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A ToA-based Approach to NLOS Localization Using Low-Frequency Sound

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Abstract

Recent localization systems do not effectively estimate the location of a target in the presence of dynamic obstacles. This paper presents non-line-of-sight (NLOS) localization technique and system for a quiet and known environment based on the measured time-of-arrival (ToA) of first arrival low-frequency acoustic signals. The true ToA is estimated using the modelled map, and then compared with the detected ToA to update the target position. The strength of the proposed technique is that the positioning accuracy is not corrupted by small or known obstacles. The performance of the system was investigated using different techniques and experimental setups. The numerical results show successful localization of a target in various situations, demonstrating the effectiveness of the technique and the system as a possible solution to the NLOS localization problem.

1 Introduction

The NLOS localization problem is concerned with finding the position of a target in an environment, where there are blockages in its direct and straight paths to base stations, referred to as the line-of-sight (LOS) paths. Typical examples of the environment include a building where there is a leakage of toxic gas and the building structures block the LOS path. Such an environment requires prior knowledge, including the positions of the base stations or prior measurement for successful localization [Nerguizian *et al.*, 2006].

Up to now, a variety of localization systems has been developed for different situations. Out of them, most well-known may be the Global Positioning System (GPS), but the unavailability of the LOS paths between the target and the satellites restricts the use of the GPS in an indoor environment [Logsdon, 1995]. Indoor localization has been challenged by many other alternatives, including vision, infrared (IR), laser, radio and sound wave sensors.

The most accurate location estimation technique for NLOS conditions is the Received Signal Strength Indication (RSSI). Existing RSSI approaches fall into two main categories [Ferris *et al.*, 2006]. The first type of the techniques is the predictive radio model, which locates a target by applying the propagation model of signals to predict the signal strength at any location based on the distances from access points [LaMarca *et al.*, 2005; Seidel and Rappaport, 1992]. These techniques show successful localization without any prior measurement, but the accuracy of these models is limited even considering the locations of walls and furniture.

The second type of the techniques establishes the “fingerprint” of the RSSI using calibrated data from pre-measurement [Bahl and Padmanabhan, 2000; Ladd *et al.*, 2004; Seidel and Rappaport, 1992]. In a static environ-ment, there is a unique fingerprint at each location. The target position in their approaches can be estimated by matching the fingerprint of detection with those in the database constructed through prior measurement at different locations. These approaches gave high positioning accuracy if adequate calibration data was available. However, they are not able to locate a target at any location for which no calibration data is available. Numerous research groups have overcome this problem through spatial smoothing [LaMarca *et al.*, 2005] and Gaussian processes [Ferris *et al.*, 2006]. These techniques demonstrated successful NLOS localization with 1-3 m positioning accuracy. The main drawbacks of these systems are the acquisition of prior measurement and the disturbance from a dynamic environment, such as moving objects.

Another popular class of the approaches to NLOS localization is the ToA. ToA measurement corrupted by NLOS errors could bias the true ToA considerably and cause an inaccurate location estimate. To mitigate the effects of NLOS contribution, [Chan *et al.*, 2005; Riba and Urruela, 2004] identified and localized the target with the LOS base stations. Their major limitation is that at least three LOS base stations are required for successful localization. [Foy, 1976; Wang *et al.*, 2005] transformed the non-linear range models to linear forms which gave closed location estimation expressions. These methods advantageously require no prior measurement, but they present unsatisfactory performance in severe NLOS scenarios.

The low cost, high accuracy and linearity of an acoustic ranging system using a ToA-based approach make it superior to the radio ranging system [Girod and Estrin, 2001]. Unlike RSSI, the ToA of a sound wave is linear to the distance between a base station and a target and less sensitive to dynamic obstacles. The cost and complexity of the acoustic ranging hardware are much

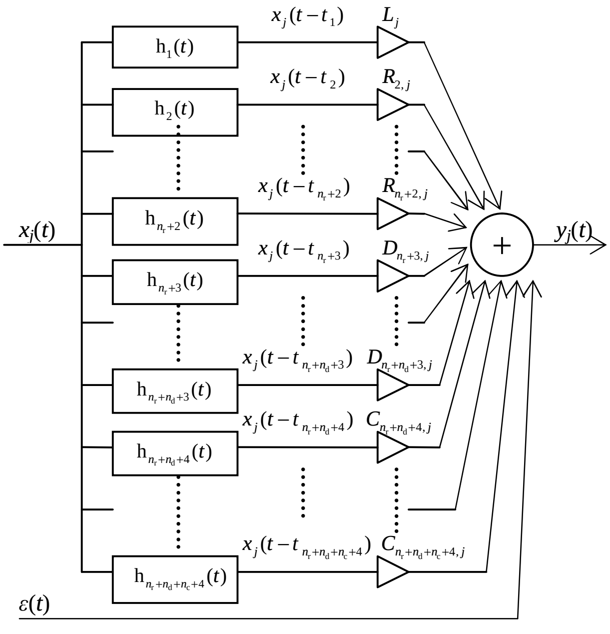


Fig.1 Time-varying filter of a wave propagation medium with n_r reflection paths, n_d diffraction paths, n_c combined path and one LOS path from the j^{th} base station to a target. h(t) is the transfer function of a time delay

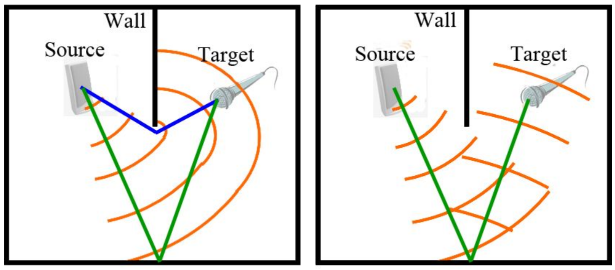
lower due to the low frequency and slow speed nature of the signals. Even a general sound card with 48-192 kHz sampling rates is able to analyze an audible acoustic signal (< 25 kHz) and to give high ranging accuracy (< 10 mm). Although the performance of acoustic localization systems degrades with an additional background noise, these systems give a less expensive and more accurate alternative in a quiet environment.

