Quality Control for Carrier Phase GPS/INS Integrated Systems for Machine Automation

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BIOGRAPHY

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A/Prof Andrew Dempster was appointed Director of Research in the School of Surveying and SIS, UNSW, in mid-2004. His research interests are signal processing in GPS receivers, software-based approaches, and new positioning technologies. His previous appointment was with the Department of Electronic Systems at the University of Westminster, London, where he was appointed in 1995 after completing his PhD at University of Cambridge. Prior to that, at Auspace Limited, he was the Project Manager and System Engineer on the first GPS receiver development in Australia.

ABSTRACT

Integrated GPS and INS systems have been in existence for many years now and offer a compelling advantage for precise location applications and machine automation. The short term accuracy and high availability of the INS system combines well with the long term accuracy of GPS to provide a more robust and reliable outcome than either individual system can alone. The improvements in INS systems are also allowing better dynamic modelling at lower costs allowing much more widespread adoption of these types of systems. The use of integrated INS/GPS systems in machine automation is a growing field and of increasing importance is the ability of such systems to detect, isolate and remove erroneous measurements before they are incorporated into a position solution. The application examined in this paper will be the use of an automated tractor for crop farming.

While there are many techniques developed for quality control of GPS receivers, integrated systems for machine automation, and more specifically for crop farming, present some unique challenges through the inherent kinematic properties of the application. Typically, a lot of focus has been put on the integer ambiguity resolution problem in integrated systems. However, once the integer ambiguity has been resolved it is still necessary to monitor the quality of the measurements to ensure that the position solution stays within predetermined limits for accuracy, integrity and availability. In the situation of crop farming, the majority of benefits that can be realized through the use of machine automation include the production of high quality yield maps and the reduction in overlapping across rows amongst other benefits, however all these factors are reliant on having a high quality position solution whose integrity can be trusted.

Simulations for the identification and detection of faults present in an integrated system will be presented with the faults occurring as both single system instantaneous faults in both the GPS system and the INS system and then as a

simultaneous multiple system failure across both systems. The use of the non-holomic properties of a land based automated system will also be investigated in these scenarios to lower the detection threshold for faults.

INTRODUCTION

GNSS systems, including GPS, have been increasingly combined with inertial navigation systems (INS) in order to provide positioning and location functionality for a number of different applications. With the continuing maturity of this technology there is an increasing focus on the quality of the position solution and hence, an increasing focus on methodologies for ensuring that any errors in either of the underlying systems can be detected and where possible excluded from the final position calculation.

This paper is concerned with looking at various strategies to implement integrity monitoring on a tightly integrated carrier phase GPS and INS system and discussing the most effective way of dealing with various forms of faults that can occur in either system. Faults that can occur in such a system include but aren't limited to; slow growth errors, instantaneous faults and cycle slip detection amongst others. The faults that will be discussed here include single system faults and failures that occur across multiple systems and ways to detect and exclude these from the position solution calculations.

The operating environment that is being considered in this paper is an agricultural vehicle that will operate in a low dynamic environment. While the data used to implement the quality control algorithms is not an agricultural vehicle, its low dynamic behaviour will be adequate to simulate an agricultural vehicle in normal operation. It is important to note the vehicle will be operating with low dynamics that will allow the use of a simplified dynamic model to be discussed later.

INS systems, while autonomous and, depending on the implementation, largely immune to signal interference, can suffer from time dependent unbounded navigation errors that increase exponentially. Alternatively, while GPS is limited by signal quality, potentially suffering from interference effects and satellite availability, it does exhibit very good long term stability. The advantages of integrating the two systems utilizing the carrier phase GPS range include dramatically improved short term and long term accuracy over what either individual system can provide as well as providing a higher frequency position update than standalone GPS thanks to the update rates of most INS systems.

