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Achieving Integrity in an INS/GPS Navigation Loop for Autonomous Land Vehicle Applications

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Abstract

The objective of this paper is to introduce and investigate the issue of integrity in an INS/GPS navigation loop for autonomous land vehicle applications. The paper briefly outlines the standard fusion algorithm for the INS/GPS loop, while the focus is on the detection of possible faults both before and during the fusion process. The concept of fault detection will centre on the low frequency faults of the INS, caused by bias and drift, and the high frequency faults of the GPS unit caused by multipath errors and changes in satellite geometry.

1 INTRODUCTION

In pursuit of autonomous land vehicles operating in real environments, the need for ultra-high integrity navigation systems has been of major concern. The navigation system must provide accuracy, robustness and integrity in order for the system to be used in real autonomous operations. If the navigation system is used to close the loop in the control structure, then erroneous estimates of the states of the vehicle can render the vehicle uncontrollable and have a drastic effect on the safety of the system and its surroundings.
The automation of land vehicles has been investigated by a number of research groups around the world [5], [3], [4] and [11]. However, the need for reliability and integrity has rarely been considered. With the advent of autonomous systems in mining, stevedoring and agriculture, the issue of reliability and integrity has become a major concern.
The objective of the High Speed Vehicle (HSV) Project at the Australian Centre for Field Robotics (ACFR) is to investigate a sensor suite that provides accuracy, robustness and integrity, through the implementation of two independent navigation loops. The first loop employs both INS and GPS sensors, while the second loop involves the fusion of a Millimetre Wave Radar with velocity and steering encoders, both loops providing estimates of position and heading.
Work has been carried out by the ACFR in fault detection of multi-sensor multi-loop systems [9]. However, each loop must also have its own fault detection techniques in order to detect known faults that can occur within the loop. Consequently, this minimises the chances of undetected faults passing through the loop and into the main fault detection routines of the system where it may also go undetected.
The focus of this paper is on the implementation of fault detection techniques that increase the integrity of the INS/GPS navigation loop. The implementation processes adopted have been developed to allow modularity. That is, the ability of the loop to detect the occurrences of faults irrespective of the accuracy of the sensors implemented. As a result, the accuracy of the fusion process of the two sensors will be based on the accuracy of the individual sensors however, the fault detection techniques remain the same.

1.1 Structure

The paper will firstly provide a summary of the data fusion technique in Section 2. For further detail refer to [7] and [10]. It is assumed that the fundamentals of INS and GPS are known. For a detailed explanation of these systems refer to [8], [2] and [1]. The known faults that occur with the INS and GPS units along with techniques implemented to tackle such problems will be discussed in Section 3. Post-

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processed results of real data will then be presented in Section 4.

2 FUSION PROCESS

The objective of the fusion process is to merge the information from the INS and the GPS sensors and provide estimates of the states of the vehicle with greater accuracy than relying on the information from the individual sensors. The method implemented in this work uses a Kalman Filter in a 'loosely-coupled' architecture as illustrated in Figure 1. In this arrangement the acceleration and attitude data from the INS in the body frame is converted to position and velocity information in the navigation frame (North, East and Down). Similarly the differential GPS position and velocity data is also converted to this frame. The INS data is continuously transmitted so that it can be either logged or used for guidance purposes. When a GPS fix is obtained, an observation is evaluated (this is the difference between the INS and GPS data) and the filter then estimates the errors as produced by the INS. These errors are then used to correct the INS unit. Such an arrangement allows the continuous transmission of the high frequency data from the INS. The objective of the Kalman Filter is to estimate the

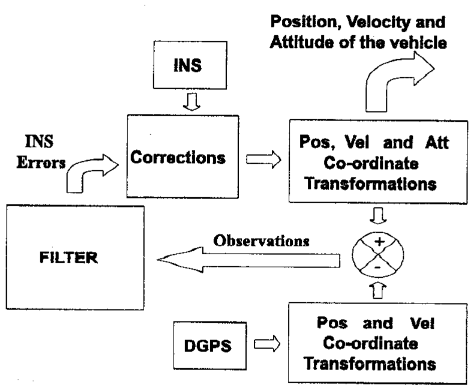

Figure 1: Loosely-Coupled architecture.