This paper describes a novel NLOS localization technique using the measured ToA of 0.5-2 kHz acoustic signals and the estimated true ToA of the signals in a known and quiet environment. Because of the high diffraction ability of low-frequency sound, the signals from base stations firstly arrive at a target through their shortest paths, rather than multiple paths. The NLOS errors being corrected accurately by the proposed ToA estimator, the base stations with known positions can locate the target precisely even in NLOS conditions. The most significant contribution of this paper is exploiting a modelled map for predicting the true ToA from NLOS base stations, instead of linear estimators as in previous approaches.

This paper is organized as follows. The following section explains the NLOS errors in the ToA of acoustic signals in localization problem, whereas the mathematical models of the NLOS localization technique are presented in section 3. In section 4, the implementation of the acoustic ranging system is illustrated. Then, the efficacy of the developed system is demonstrated through numerical results in section 5 and conclusions are summarized in the last section.

2 NLOS Errors in ToA of Acoustic Signals

This section reviews the characteristics of wave propagation at different frequencies and the nature of the



(a) Low-frequency Wave (b) High-frequency Wave

Fig.2 Possible paths of a detectable acoustic signal in NLOS Condition. The green lines and the blue line represent the reflection paths and the diffraction path respectively.

ToA errors in NLOS conditions caused by the multipath effects. The NLOS errors can be minimized if the ToA of the signal from the shortest path is detected.

2.1 Wave Propagation Model

The wave propagation medium can be regarded as a time-varying filter [Harrison and Robins, 1998]. An acoustic signal from the base station can reach a target through its LOS path, reflection paths, diffraction paths and their combination. Consider a scenario with maximum numbers of n base stations, n_r reflection paths, n_d diffraction paths, n_c combined path and one LOS path from the j^{th} base station to a target, the received signal $y(t)$ at the target is given by

$$y_j(t) = x_j(t-t_{1,j})L_j + \sum_{i=2}^{n_r+2} x_j(t-t_{i,j})R_{i,j} + \sum_{i=n_r+3}^{n_r+n_d+3} x_j(t-t_{i,j})D_{i,j}$$
$$+ \sum_{i=n_r+n_d+4}^{n_r+n_d+n_c+4} x_j(t-t_{i,j})C_{i,j} + e(t),\ \forall j \in \{1,\dots,n\}\ ,(1)$$

where i is the i^{th} path to the target, t is the time, $x(t)$ is the emitted signal from the base station, $\varepsilon(t)$ is the background and system noise at the source, and L_j, $R_{i,j}$, $D_{i,j}$ and $C_{i,j}$ are the weighting factors for LOS path, reflection paths, diffraction paths and combined paths respectively. Figure 1 illustrates the time-varying filter representing a wave propagation medium. The time delay $t_{i,j}$, or ToA, of the signal through the i^{th} path with distance $d_{i,j}$ is given by

$$t_{i,j} = \frac{d_{i,j}}{v_{air}}, \quad (2)$$

where v_{air} represents the signal speed in air. The magnitudes of the factors are inversely proportional to the signal strength losses of their correspondent paths. Each weighting factor depends on its path distance and geometric spreading. Additionally, the weighting factor $R_{i,j}$ is dependent on the surfaces and positions of obstacles, while the factor $D_{i,j}$ is dependent on the frequency of the signal, the shape and positions of obstacles. The factor $C_{i,j}$ can be expressed as

$$C_{i,j} = D_{i,j}R_{i,j}. \quad (3)$$

In a dynamic environment, all of the weighting factors may change with time depending on obstacles. Modelling RSSI in such an environment requires taking all information of the movements, sizes, shapes and surface materials of all obstacles into account, which is unfeasible. In NLOS conditions, where the LOS path is not available, the LOS path weighting factor L_j is zero. The diffraction of an acoustic signal increases with the increase in the ratio between the wavelength and the obstacle size [Kapralos *et al.,* 2005]. The diffraction of a high-frequency signal, such as ultrasonic, with short wavelength is neglectable. Therefore, for a high-frequency signal, $D_{i,j}$ and $C_{i,j}$ are approximately zero, which means the signals through the diffraction and combined paths are too weak to be detected. Figure 2 illustrates the possible paths of detectable low-frequency and high-frequency acoustic signals in a NLOS condition. Consider a small dynamic obstacle obstructing a signal path, the low-frequency acoustic signal will pass through the obstacle if its wavelength is larger than the dimensions of the obstacle, although the correspondent weighting factor decreases. As a result, small dynamic obstacles do not hinder any low-frequency signal.

Since the LOS path is the straight line segment connecting the base station to the target, its distance $d_{1,j}$ is always shorter than other path distances. Application of equation (2) gives the relationship as follows:

$$t_{1,j} < \min\{t_{i,j} \mid \forall i \in \{2,...,n_\mathrm{r}+n_\mathrm{d}+n_\mathrm{c}+4\}\},\ \forall j \in \{1,...,n\} \ . \tag{4}$$

Observing above inequality, the ToA of a signal from the LOS path, if available, is always the smallest.

2.2 Nature of NLOS errors

The following sections of this paper are based on the assumptions listed as follows:

Assumption 1: The system and background noise are small $e(t) \approx 0$ and the emitted signal is strong, thereby the signal-to-noise ratio (SNR) being high.

Assumption 2: The system can detect the ToA of a low-frequency signal from any possible path, including the shortest path, with the corresponding weighting factor not equal to zero.

