated by the green colouring of the area shown in Figure 8.9(d).



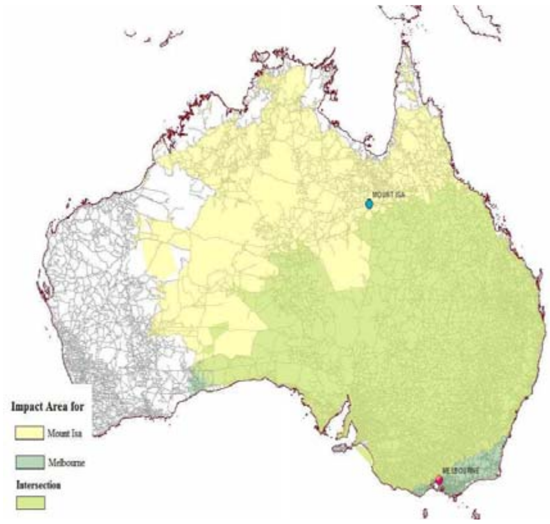
(a) Impact Areas for Mount Isa and Melbourne using the minimum distance of the day tours



(b) Impact Areas for Mount Isa and Melbourne using the average distance of the day tours

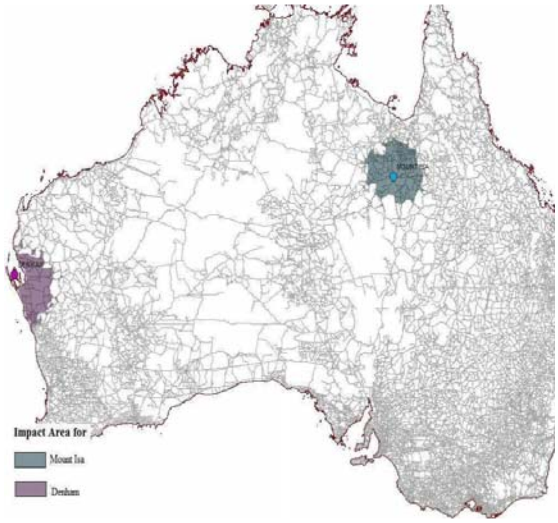


(c) Impact Areas for Mount Isa and Melbourne using the maximum distance of the day tours

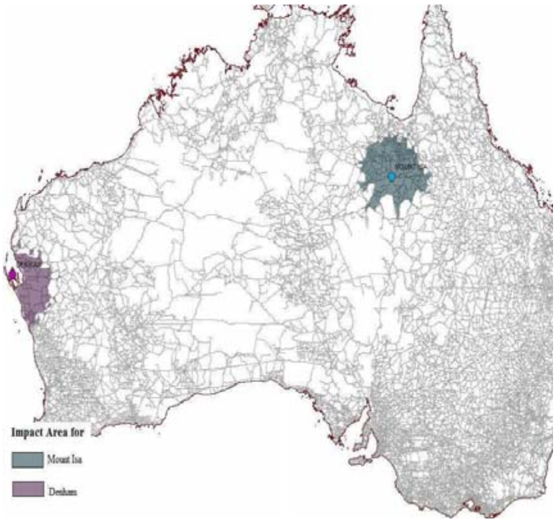


(d) Impact Areas for Mount Isa and Melbourne using the Hausdorf between road trips

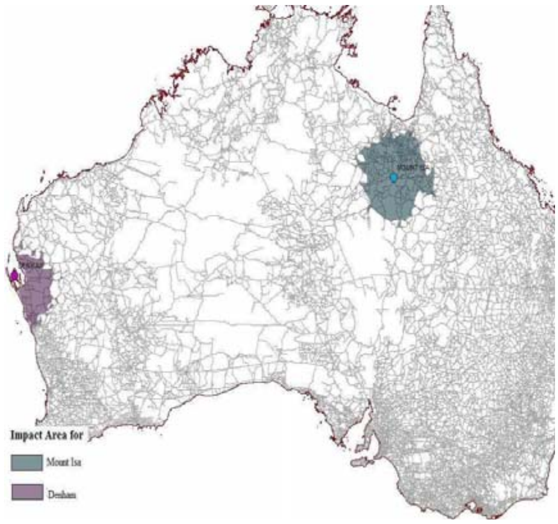
Figure 8.8: Impact Areas for Mount Isa and Melbourne generated using day tour distances from their respective closest road trips (*Trip 19* and *Trip 15*)