Currently, research into quality control methods has found that the most effective procedures are generally based on the prediction residuals (innovations) in a Kalman filter or a derivation of the maximum solution separation method. Tuenisson (1990) presents an algorithm for quality control in integrated systems using a combination of innovations and recursive filtering while an algorithm adapted to the integrated case based on the GPS solution separation method is presented in Brenner (1995). Gillesen & Elema (1996) present the results of an innovation based detection, identification and adaption (DIA) procedure with a reliability analysis in an integrated navigation system while Lee & O'Loughlin (2000) present the findings from two integrity procedures, the extrapolation and separation methods, with respect to the detection of the presence of slow growth errors. Wang, Stewart and Tsakiri (1997) presented the results from a measurement mean shift model, applicable to any dynamic Kalman filter integrated system. More recently, Nikiforov (2002) present fault, detection and exclusion algorithms for multi-sensor integrated navigation systems based on Kalman filter innovations while Hewitson & Wang (2006) presented their research into detection, identification and exclusion based on the adaptation of the RAIM algorithms to integrated systems utilizing multiple GNSS constellations.

In this paper, the algorithms described in Hewitson *et al* (2004) and Hewitson and Wang (2006) detailing the adaptation of RAIM quality control procedures to integrated systems will be extended to apply to GPS/INS systems utilizing carrier-phase precision. The algorithms are derived from the least squares estimators of the state parameters in a Guass-Markov Kalman filter (Wang *et al.,* 1997) and are applied to a tightly integrated Kalman filter solution for outlier detection. The measurement mean shift model is also evaluated as to its performance in a low dynamic environment utilizing carrier phase measurements. The use of a vehicle dynamic model is discussed to limit the growth and aid detection of errors in the inertial measurement system while the combination of the two approaches is discussed to detect and isolate instantaneous errors in both systems.

GPS/INS INTEGRATION

The integration between the GPS and INS systems used here is performed by a 24 state tightly coupled Kalman filter, 3 states each are used for position, velocity and attitude errors for the first 9 states, the next 9 states are used as INS error states to store the accelerometer bias and scale errors as well as the gyro bias errors. The final states are used to model the gravity vector, 3 states, and another 3 to model the error for the lever arm offset of the GPS receiver centre from the centre of the INS unit. In this case, the INS unit used is a tactical grade C-MIGITS unit with three accelerometers and three gyroscopes. The input to the Kalman filter is the error between the GPS Calculated double difference measurements and the INS predicted double difference measurements which will be explained in greater detail later. Irrespective of this, we consider the state evolution model of the Kalman filter to be as follows:

$$\hat{x}_k^- = \Phi_{k,k-1}\hat{x}_{k-1} + w_k \tag{1}$$

And the linearized measurement model relating the measurements to the systems states can be written as:

$$z_k = H_k x_k + \varepsilon_k \tag{2}$$

Where Phi Φ can be considered the m_k x m_{k-1} state transition matrix from epoch k-1 to epoch k such that if x_{k-1} is the m x 1 updated state parameter for epoch k-1 then x_k is the m x 1 predicted state parameter for the epoch k made at epoch k - 1. w_k can then be considered to be the m_k x 1 random error vector at epock k representing the dynamic process noise. Z_k is the n_k x 1 measurement vector at epoch k while H_k is the n_k x m_k design matrix relating the measurement vector z_k to the state vector x_k at epock k. ε_k is the n_k x 1 error vector representing the measurement noise values at epoch k.

The Kalman filter implementation used in this paper is slightly different to the norm in that at the start of each epoch the INS bias errors are feed back to the raw INS measurements such that the predicted state is always zero. The following diagram demonstrates this arrangement.