Consider a scenario that the j^{th} base station emits a signal $\breve{x}_j(t)$ at time t_e and a target receives the signal in a NLOS condition. This means that if there exists a target at $\mathbf{x}^\mathrm{t} \notin {}^{L_j}\Upsilon \subseteq \mathbb{R}^2$ at time step *m*, then there is a blockage of the LOS path from the target to the j^{th} base station, referred to as a NLOS base station, where $\mathbb{R}^2$ represents the two-dimensional (2D) space of the environment. The signal $x_j(t)$ can be formulated as

$$x_j(t) = \begin{cases} 0, & \text{for } t < t_\mathrm{e} \\ \breve{x}_j(t), & \text{for } t \geq t_\mathrm{e} \end{cases} . \tag{5}$$

The ToA $t_j^\mathrm{d}(f)$ can be obtained as

$$t_j^\mathrm{d}(f) = t_j^\mathrm{d}(f) - t_j^\mathrm{e}, \tag{6}$$

where *f* represents the frequency of the signal and $t_j^\mathrm{d}(f)$ represents the time at which the received signal $y_1(t)$ is first higher than the threshold *g*, which is set to be small for a quiet environment. In other words, the receiver detects the first arrival signal at $t_j^\mathrm{d}(f)$. As the weighting factor L_1 in such a scenario is zero, the receiver cannot detect the LOS signal. Thus, the target can only detect the signals through NLOS paths. The detected ToA $t_j^\mathrm{d}(f)$ in NLOS conditions can be expressed as

$$t_j^\mathrm{d}(f) \geq \min\{t_{i,j} \mid \forall i \in \{2,...,n_\mathrm{r}+n_\mathrm{d}+n_\mathrm{c}+4\}\}. \tag{7}$$

Substitution of equation (7) for equation (4) yields

$$t_j^\mathrm{d}(f) > t_{1,j}, \tag{8}$$

which shows the detected ToA in NLOS conditions is always larger than the ToA of a signal through its LOS path. Since the recent ToA-based localization techniques [Chan *et al.*, 2005; Gezici *et al.*, 2005; Riba and Urruela, 2004] referred to the ToA $t_{1,j}$ from its LOS path as the true ToA, t_j^t, the delay in the detected ToA resulted in a systematic error in the detected ToA Δt_j^d, also known as the NLOS error. Rearranging equation (8) gives

$$\Delta t_j^\mathrm{d}(f) = t_j^\mathrm{d}(f) - t_j^\mathrm{t} = t_j^\mathrm{d}(f) - t_{1,j} > 0, \tag{9}$$

which implies the NLOS error was always positive bias under the assumption in the recent approaches. Its magnitude was dependent on the obstacles in the scenario.

3 NLOS Localization Technique

In this section, the proposed localization technique to correct the NLOS errors mentioned in the previous section is described. The utilization of the ToA of the first arrival low-frequency acoustic signals in the NLOS localization problems minimizes the bias errors, whilst the ToA estimator based on the modelled map of a known environment corrects the errors effectively. The technique bases on the assumptions 1, 2 and two additional assumptions as follows:

Assumption 3: The initial location $\mathbf{x}_0^\mathrm{t} \in \mathbb{R}^2$, and the kinematic constraints of the target, such as its maximum speed, are known.

Assumption 4: The map of the environment and all of the large static obstacles are known. Furthermore, there is no large dynamic obstacle in the environment.

3.1 Low-frequency acoustic signal

The use of low-frequency acoustic signals proposed in this paper minimizes the NLOS errors. As mentioned in subsection 2.2, the target is not able to detect high-frequency signals via their deflection or combined paths. The detected ToA $t_j^\mathrm{d}(f)$ for high-frequency ($f = f_\mathrm{H} \geq 25\text{kHz}$) and low-frequency ($f = f_\mathrm{L} < 2\text{kHz}$) acoustic signals in a NLOS condition $\mathbf{x}^\mathrm{t} \notin {}^{L_j}\Upsilon$ can be formulated by the modification of equation (7):

$$t_j^\mathrm{d}(f_\mathrm{H}) \geq \min\{t_{i,j} \mid \forall i \in \{2,...,n_\mathrm{r}+2\}\} \tag{10}$$

and

$$t_j^\mathrm{d}(f_\mathrm{L}) \geq \min\{t_{i,j} \mid \forall i \in \{2,...,n_\mathrm{r}+n_\mathrm{d}+n_\mathrm{c}+4\}\}. \tag{11}$$

The target can detect the ToA of the low-frequency signal via the shortest paths among all possible paths including diffraction, reflection and combined paths in a NLOS condition, while it can only detect the ToA of the high-frequency signal via the shortest reflection path. Notice that the shortest reflection path may be longer than other types of the shortest paths. Combining equations (10) and (11) yields:

$$t_j^\mathrm{d}(f_\mathrm{L}) \leq t_j^\mathrm{d}(f_\mathrm{H}), \tag{12}$$

and the substitution of equation (9) further gives

$$\Delta t_j^\mathrm{d}(f_\mathrm{L}) \leq \Delta t_j^\mathrm{d}(f_\mathrm{H}). \tag{13}$$

The inequalities (12) and (13) indicate that the detected ToA and NLOS error of low-frequency sound wave are always equal to or smaller than those of high-frequency wave. Hence, the NLOS errors can be ameliorated by the utilization of low-frequency acoustic signals, rather than high-frequency signals.

The detected ToA of a low-frequency signal with long wavelength is not influenced by any small obstacles. As the ratio between the wavelength and obstacle size is high, the signal can pass through the obstacle by diffraction with a small signal strength loss and a neglectable increase in the detected ToA. Thus, the positioning error of the proposed technique using low-frequency signal is resistant to small unknown or small dynamic obstacles.