position, velocity and attitude errors of the INS. Hence the state model of the Kalman Filter, F, is an error model of the INS. A simplified Pinson error model [6] is implemented in this work. F is a 9×9 state model comprising of the accelerations (A^n) and angular rotational rates (Ω^n) of the three axes of the INS in the navigation frame. In the complete error model, the Schuller and Coriolis terms are included. However, the Schuller terms have a major effect only when the INS runs alone for greater than 84 minutes. This can be disregarded since the INS is reset each time a GPS fix is obtained which can occur at up to 10Hz. Similarly, since the angular rotation of most land vehicles is quite small, then the Coriolis terms can also be ignored. The resultant error model is a 9×9 matrix with only 15 terms as indicated in equation (1).

$$F = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & A^D & -A^E \\ 0 & 0 & 0 & 0 & 0 & 0 & -A^D & 0 & A^N \\ 0 & 0 & 0 & 0 & 0 & 0 & A^E & -A^N & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & -\Omega^D & \Omega^E \\ 0 & 0 & 0 & 0 & 0 & 0 & \Omega^D & 0 & -\Omega^N \\ 0 & 0 & 0 & 0 & 0 & 0 & -\Omega^E & \Omega^N & 0 \end{bmatrix} \tag{1}$$

This model represents the propagation of the three position errors, $\delta p^N, \delta p^E$ and δp^D, the three velocity errors, $\delta v^N, \delta v^E$ and δv^D and the three attitude errors, $\delta\psi^N, \delta\psi^E$ and $\delta\psi^D$ in the NED frame as represented in the state x

$$x = \begin{bmatrix} \delta p^N & \delta p^E & \delta p^D & \delta v^N & \delta v^E & \delta v^D & \delta\psi^N & \delta\psi^E & \delta\psi^D \end{bmatrix}^T$$

3 FAULT CHARACTERISTICS AND DETECTION

The faults associated with this navigation loop are classified into two groups: high frequency faults due to multipath errors and jumps in the GPS observations, and low frequency faults caused by biases in the INS and drift in the state evaluation due to noise. The high frequency faults are detectable if they lie outside a threshold set by the accuracy of the observation obtained before fusion occurs. Low frequency faults however, vary slowly with time and hence are difficult to detect during the fusion process. Hence calculations are carried out prior to the fusion process in order to detect the errors and consequently minimise their effect.

3.1 INS Faults

The acceleration and angular rotation rate measured by the accelerometers and gyros respectively is represented as

$$A^i = A^{i_T} + b_{A^{i_T}} + \nu \tag{2}$$

$$and\ \dot{\theta}^i = \dot{\theta}^{i_T} + b_{\dot{\theta}^{i_T}} + \nu \tag{3}$$

where A^i is the measured acceleration of the i^{th} accelerometer, A^{i_T} is the true acceleration that should be measured by the accelerometer and $b_{A^{i_T}}$ is the bias found on this accelerometer. The same notation is used for the gyros. ν represents white noise.
The incremental velocity, position and rotation values are then obtained by integrating equations (2) and (3).

$$
\begin{aligned}
V^i &= V^{i_T} + b_{A^{i_T}} t + \int \nu \, dt && (4)\\
P^i &= P^{i_T} + \frac{b_{A^{i_T}} t^2}{2} + \int \int \nu \, dt && (5)\\
\textit{and} \;\; \theta_i &= \theta^{i_T} + b_{\dot{\theta}^{i_T}} t + \int \nu \, dt && (6)
\end{aligned}
$$

As presented in equations (4) to (6), the bias in the sensors play a major role in causing drift in the velocity, position and attitude information provided by the unit. Namely, the bias terms increase the velocity and attitude errors linearly with time, and the position quadratically. Consequently, by removing the bias, these errors are then minimised.
The simplest method of obtaining the biases in the INS is to measure the readings from each sensor whilst the vehicle is stationary. These values depict the bias on each sensor and thus can be removed from the sensor readings each time a measurement is taken. Figure 2 presents the bias measured on the accelerometers of the Watson unit over a period of six hours whilst the unit was stationary. Evidently the biases do not re-