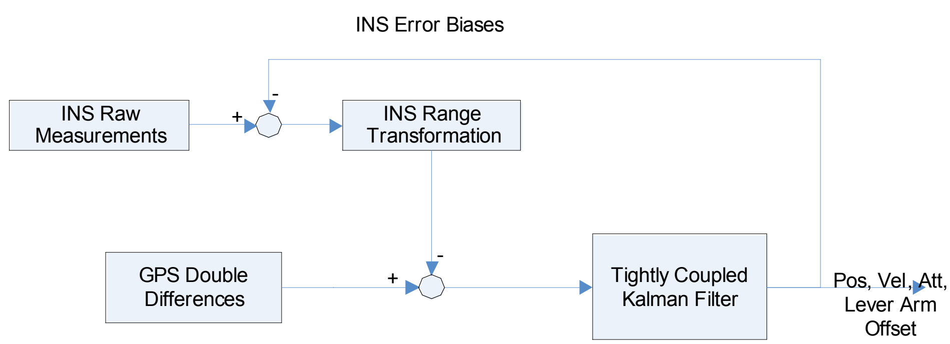

Figure 1: Kalman Filter Structure

The net effect of this arrangement is that the Kalman filter can be considered to be a 6 state Kalman filter at the GPS update step as the velocity and attitude states are derived from INS, the only states that are updated from new GPS measurements are the three position error states and the three lever arm error states. However due to the fact that the Kalman filter's input is the difference between the GPS double difference measurement and the predicted double difference measurement derived from the INS system the net effect of having the predicted INS biases set to zero (ie, feed back into the raw INS measurement) at the start of each update epoch is that this information is captured within a different section of the design matrix relating the measurement vector z_k to the state vector x_k. The net effect of this mechanism is to set the entries in the design matrix, relating the measurement vector z_k to the INS error states in the state vector x_k to zero. The input to the Kalman filter can be represented as in equation 3 where GPSDD is the double difference measurements calculated from the GPS satellites and INSPDD is the predicted GPS double differences from the INS estimated position.

$$z_k = GPSDD - INSPDD \tag{3}$$

GPS OUTLIER DETECTION

The adoption of least squares principles for the state estimation in the Kalman filter solution the single epoch snapshot solution algorithms can be adapted for integrity monitoring see Hewitson (2006). By then including the predicted state parameters into the measurement parameter this allows the detection of outliers in the predicted states and hence potential errors in the system transition matrix. The inclusion of the predicted states also increases the redundancy of the system which has a significant effect on quality control. For a detailed background to this method, known as the detection, identification and adaption algorithms see Wang and Chen (1994), Hewitson et al (2004) and Hewitson and Wang (2006).

Wang *et al.* (1997) showed that by combining the predicted states $\hat{x}_k^-$ with the measurement vector z_k optimal estimates of the state parameter can be obtained by using least squares principles. The corresponding model is (e.g. Wang *et al* 1997)

$$l_k = A_k x_k + v_k \tag{4}$$

Where $l_k = \begin{bmatrix} z_k \\ \hat{x}_k^- \end{bmatrix}$; $v_k = \begin{bmatrix} v_{z_k} \\ v_{\hat{x}_k^-} \end{bmatrix}$; $A_k = \begin{bmatrix} H_k \\ I \end{bmatrix}$; l_k is the least squares measurement vector containing the Kalman filter measurement vector z_k and the predicted states parameter vector $\hat{x}_k^-$; A_k is the $(n_k \times m_k) \times n_k$ design matrix ; v_{z_k} is the $(n_k \times 1)$ residual vector of the measurements z_k ; $v_{\hat{x}_k^-}$ is the $(n_k \times 1)$ residual vector of the predicted state vector $\hat{x}_k^-$ and I is the $(m_k \times m_k)$ identity matrix.