3.2 ToA Estimator

The true ToA t_j^{t} depends on the frequency of the signal and the positions of the obstacles and the target. In either LOS or NLOS conditions, the receiver can detect the ToA t_j^{d} of the first arrival low-frequency signal from the shortest path giving the smallest time delay. The proposed technique regards the ToA from the shortest paths as the true ToA. Finding the shortest path between two points in a known environment can be easily implemented into computers as appeared in [Storer and Reif, 1994]. Consequently, the shortest path distance between the j^{th} base station and a point $\mathbf{y}_p \in \mathbb{R}^2$ can be predicted by the application of the modelled map of the environment. The estimated true ToA $t_{p,j}^{\mathrm{e}}$ can be obtained by

$$t_{p,j}^{\mathrm{e}} = \frac{d_{p,j}^{\mathrm{sp}}}{v_{\mathrm{air}}}, \qquad (14)$$

where $d_{p,j}^{\mathrm{sp}}$ is the shortest path distance between the j^{th} base station and $\mathbf{y}_p$. Notice that $t_{p,j}^{\mathrm{e}}$ is exploited for localization described in the next subsection. When $\mathbf{y}_p$ is very close to the true location of the target $\mathbf{x}^{\mathrm{t}}$, $t_{p,j}^{\mathrm{e}}$ can be expressed as

$$t_{p,j}^{\mathrm{e}} \approx \begin{cases} \min\{t_{i,j} \mid \forall i \in \{1,\ldots,n_{\mathrm{r}}+n_{\mathrm{d}}+n_{\mathrm{c}}+4\}\} = t_{1,j}, \mathbf{x}^{\mathrm{t}} \in {}^{\mathrm{L}_j}\Upsilon \\ \min\{t_{i,j} \mid \forall i \in \{2,\ldots,n_{\mathrm{r}}+n_{\mathrm{d}}+n_{\mathrm{c}}+4\}\}, \qquad \mathbf{x}^{\mathrm{t}} \notin {}^{\mathrm{L}_j}\Upsilon. \end{cases} \qquad (15)$$

3.3 NLOS Localization

Consider a scenario with n base stations carrying transmitters and a target carrying a receiver with an estimated position $\mathbf{x}_m^{\mathrm{e}} \in \mathbb{R}^2$ in time step m. Localization can be achieved by a pattern-matching algorithm as follows:

1. The forward reachable set Γ_{m+1} of the target in time step m+1 is determined by the consideration of the kinematic constraints and the estimated position x_m^{e} in time step m.
2. The true ToA from the j^{th} base stations to the points $\mathbf{y}_p \in \Gamma_{m+1}, \forall p \in \{1,\ldots,q\}$, is estimated as $t_{p,j}^{\mathrm{e}}$ by the ToA Estimator. The number of the points q limits the resolution of the localization.
3. The estimated fingerprint $\boldsymbol{\tau}_p^{\mathrm{e}}$ at $\mathbf{y}_p$ is given by
$$\boldsymbol{\tau}_p^{\mathrm{e}} = [t_{p,1}^{\mathrm{e}},\ldots,t_{p,n}^{\mathrm{e}}]. \qquad (16)$$
4. The fingerprint of detection $\boldsymbol{\tau}^{\mathrm{d}}$ is obtained by

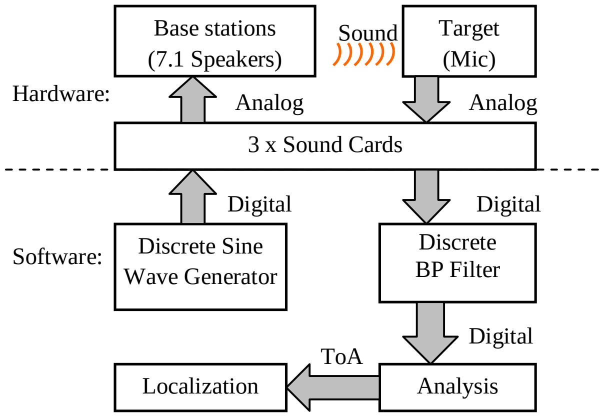


Fig.3 Schematic Diagram of the Localization System

$$\boldsymbol{\tau}^{\mathrm{d}} = [t_1^{\mathrm{d}},\ldots,t_n^{\mathrm{d}}]. \qquad (17)$$

5. The Euclidean distance E_p between estimated fingerprint $\boldsymbol{\tau}_p^{\mathrm{e}}$ at $\mathbf{y}_p$ and the fingerprint of detection $\boldsymbol{\tau}^{\mathrm{d}}$ is given by
$$E_p = \| \boldsymbol{\tau}^{\mathrm{d}} - \boldsymbol{\tau}_p^{\mathrm{e}} \|. \qquad (18)$$
6. The position of the target $\mathbf{x}_{m+1}^{\mathrm{e}}$ in time step m+1 is $\mathbf{y}_k$ with the smallest Euclidean distance as appeared in [Bahl and Padmanabhan, 2000]:
$$\mathbf{x}_{m+1}^{\mathrm{e}} = \mathbf{y}_k, \text{ where } k = \arg\min_p [E_p], \forall p \in \{1,\ldots,q\}. \qquad (19)$$
7. Repeat the steps 1-6 for next time step m+1.

The proposed technique utilizes low-frequency acoustic signals and the ToA estimator to predict the true ToA t_j^{t} of received signals at the possible locations around the prior target position. Under assumption 2, the estimated $t_{p,j}^{\mathrm{e}}$ and detected ToA $t_j^{\mathrm{d}}(f_{\mathrm{L}})$ are close. The NLOS error of the proposed technique $\Delta t_j^{\mathrm{d}}(f_{\mathrm{L}})^*$ is thus given by

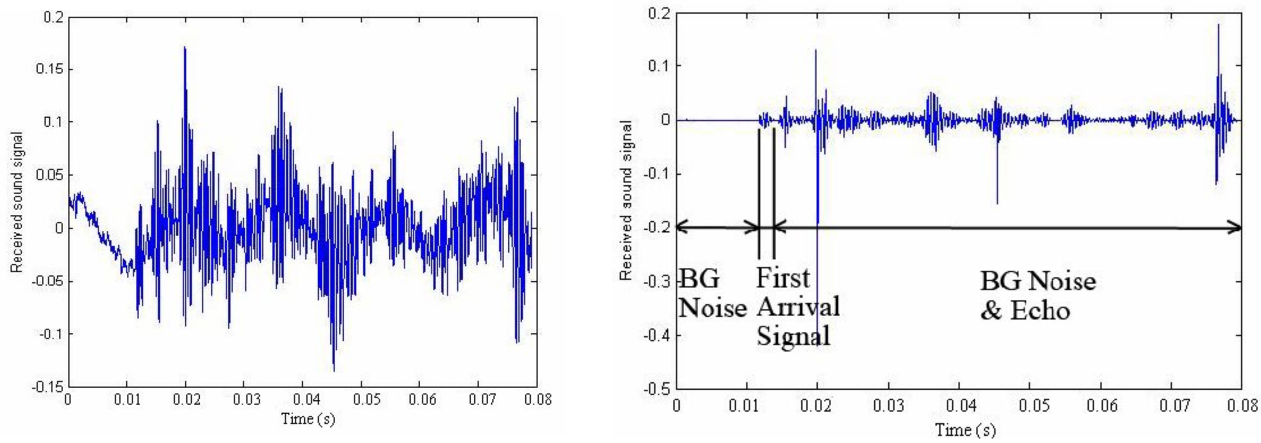
$$\Delta t_j^{\mathrm{d}}(f_{\mathrm{L}})^* = t_j^{\mathrm{d}}(f_{\mathrm{L}}) - t_j^{\mathrm{t}} = t_j^{\mathrm{d}}(f_{\mathrm{L}}) - t_{p,j}^{\mathrm{e}} \approx 0. \qquad (20)$$