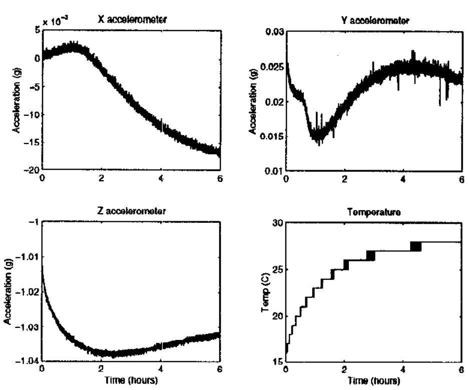

Figure 2: The change in bias values of the accelerometers are due to the internal temperature change of the INS unit and ambient temperature variations.

main constant. The changes in the bias values occur due to an increase in the temperature of the unit from the internal circuitry and due to ambient temperature variations. Thus the biases are obtained each time the vehicle is stationary in order to counteract the changing bias values.
The removal of bias from the sensors does not however provide perfect solutions. This is due to the integration of white noise ($\int \nu \, dt$) which in turn places an increasing error term on the sensors known as Random Walk as presented in equations (4) and (6).
The standard deviation of the error due to unity Gaussian white noise at any particular moment in time is

$$\sigma_\nu = \sqrt{t} \qquad (7)$$

Thus without any external resetting properties, the white noise will cause an unbounded error growth in the INS sensors whose value at any particular point in time t will be within $2\sqrt{t}$ 95% of the time.
If the noise is not of unity value but instead of K times, then the error is represented as $\sigma_\nu = K\sqrt{t}$. The larger the magnitude of the noise, the greater the standard deviation of the error potentially attainable. Thus any vibrations in the vehicle that transmit to the INS will in turn increase the magnitude of the noise and hence increase the magnitude of the random walk. The vibrations can be suppressed by mounting the unit on vibration absorbers (as employed in this work) or through frequency analysis of the vehicle's vibration.

3.2 GPS Faults

The long term errors in the INS are bounded by the accuracy of the GPS. Thus the greater the accuracy of the GPS, then the greater the accuracy of the fusion process. The innovation covariance matrix of the Kalman Filter, represents the uncertainty one has with the innovation, which in this case is the observation obtained. That is, it reflects the uncertainty in the observed error of the INS. If the assumption that the INS has no errors is made, then the uncertainty lies in the GPS fix and hence in the accuracy of the GPS receiver. The uncertainty in the GPS fix can then be increased depending on the vehicle's environment, that is, a higher uncertainty for a noisier surrounding. Once the uncertainty is obtained it is then increased again to reflect the inaccuracy in the INS. Thus the drift and bias in the INS is accounted for along with the accuracy of the GPS receiver.
High frequency faults however, pose a problem. When an abrupt jump in the GPS fix occurs, then the observation error will be large, and accepted into the estimation stage of the filter. Thus a large estimated error will be evaluated and an erroneous correction will occur. Thus before an estimate can be used the

observation needs to be validated. Such a validation process uses a chi-squared distribution and is implemented by using the innovation and its covariance

$$\nu^T(k)S^{-1}(k)\nu(k) \quad \leq \quad \gamma \tag{8}$$

where $\nu(k)$ is the innovation and $S(k)$ is its covariance matrix. Equation (8) is a gating function that describes the probability concentration under Gaussian assumptions. The value γ is determined prior to the fusion process and represents the percentage probability that a particular observation lies within an ellipsoid. γ is determined by the number of dimensions of the measurement vector.