The corresponding stochastic model is therefore comprised of the $(n_k \times n_k)$ measurement covariance matrix R_k and the $(m_k \times m_k)$ predicted state covariance matrix $Q_{\hat{x}_k^-}$ combined to give the following variance covariance matrix:

$$C_{l_k} = \begin{bmatrix} R_k & 0 \\ 0 & Q_{\hat{x}_k^-} \end{bmatrix} \tag{5}$$

Therefore, by using the least squares methodology to determine the optimal state parameter estimate and the covariance matrix can be determined by the following equations:

$$\hat{x}_k = \left(A_x^T C_{l_k}^{-1} A_k\right)^{-1} A_k^T C_{l_k}^{-1} l_k \tag{6}$$

$$Q_{\hat{x}_k} = \left(A_x^T C_{l_k}^{-1} A_k\right) \tag{7}$$

The filtering residuals can thereby be determined from least squares such that:

$$v_k = \begin{bmatrix} v_{z_k} \\ v_{\hat{x}_k^-} \end{bmatrix} = \begin{bmatrix} H_k \\ I \end{bmatrix} \hat{x}_k - \begin{bmatrix} z_k \\ \hat{x}_k^- \end{bmatrix} = A_k \hat{x}_k - l_k \tag{8}$$

And further, the cofactor matrix for the filtering residues can be calculated using least squares methods such that:

$$Q_{v_k} = C_{l_k} - A_k Q_{\hat{x}_k} A_k^T \tag{9}$$

W-STATISTIC TEST RESULTS

In order to detect a measurement as being an outlier in any particular epoch, especially one where the presence of an outlier has been detected using a global detection algorithm such as the variance factor test, the w-statistic test has been utilized. The w statistic is given by equation (9) and should have a normal distribution under the null hypothesis and in the case of the presence of an outlier has distribution with the non centrality detailed in equation (10) (Hewitson & Wang 2006)

$$w_i = \left| \frac{-e_i^T C_{l_k}^{-1} \hat{v}}{\sqrt{e_i^T C_{l_k}^{-1} Q_{\hat{v}} C_{l_k}^{-1} e_i}} \right| \quad (10)$$

$$\delta = \nabla S_i \sqrt{e_i^T C_{l_k}^{-1} Q_{\hat{v}} C_{l_k}^{-1} e_i} \quad (11)$$

Where e_i is the unit vector whose purpose is to isolate each test measurement for analysis.

The data collected for this analysis was collected from a ground vehicle operating in a clear area. Figure 1 shows the trajectory of the vehicle while figure 2 shows the ground track without the height component.

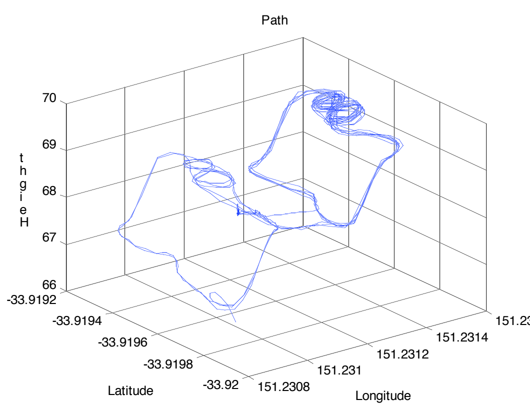

Figure 2: Vehicle Trajectory

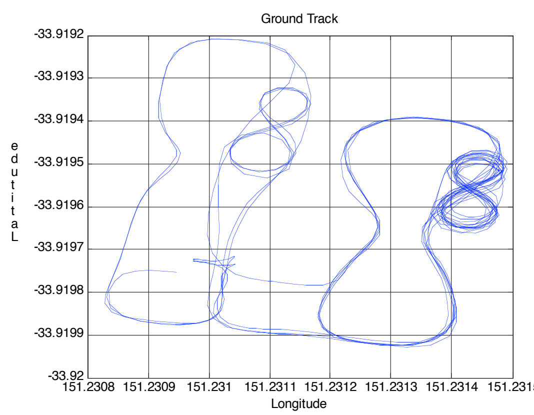

Figure 3: Ground Track of Vehicle

The initial results for the w-statistic test in this instance reveals some interesting behaviour when the predicted measurement states are included as part of the measurement vector for the least squares analysis. Figure 3 shows that for the first 50 epochs the w-statistic test fails in this instance while passing when the predicted states are not included in the measurement vector. This is due to the initial convergance of the Kalman filter states brought about by the training of the Kalman filter. In this example 5 double difference measurements are used for precision.