Since the ToA estimator considers all known static obstacles modelled in the map, those obstacles do not contribute to considerable NLOS errors as appeared in [Foy, 1976; Wang *et al.*, 2005]

4 NLOS Localization System

This section explains how the developed NLOS localization system implements the proposed technique. As mentioned in the previous section, the NLOS error is minimized by detecting the ToA of the signal from its shortest path. In reality, the signal from the shortest path, comparing to that of LOS path, is significantly weak in a coarse NLOS environment which may not be completely quiet, so that several techniques are applied in this system to make assumption 2 valid in a moderately noisy environment.

The schematic diagram of the developed system is shown in Fig. 3. The system consists of Creative Inspire T7900 7.1 speakers as the base stations, three sound cards supporting two channel outputs and one channel input with a maximum sampling rate of 48 kHz, a PC microphone mounted on the target as the hardware



(a) Received Signal $y_j(t)$ (b) Filtered Signal by bandpass filter $w_j(t)$

Fig.4 Received sound signal and its filtered signal. The sampling frequency is 44100 Hz. BG stands for background.

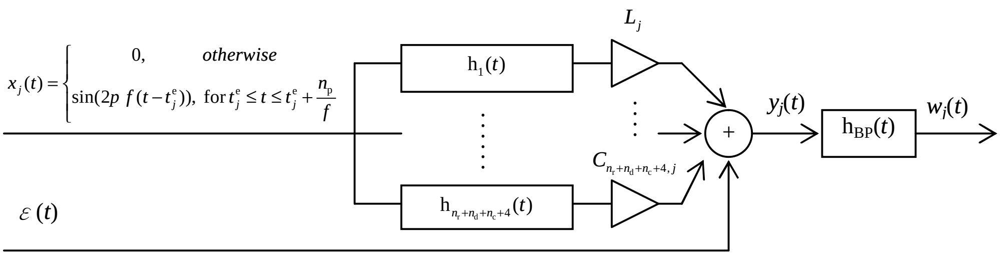


Fig.5 Block diagram of the system emitting a short sine signal at t_e from j^{th} base station. n_p represents the number of periods of the emitted sine signal and $h_{BP}(t)$ represents the bandpass filter

components and control software. The system supports maximum six base stations with a maximum output power of 8-18 W for each base station.

The procedure for measuring the ToA of the first arrival sound signals is presented as follows:

1. The program sends a discrete sine wave with a small number of cycles of 2-8 periods and a specific frequency of 0.5-2 kHz to one channel of a sound card. Only a short duration of an audible signal is emitted to minimize the noise and the echo disturbing human and next measurement respectively.
2. One of the speakers (base stations) emits the received sound signal from the sound card with a maximum power of 8-18 W.
3. The microphone measures the sound signal from the speaker and background noise.
4. The discrete bandpass filter with the central frequency same as the frequency of the emitted signal is applied to the received digital sound signal.
5. The filtered signal is analyzed, and the ToA of the signal is determined. Note that any reading will be discarded if it is notably different from the previous reading.
6. The above procedure is repeated with a different frequency and an alterative channel on the same or another sound card.

The discrete bandpass filter is applied to filter the background noise and the echo from the previous sound signals to enhance the signal-to-noise level and the sampling rate of the system. An example of a received sound signal $y_j(t)$ and its filtered sound signal $w_j(t)$ in a NLOS condition is shown in Fig. 4. The background noise in the original received signal is quite high, whereas that in the filtered signal is very small. As a Consequence, the first arrival signal from the shortest path is much easier to be recognized. The block diagram of the system is shown in Fig. 5. The ToA is determined by the first peak of the filtered signal $w_j(t)$ higher than the threshold g.

To distinguish the first arrival signal from the echo and the background noise with variable levels, the threshold g is updated before each measurement. The detected ToA $t_j^d(f)$ from the j^{th} base station is given by

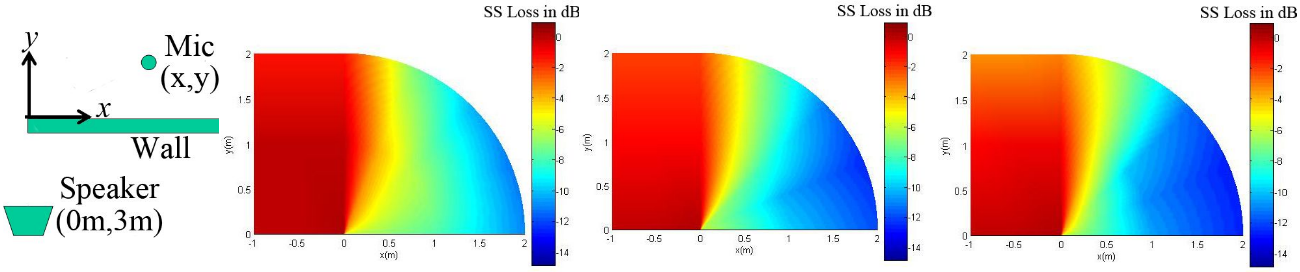
$$t_j^d(f) = \frac{n_s}{f_s}, \tag{21}$$

where n_s is the n_s^{th} sample at which the magnitude of filtered signal $w_j(t)$ is above the updated threshold g, and f_s is the sampling rate of the input channel of the sound card.