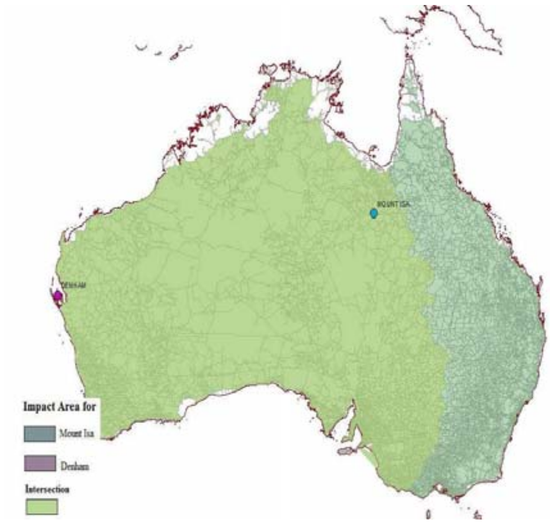
(a) Impact Areas for Mount Isa and Denham using the minimum distance of the day tours



(b) Impact Areas for Mount Isa and Denham using the average distance of the day tours



(c) Impact Areas for Mount Isa and Denham using the maximum distance of the day tours



(d) Impact Areas for Mount Isa and Denham using the Hausdorf between road trips

Figure 8.9: Impact Areas for Mount Isa and Denham generated using day tour distances from their respective closest road trips (*Trip 19* and *Trip 32*)

8.5 Discussion

The results of the previous section clearly show that the impact area approach is superior to any of the existing "fixed-value" (or naive) approaches. We could see that even for *nearness outliers* such as the nearness pair *Lawn Hill - Mount Isa*, the most general nearness notion of s-near1 still holds indicating some degree of nearness. This confirms that the influence area approach by only considering an "object $o1$ near an object $o2$ if $o1$ is inside $o2$" is not sufficient for all cases. On the other hand, most of the evaluated nearness pairs, especially the ones from the distance cluster of below 96km, did exhibit this more specific nearness property. Nearness notions that require the inclusion of at least one query point in the influence area of the other, such as s-near2, a-near3 and s-near4 tend to specify s-near1 for most nearness pairs, while the complete inclusion of one impact area in another is very rare. The incorporation of context into the generation of the impact areas resulted in very different sized and shaped impact areas across the map. This contrasts the influence area and other "fixed-value" approaches which use one specific value or Euclidean function applied to the object's spatial boundaries across the map.

The peculiar behaviour of the Hausdorf distance as break value in the negative example experiments can possibly be explained by the fact that it calculates the distances between road trips. For the negative examples, these distances were very large. While this seems to suggest that Hausdorf distance is not a very useful distance function to use for the impact area generation, I believe that it could have some interesting implications to representing nearness perception in GIS. Recall Gahegan's [48] empirical results and his conclusion that the scale of the area viewed by the user of a GIS map has an impact on proximity perception. He suggested that the bounding boxes in the area of the GIS can be used as scale indicators. Gahegan [48] suggested that scale influences nearness perceptions. Through the Hausdorf distance, it appears that an area containing both query points is "zoomed into view" thereby "changing the scale". In this case query places will always "look" near. For example, the distances such as these displayed between the negative example query pairs span a large part of the Australian continent. If I would like to see both places on a map, I would have to display a much larger area than for the positive examples. By doing this, I change the my scale of perception. Further investigations into Hausdorf distances within the impact area model could yield interesting results with respect to perceptual scale change.

Chapter 9

Conclusions and Future Work

This thesis examined spatial proximity with a focus on how it is perceived and reasoned about by humans. Its goal was to find a representation which mimicks this human mental process, at least to some extent, and is implementable to support the development of more intuitive tools for spatial proximity analysis in spatial data processing. This goal was approached by developing a model of context-adaptive proximity with the hypothesis that there is a suitable nearness notion based on context that goes beyond fixed buffer zones, fuzzy membership functions and stipulated natural language expressions. The outline of this chapter is as follows:

1. a reminder on the key notion and its importance,
2. a summary of the main contributions and
3. a discussion of further work.

9.1 The notion of spatial proximity

The concept of proximity is an important aspect of human reasoning. Despite the diversity of applications that require proximity measures, the most intuitive notion is that of spatial nearness. Toblers First Law of Geography [78] emphasises the importance of nearness for any sort of relevance in space. However, proximity also plays a role in areas such as concept categorisation, data-mining and machine learning, case based reasoning and of course spatial reasoning, just to name a few. Nearness is also one of the central concepts utilised in many practical applications of data mining, where some nearness measure is used to determine the distribution of attribute values in the database, i.e., to cluster related attributes (see Berson et al. [10] for an overview). In case-based systems, nearness measures are used to determine the nearness between cases (e.g. Sefion et al. [107]). Hence, the results of this thesis and all future work that stems from it, will also be of direct relevance to the many non-spatial areas that utilise nearness notions.

9.2 Main contributions of this thesis

In summary, the research presented in this thesis makes three important contributions: a synthesis of disparate literature that pertains to the topic of proximity, an analysis of the wide array of existing work and the derivation of new proximity measures. Let us take a closer look at each of these contributions. The following will also discuss how they might contribute to future work in the field and what their practical implications to new technologies might be.