Once the innovation is obtained, the gating function is implemented, and if the result is less than or equal to γ, then the observation is accepted and the estimate proceeds. However, due to satellite geometry, the GPS fix in the vertical plane is significantly less accurate than that in the horizontal plane. That is, the fix in North and East may lie well within the validation region, whilst that of Down may exceed it and force the result of the gating function beyond the gamma threshold. Thus one chooses a γ which best suits the environment and the probability region allowed, considering that although a larger γ will include the vertical fix, it will also accept erroneous horizontal fixes. Similarly, changes in the satellite geometry cause the dilution of precision (DOP) to vary. This value is a measure of the accuracy of the GPS fix. Consequently, a change in DOP will affect the GPS fix causing jumps in the solution. These jumps can be detected using the same technique as discussed for multipath errors. However, these changes are not as large as those encountered for multipath errors and generally go undetected, unless the accuracy of the INS is comparable to that of the GPS unit.

The value of γ is usually set to reject innovations exceeding the 95% threshold. Apart from rejecting the erroneous position fixes caused by multipath, the gating function allows the filter to remain optimal by keeping the innovations within the two standard deviations.

During the rejection of multipath errors, the fusion process remains at the prediction stage, and subsequently, the INS determines the navigation states. Thus the risk of the INS wandering off and missing all GPS fixes is apparent. As a result, the tuning process of the filter is a crucial step in the fusion implementation. The process noise matrix needs to be tuned so that the covariance increases at a rate fast enough to grasp the first available GPS fix that satisfies the gating function. The process noise matrix represents the inherent inaccuracy of the unit along with the confidence in its calibration and alignment.

4 RESULTS

The equipment used in this work is illustrated in Figure 3 and includes:

- An Ashtech G12 GPS in standard differential mode. The unit delivers fixes at 10Hz as long as there are at least four satellites available;
- A Watson Inertial Measurement Unit. The sampling rate of the unit is approximately 84Hz; and
- A transputer based logging system. The logging system is used to obtain the data from the two sensors along with time stamps of when the data was received from the sensors.

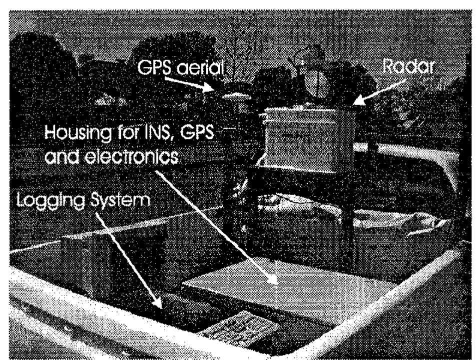

Figure 3: The sensors along with the necessary equipment are fixed to the back of the utility.

In the following figures, the light coloured crosses are the GPS fixes while the darker line is the fused data. Figure 4 presents the raw data taken from the INS and GPS in a run around the university. The area is heavily populated with tall buildings thus causing substantial multipath errors in particular areas. Similarly, the INS data is extremely poor. This is due to two reasons:

- Firstly, the unit was powered for only a short period of time and consequently changes in the bias occur during the run; and
- Secondly, the unit was mounted directly onto the vehicle. As a result, the vibrations of the vehicle were transmitted directly to the unit.

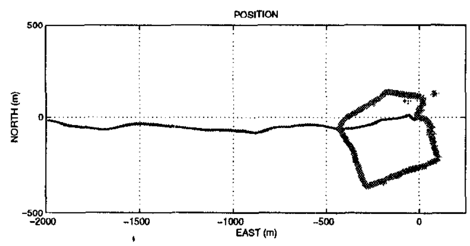

Figure 4: Raw data from the INS and GPS. The INS solution wanders off due to the changing bias terms and due to the unit being mounted directly onto the vehicle.

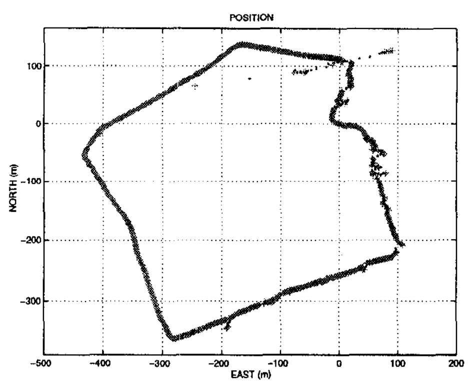

Figure 5: Fusion of the INS and GPS data with no multipath rejection.