Since the signals from the multiple paths are ignored once the first arrival signal from the shortest path has been recognized, the system becomes insensitive to the multipath effects. So the performance of the system is not affected by any obstacles away from the shortest paths.

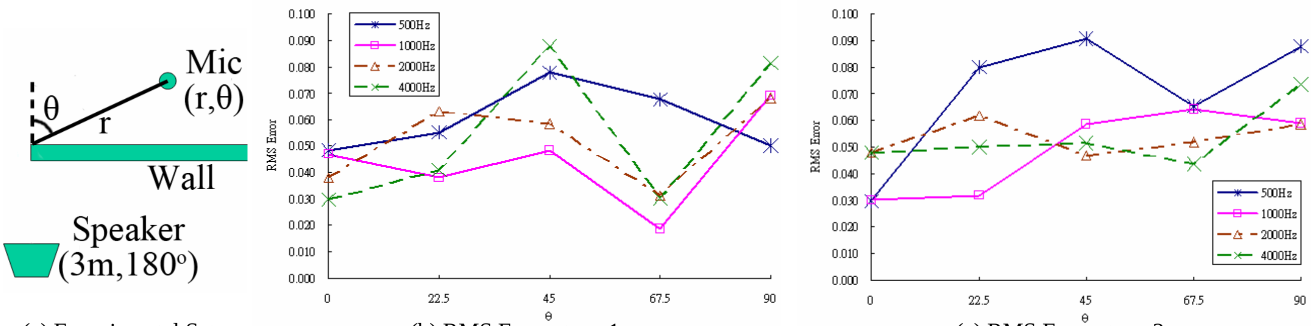
5 Experimental Results

The experimental results presented in this section investigate the performance of the system in three NLOS conditions. The proposed NLOS localization technique



(a) Experimental Setup (b) Signal Strength Loss at frequency = 1 kHz (c) Signal Strength Loss at frequency = 2 kHz (d) Signal Strength Loss at frequency = 4 kHz

Fig.6 Signal strength loss of first arrival signal due to Wall Effect



(a) Experimental Setup (b) RMS Error at r = 1m (c) RMS Error at r = 2m

Fig.7 RMS error of ToA of a signal with a known obstacle in NLOS condition

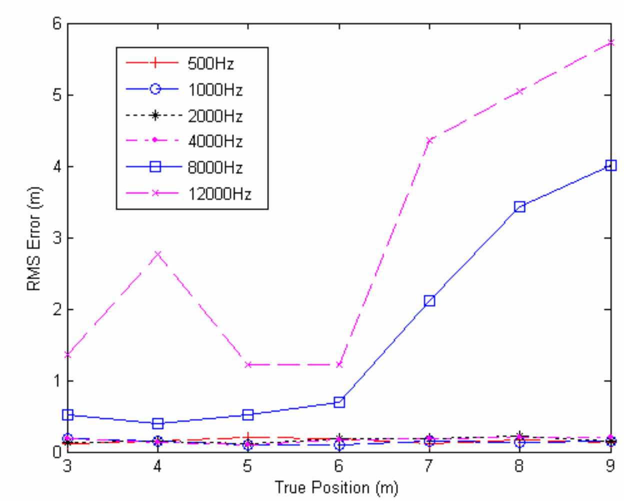


Fig.8 RMS Error of ToA of signal with unknown obstacles

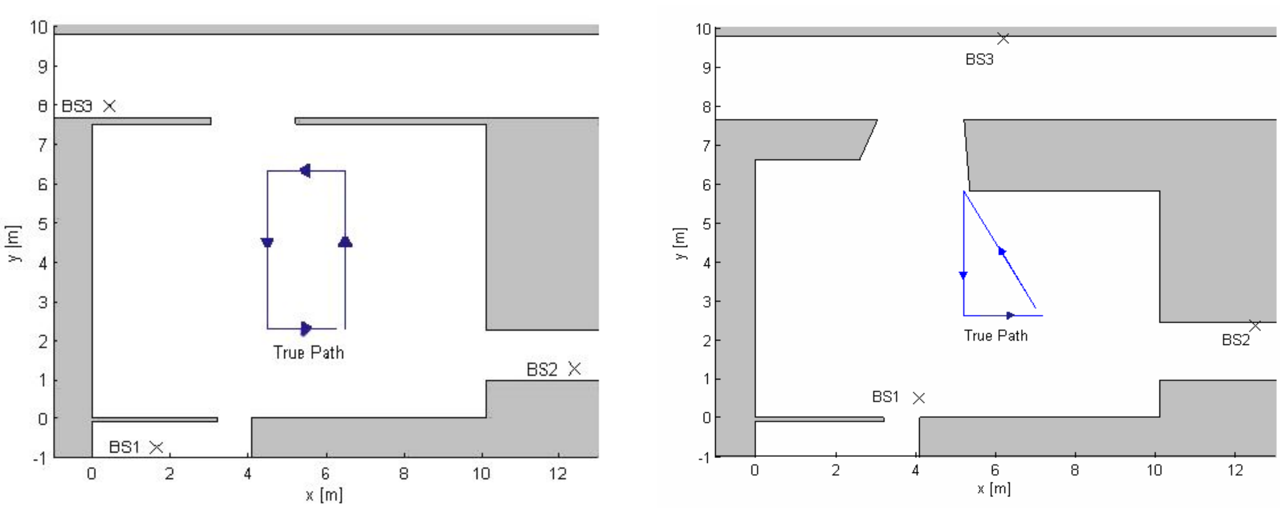
Fig.9 Testing environment

was compared with a LOS localization technique. Note that all experiments were conducted in a quiet environment.