9.2.1 A Synthetic View of Spatial Proximity

Proximity is a difficult notion that keeps resisting formal treatment due to its context-dependency. Consequently, discussions on the actual nature of proximity have been the source of an ongoing debate in the scientific literature resulting in a varied and wide-spread body of work. In the context of spatial reasoning this is even more prelevant. While for other spatial notions such as topological and direction relations some unified views have formed within the research community, no such thing has happened for spatial proximity yet. Two main schools of thought have developed, although the distinction is not always clear throughout the literature. One school considers proximity as a distance measure that can sufficiently be described by quantitative or qualitative distances. The other school aims at developing proximity measures where distance becomes a modifying factor instead of the measure itself. The work presented in this thesis subscribes to the latter. However, looking at both sides of the argument, the thesis offers a thorough and comprehensive synthesis of the disparate literature pertaining to the topic of proximity. A wide set of prior works are woven together into a single and clear account of the complexities and nuances of this field. This synthetic view of spatial proximity provided here is the result of the gathering together of disparate accounts from often disparate disciplines under the spatial proximity paradigm. It will no doubt stir the ongoing debates in the scientific literature on the nature of spatial proximity.

9.2.2 Analysis of existing Methods for Reasoning with Spatial Proximity

Given the huge body of theoretical work that dedicates itself to spatial proximity, it is not surprising that a wealth of diverse methods has been developed to support more practical applications. However, as with the theoretical work, these methods are disparate and it is often hard to decide which ones are the most appropriate for different purposes. This thesis offers an insight into why some of the existing methods for reasoning with spatial proximity work, or do not work, where they are strong, and where they are lacking. Researchers and developers will find this analysis useful when looking for suitable methods to address their specific questions. This is even more so important with the advent of personal navigation systems available from mobile phones and PDAs, that will require sophisticated implementations of notions such as spatial proximity.

9.2.3 New Proximity Measures

The final contribution of this thesis is the derivation of new proximity measures and their evaluation, backed up by some personal experiments and reflections. The new measures have been formally described in a unified and compelling way.

Nearness between two objects is formally described by the relationship between their impact areas. The notion of impact area is a generalisation of the psychological concept of influence area [69], which describes an imaginary area surrounding objects perceived in the environment in order to grade proximity. In contrast to the influence area of an object o, which is totally determined by its spatial boundaries, with no consideration whatsoever for what o actually is, and o's surrounding environment; the impact area takes o's functionality and the surrounding environment into account through a context variable. Further, the model considers the impact areas of both objects whose degree of nearness is to be assessed, as opposed to the impact or influence area of only one of both objects, seen as a reference to assess the nearness of the other to it. This generalisation allows one to consider objects to be near as soon as their impact areas intersect. The stronger the correlation between the impact areas, the stronger the proximity between the associated places.

The generality of this framework makes it applicable in any spatial setting. But as a consequence of being general, it requires further interpretations for specific domains or contexts in order to be operational and readily available for practical use. One such interpretation was examined in Chapter 8 for the specific context of touristic road travel. The outcome of this confirmed the approach taken in this thesis.

9.3 Future work

There are several areas of future research that follow directly from the work presented in this thesis. In order to provide some verification of the proposed framework, it was implemented with GIS data in the specific context of touristic road travel. Two data sets were used, one as domain specific knowledge and the other as verification data. The model can be deemed successful in the frame of personal verification and reflection with the results of the experiments corresponding to the verification data. However, there are limits to such a verification process as the framework was not tested by other users to fully verify the inuitiveness of any of its implementations, third party evaluation is therefore subject to future work.

In addition to the fact that the framework adds to the repertoire of researchers and developers of evolving technologies such as personal navigation systems which will very possibly require implementable notions of spatial proximity, a greater emphasis on operationality of the model would make it more accessible to practical applications. The *Impact Area Generation Model* requires in addition to GIS data, domain specific knowledge of a given context and an impact function to generate the impact areas. Impact functions are a generic concept and in the context of Touristic Road Travel a specific mapping function was developed. However, the development of generic impact functions for more general contexts such as navigation would provide useful operational models that could be applied without any or only minor modifications to different applications in these contexts. In addition to context specific operational impact functions, the development of context specific ontologies would provide standardised context representations as impact function input.

The domain specific knowledge for a given context is currently explicitly stated. Finding ontologies for different contexts would greatly facilitate the generic application of the framework. These ontologies could be approached in a similar way to XML schemata. Geographic Information Systems at the moment do cater largely for information management and representation, adding context in the form of ontologies could open up a whole new avenue in the direction of Knowledge Management.

In conclusion, we can say that this thesis makes several important contributions to the field of spatial reasoning and offers numerous opportunities for future work. Since the concept of proximity or nearness is an important aspect of human reasoning in general, future work has the potential to go beyond spatial proximity related enquiries.

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