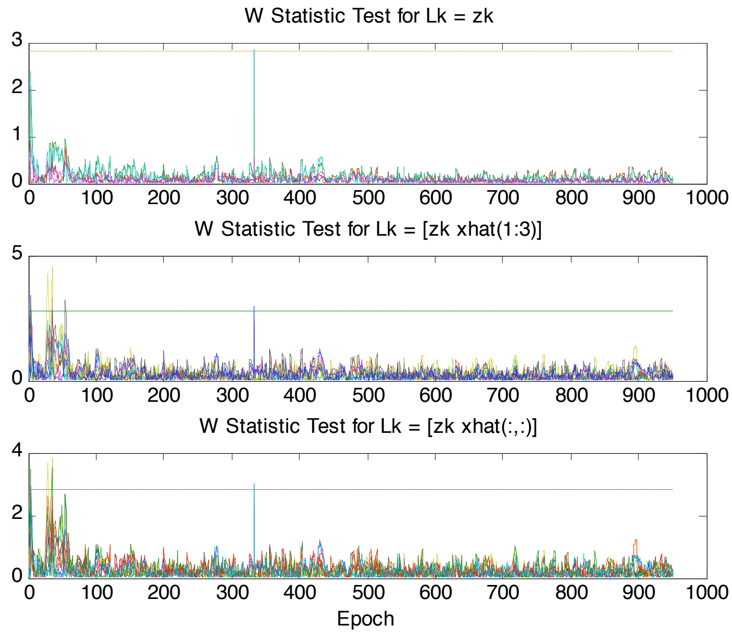

Figure 4: W Test results for the case where $L_k = z_k$, for L_k = [z_k xpos ypos zpos] and L_k = [z_k x]. (alpha$_w$ = 0.1%)

INS OUTLIER DETECTION

Outliers that occur within the INS measurement model are much harder to detect using the w-statistic test in this instance as the INS measurements are input into the Kalman filter after being converted into the range domain and differenced with the GPS double difference measurements. As such, an instantaneous error in the INS will manifest itself in every input measurement. As such, the problem becomes detecting the difference between an outlier in the GPS double differences and the INS measurements as it manifests itself in a manner similar to an outlier in the reference satellite for the double differences. Figure 4 shows the w-statistic test with an instantaneous INS error injected into epoch 334 while table 1 shows the individual w-statistic test values for epoch 334.

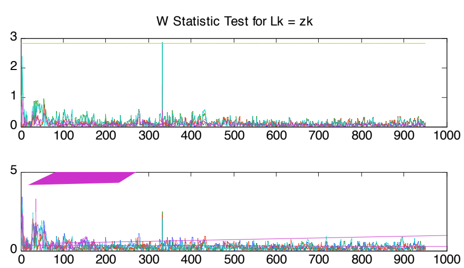

Figure 5: W-Statistic test results with INS outlier injected at epoch 334 and (alphaw = 0.1%)

	[Z_k X_k] k=1,..,6	[Z_k X_k] k=1,..,3	[Z_k]
Z_1	2.3327	2.4854	0.39269
Z_2	3.2306	3.045	3.5215
Z_3	2.8678	2.8242	-1.7708
Z_4	2.6748	2.5781	3.5175
Z_5	2.7727	2.8551	0.66047
X_1	-0.06892	0.0036091	
X_2	-0.97484	-1.088	
X_3	-3.6722	-3.6868	
X_4	0.18636		
X_5	0.96919		
X_6	3.7177		

Table 1: W-statistic test for epoch 334 with INS outlier injected

We can see from table 1 that the INS error manifests itself in the position error state corresponding to height when the measurement vector is augmented with the predicted state vector. This would typically be congruent with detecting an error in the dynamic model of the system, however the w-statistic test for the measurement inputs are also inflated leading to a possible false detection of an outlier in the GPS measurements. The w-statistic test for the case where the measurement vector is not augmented by the predicted states also shows that the INS measurement causes two of the

GPS measurements (Z_2 and Z_4) to be flagged as potential outliers. This indicates that differentiating between a true GPS outlier and an instantaneous fault in the INS system becomes critical in this system architecture and will be discussed in the next section.