Figure 6 shows an example of how a wall alters the weighting factor of an acoustic signal from its shortest path. Note that the magnitude of the factor is inversely proportional to the signal strength loss of the first arrival signal. A speaker was located 3m away from one of the ends of the wall and a microphone was located at the other side of the wall to measure the signal strength of the first arrival signals from their shortest paths. The signal strength measured by the microphone was compared with the signal strength at the reference point $[0,0]^T$ in Fig. 6a. The signal strength losses in dB were determined in the equation as follows:

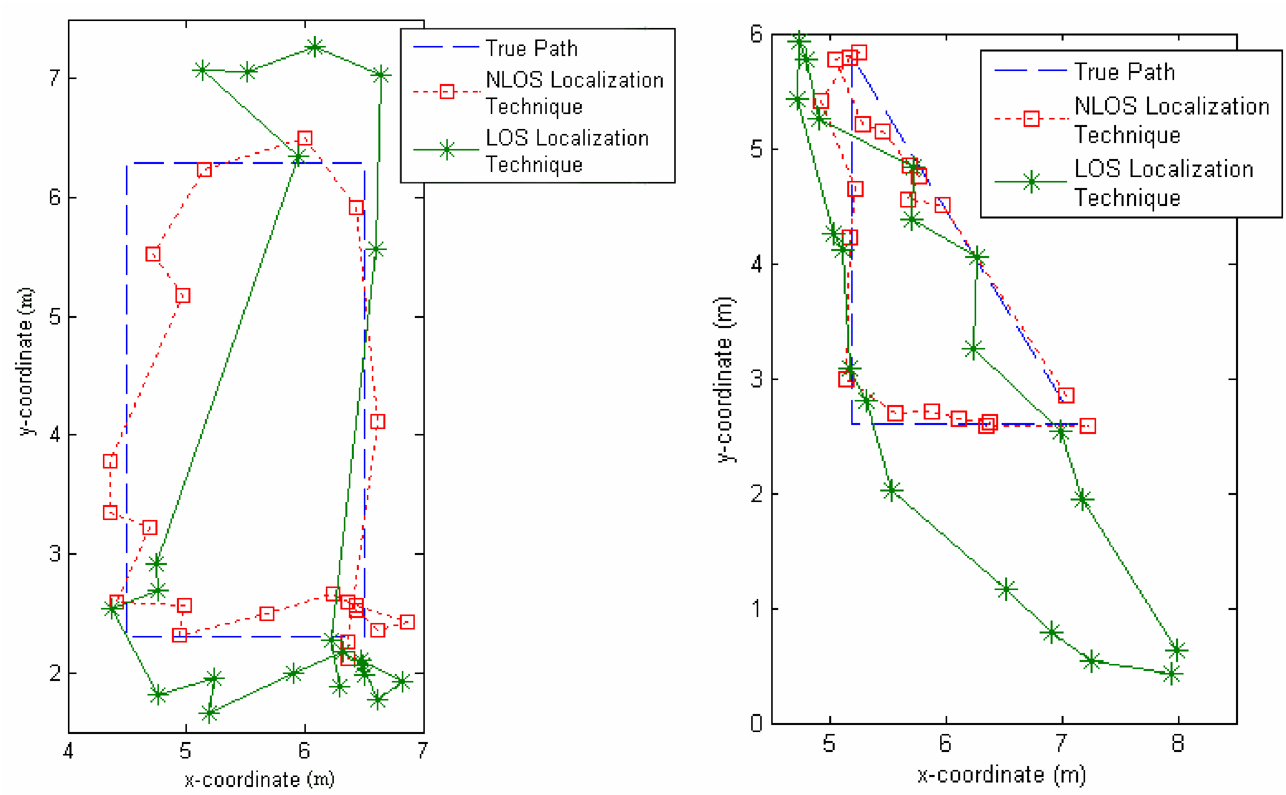
$$m_L(\mathbf{z}) = \log_{10}\frac{m(\mathbf{z})}{m_R}, \qquad (22)$$

where $m_L(\mathbf{z})$ was the signal strength loss of the first arrival signal at $\mathbf{z}\in\mathbb{R}^2$ in dB. m_R was the reference signal strength at $\mathbf{z}=[0,0]^T$ and $m(\mathbf{z})$ was the measured signal strength at the point $\mathbf{z}$. Both of the speaker and the microphone were at 1m height.



(a) Experiment 1 (b) Experiment 2

Fig.10 Positions of base stations, modelled map and true paths of moving targets



(a) Experiment 1 (b) Experiment 2

Fig.11 True paths and estimated paths by two techniques

The results shown in Fig. 6 indicate the signal strength loss due to the wall effect rises with the increase in the frequency. When the frequency was higher than 8 kHz, the signal strength from its shortest path was too weak to be detected because of the low diffraction ability of the high-frequency signal. As a result, the first arrival signal from its shortest path can be detected in some NLOS conditions when the frequency is lower than 4 kHz. In conclusion, a low-frequency sound wave is more suitable for a ToA-based localization system in a severe NLOS environment.

Figure 7 shows the root means square (RMS) error of the detected ToA of acoustic signals at different frequencies in a NLOS condition. The experimental arrangement was similar to the previous one, except that the RMS errors of the ToA instead of the signal strength were concerned. The errors of the ToA of the signal below 4 kHz are all below 0.1 m when $\theta > 0^o$, indicating the system able to detect the signals from their shortest paths in a NLOS condition, although most of the errors in the NLOS conditions are higher than those in the LOS conditions ($\theta = 0^o$). The results clearly indicate the validity of assumption 2 in this case.

Figure 8 shows the RMS errors in the ToA of first arrival signals with small and unknown obstacles between the speaker and the microphone. Both of the speaker and microphone were 1 m away from floor, whilst two chairs with minimum dimensions of 0.4 m, as the small obstacles, were placed between and 1 m away from the speaker and the microphone respectively to block the LOS path. Since the obstacles were not considered in the map, they contributed to positive bias errors. The averages of RMS positioning errors at different true positions for 0.5-4 kHz sound signals are all below 0.17 m, whilst those for 8-12 kHz are all above 1.6 m. This indicates that the low-frequency signals pass through small obstacles by diffraction with the small increases in the detected ToA, while the high-frequency signals can only reach the target through their reflection paths, which add much higher positive bias errors. The results shown in Figs. 7 and 8 reconfirm the validity of assumption 2 in a couple of cases when the frequency of sound signal is below 4 kHz. They also demonstrate that the ToA errors are resistant to small and unknown obstacles, such as dynamic obstacles.