Figure 5 presents the fused data without GPS fault detection. Figures 6 and 7 present enlarged views of two areas where multipath has occurred. Since no fault detection was implemented, and consequently the high frequency faults were not rejected, the fused data was drawn into the multipath region. The innovation sequences of the states show large spikes due to the multipath errors being accepted. This occurs more than 95% of the time. As a result, the filter cannot be considered optimal.

Figures 8 and 9 show the same multipath regions with the fault detection technique implemented. The gamma threshold was set to ignore innovations exceeding the 95% boundary. Hence the multipath signals were rejected and the innovation remained within the two standard deviations.

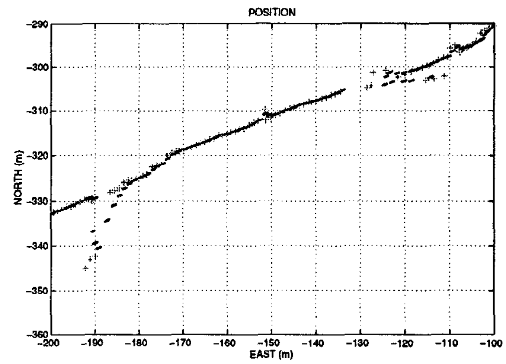

Figure 6: Enlarged view of region 1 where GPS multipath errors have occurred.

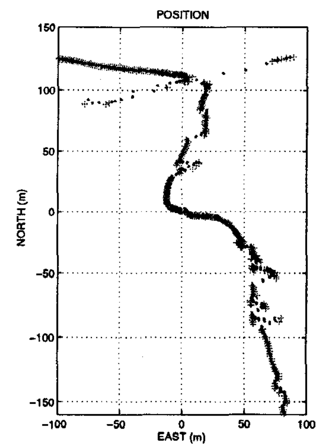

Figure 7: Enlarged view of region 2 where GPS multipath errors have occurred.

5 CONCLUSION

The benefits of applying INS/GPS navigation loops to land vehicles are overwhelming. However, attention needs to be given to the characterisation and detection of faults in order for the loop to be effective in the design of real autonomous systems. With the advent of commercially motivated autonomous land vehicles, the need for integrity is fundamental. This paper has focused on the issue of integrity in an INS/GPS navigation loop for land vehicle applications. The work has been designed to investigate this issue, and in particular, the techniques implemented need to be as general as possible so that the modularity of the loop is sustained. The faults were classified into two groups:

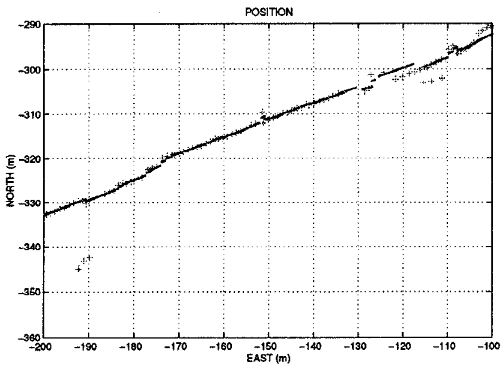

Figure 8: Enlarged view of region 1 with multipath rejection.

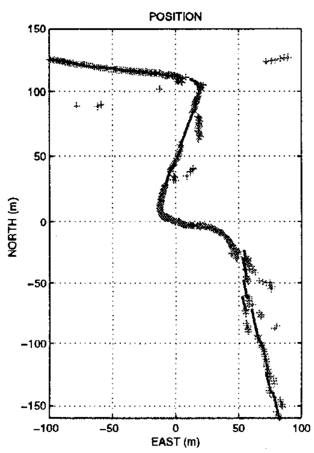

Figure 9: Enlarged view of region 2 with multipath rejection.

high frequency faults in GPS, and low frequency faults in INS. The high frequency faults were found to be easily detectable implementing a gating function on the innovation. The low frequency faults however, were tackled before the fusion process due to the difficulty in detecting them online. Finally, by considering these faults, the accuracy of the fusion process increased when the sensors were performing inaccurately, thus justifying the need for the fault analysis.

Acknowledgements

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