NON-HOLOMIC VEHICLE CHARACTERISTICS

The use of a non-holomic vehicle model for the detection of INS errors is an area that hasn't received a great deal of attention due to the fact that INS errors can usually be compensated for when handling the biases inherent in all INS systems. However, due to the nature of this implementation detecting instantaneous INS errors becomes important in order that the GPS double difference measurements are not incorrectly flagged as outliers. A non-holomic vehicle is one where the dynamic behaviour of the vehicle is bounded and has limited degrees of freedome. This additional information on the vehicles behaviour can be used to provide an upper bound on the expected measurements from the INS unit.

In this instance, as the vehicle in question is an agricultural tractor, a simple vehicle model derived from Fierro & Lewis (1996) can be used such that at each instantaneous epoch the vehicle motion can be considered to be only in the forward direction with the movement of the vehicle in any other direction bounded by the measurement noise parameter. A model such as this allows us to detect and bound the raw INS measurements in each direction such that any instantaneous fault in the INS system can be detected as well as bounded so the INS measurements can still be used in the position calculation. The following three equations can be used as a simple model to describe the vehicles motion in such a system.

$$\begin{aligned} \dot{x} &= v + w \\ \dot{y} &= w \\ \dot{z} &= w \end{aligned} \tag{12}$$

Where x,y,z is the vehicle velocity in the x,y and z directions in the body frame and w is white noise parameter. By using this dynamic model of the vehicle motion to bound the position solution from the INS measurements it is possible to flag the case where the INS measurement has suffered an instantaneous fault and either bound the measurement to the magnitude of the measurement noise or the measurement noise plus the maximum velocity of the vehicle. Preliminary results suggests that this approach may offer advantages if the instantaneous fault occurs in the y or z directions however it's effectiveness in the x direction is dependent on the actual speed of the vehicle.

CONCLUSION AND FUTURE WORK

In this paper a fault detection algorithm has been investigated for use in a tightly integrated INS/GPS system utilizing carrier phase precision. Results have shown that the w-statistic test is effective in detecting instantaneous single satellite outliers that don't occur in the base satellite. It has also been shown that instantaneous errors that occur in the INS system appear in the w statistics similar to the effect an instantaneous error in the reference satellite has on this statistic. A method to distinguish between a reference satellite outlier and an instantaneous error in the INS system has been suggested based on extended knowledge of the vehicle dynamics and bounds of motion utilizing a kinematic model for the nonholomic restricted movement possible for an agricultural land vehicle.

More work needs to be done to investigate the variance matrices both for the measurements including the GPS double differences as well as the variance for the state parameters utilized within the Kalman filter. By increasing the accuracy of the variance matrices the reliability of the w-statistic test can be improved. Further investigation also needs to occur into the relationship between the design matrix of the system and the method of feedback that allows the predicted INS error states to be set to zero at the start of each epoch. Further investigation also needs to occur into other types of systematic errors such as slow growth errors. The use of multiple solution systems to detect base satellite errors could also be investigated to help provide resolution between instantaneous INS errors and reference satellite outliers.

The full implementation of the kinematic model of the vehicle dynamics also needs to be more fully investigated as well as further developing this model. In the non homogenous environment that is the typical operating environment of an agricultural tractor a vehicle model that considers factors such as tyre slippage and loose soil slips should provide for a more accurate description of the vehicles motion.

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