The other two experiments (experiments 1 and 2) were conducted with a moving target in a laboratory at UNSW as depicted in Fig. 9. Figure 10 illustrates the true path, the positions of base stations and the modelled maps of the laboratory in the experiments. In each experiment, a microphone, as the moving target, was held by a human operator and traced the path marked on the floor. All unknown obstacles which were not modelled in the map were located at positions that did not block the shortest paths between the target and the base stations. In experiment 1, half of the path was completely in the NLOS conditions, whilst the other half was only partly in the NLOS conditions with only one LOS base station. Meanwhile, in experiment 2, the positions of the base stations and some of the known obstacles were changed so that the whole path was partly in the NLOS condition; with only one LOS base station. Three frequencies (500 Hz, 1 kHz and 2 kHz) of the acoustic signals were used.

The positions of the target were evaluated by the proposed NLOS localization technique and a LOS localization technique. The LOS localization technique used a least-square technique, with the procedure described in subsection 3.3, although Equation (16) was replaced by

$$\boldsymbol{\tau}^{e}_{p} = [t^{L}_{p,1},...,t^{L}_{p,n}], \tag{23}$$

where $t^{L}_{p,j}$ stands for the LOS distance between the j^{th} BS and the point $\mathbf{y}_p$. The LOS localization technique considers the ToA from LOS path, instead of the shortest path, as the true ToA.

Figure 11 shows the true path and the estimated paths by the two techniques in the experiments. In the figure, the estimated paths by the proposed technique are closer to the true paths in both of the experiments. The result indicates the superiority of using the ToA estimator in the NLOS localization problem.

Figure 12 shows the cumulative probabilities of

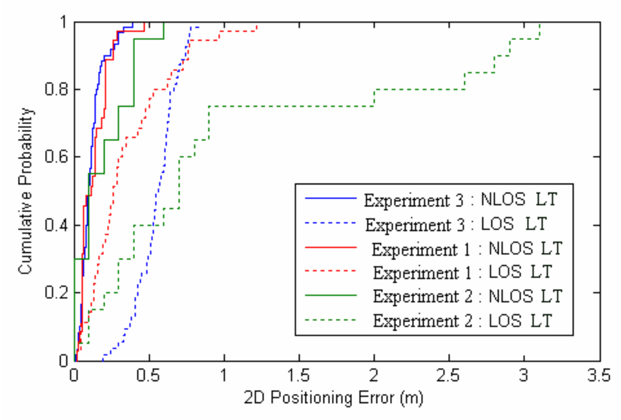


Fig.12 Comparison of 2D positioning errors for three experiments. LT stands for Localization Technique.

2D positioning errors with the moving target in the two experiments and a static target (experiment 3). All experiments were carried out by the two techniques. The moving target was held by the operator which might give uncertainties to the experimental results. It can be observed in Fig.12 that the performance of the proposed technique is better than the LOS localization technique. The proposed technique gives 2D positioning RMS errors of 0.12 m and 0.23-0.25 m for static and dynamic objects respectively. It ameliorates the 2D positioning accuracies of LOS technique by 250% and 490% for the static target and the dynamic target respectively.

The resulting key properties of the developed system are listed in Table 1. The sampling rate of the system depends on the size of the environment of concern. A higher sampling rate can be achieved if the environment is smaller. The range is affected by the background noise and the positions and shapes of obstacles. The developed system is very cost-effective, comparing to the GPS or wireless network, which cost AU$200 - AU$800. The most significant achievement of this system is its high positioning accuracy even under NLOS conditions in a quiet and known environment. Its comparison to the NLOS systems in the literature [Bahl and Padmanabhan, 2000; Ladd *et al.*, 2004; Ferris *et al.*, 2006; Nerguizian *et al.*, 2006; Seshadri *et al.*, 2005] indicates that the developed system improves the 2D positioning accuracy by 4-8 times.

Owing to the high diffraction of low-frequency acoustic signals utilized in this system, the LOS localization technique gives 0.6-1 m 2D positioning precision even if the map is unknown. This demonstrates the advantage of the low-frequency wave in a ToA-based NLOS localization system over high-frequency wave.

Table 1 Summary of developed system

Sound frequency	0.5-2 kHz
Power per channel	8-18W
RMS positioning error	0.12-0.25 m
Sampling rate	0.5-1Hz
Cost (Excluding a standard PC)	AU$200
Range	60-400 m^2

6 Conclusions and Future Works

A new NLOS localization technique for a known and quiet environment using low-frequency sound has been presented. The true ToA was predicted accurately by considering the shortest paths from base stations in the modelled map, and the predicted ToA was exploited for NLOS localization. A low-cost NLOS localization system was developed and tested successfully without any prior measurement. The advantage of the proposed technique is that the positioning accuracy does not deteriorate in the presence of small or known obstacles. The experimental results show the benefit of low-frequency sound wave in NLOS localization problems and 0.12-0.25 m 2D positioning accuracy of the system, demonstrating the efficacy of the technique and the system as a feasible solution to the NLOS localization problem in a quiet and known environment.

Despite the outstanding accuracy of the system, there are three drawbacks. Firstly, the range of the system is limited because of the weak signals from their shortest paths. The second weakness results from the low sampling rate. The system has to wait for 0.2-0.5 s before the echo from previous sound signal disappears. Lastly important is the disruption to people caused by the audible sound from the base stations. Additional background noise degrades the accuracy, sampling rate and range of the system by decreasing the SNR of the first arrival signal. They would be ameliorated if a low-frequency inaudible radio wave is used instead of a sound wave because the background noise and the speed of the radio wave are lower and much higher respectively.

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