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Developing a Low-cost MEMS IMU/ DGPS Integrated System for Robust Machine Automation

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BIOGRAPHY

Yanrui Geng is currently a Research Associate within the School of Surveying and Spatial Information Systems at the University of New South Wales (UNSW). He obtained a Doctor of Philosophy in Precision Instruments and Mechanology from the Beijing University of Aeronautics & Astronautics, China, in 2002.

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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.

Chris Rizos is a graduate of the School of Surveying, UNSW; obtaining a Bachelor of Surveying in 1975, and a Doctor of Philosophy in 1980. Chris is currently Professor and Head of School. Chris has been researching the technology and high precision applications of GPS since 1985, and has published over 200 journal and conference papers. He is a Fellow of the Australian Institute of Navigation and a Fellow of the International Association of Geodesy (IAG). He is currently the Vice President of the IAG and a member of the Governing Board of the International GNSS Service.

Jinling Wang is currently a Senior Lecturer at the School of Surveying & SIS, UNSW, Sydney, Australia. He obtained a Doctor of Philosophy in 1999 from the Curtin University of Technology, Perth, Australia. He is Editor-in-Chief of the *Journal of Global Positioning Systems.*

ABSTRACT

A navigation system based on a low-cost, low-grade MEMS inertial measurement unit (IMU) integrated with differential GPS has been developed for machine automation applications. Because the inertial sensors have no ability to measure Earth rotation, the attitude errors of pitch and heading cannot be obtained using only IMU measurements. To overcome this deficiency, two Kalman filters are used for robust estimation of navigation parameters and the errors of inertial sensors. An adaptive fading factor Kalman filter uses a GPS dynamic model to generate the velocities and accelerations which can be used to acquire approximate pitch and heading values. Another Kalman filter is used to integrate position, velocity and attitude from both the IMU and GPS so that position and attitude can be estimated directly - due to their individual observabilities. The drift error of the inertial sensors is also well compensated. The proposed algorithm has been implemented into post-processing integration software and has been tested in the field. The test results demonstrated that this robust MEMS/DGPS integrated system has the capability of providing continuous and reliable navigation for machine automation applications.

INTRODUCTION

Agriculture is fundamental to the world's economy. In the next decade, machine automation will play an important role in the agriculture revolution. Already the impact of automating process such as ploughing, planting and application of fertilizers is being felt in many types of farming. Other examples of machine automation are guidance of dozers, drills, draglines and shovels in mining and grader excavators and pavers for construction.

Traditionally, machine automation products used a GPS-based navigation system to report position information. Such products suffer from a number of problems which hamper the uptake of machine automation within industry:

- GPS suffers "outages", i.e. periods when positioning is not possible, for various reasons but particularly where obstruction of the satellites by trees occurs. This affects both the amplitude and phase of received satellite signals and causes the receiver to lose lock on a blocked satellite, meaning it needs both to reacquire the signal, and to resolve ambiguities in the phase measurements. Both these processes take time, and if several satellites are affected, the receiver cannot provide a position solution for a significant period of time. If interruptions to GPS signals occur repeatedly, then ambiguity re-initialization is at the very least an irritation and at worst a significant weakness of current GPS carrier-phase-based systems.
- The data rate for GPS is too low. For the type of control loops used in automating large agricultural machines, the latency between 20 Hz measurements is too great for the precision required.

Both of these problems can be solved by "aiding" the GPS receiver, using gyroscopes and accelerometers, configured as an inertial navigation system (INS) which updates position much more rapidly. However, low-cost inertial sensors have a problem of their own: they experience significant drift and are very susceptible to time dependent errors. So a navigation system based on low-cost, low-grade MEMS inertial measurement unit (IMU) integrated with differential GPS has been developed for machine automation applications in this paper to address these deficiencies.

The purpose of this study is to develop a navigation system by sensor fusion integration of a low-cost, low-grade MEMS inertial measurement unit (IMU) and differential GPS for machine automation applications. Two Kalman filters are used for robust estimation of navigation parameters and the errors of inertial sensors. An adaptive fading factor Kalman filter uses a GPS dynamic model to generate velocity and acceleration values which can be used to acquire approximate pitch and heading values. Another Kalman filter is used to completely integrate position, velocity and attitude from both the IMU and GPS so that position and attitude can be estimated directly - due to their individual observabilities.

The environment considered in this study is for an agricultural tractor operating on a low-value row crop. This is a unique automation environment in that row cropping activities typically occur in open fields with good satellite visibility and relatively flat terrain. A key indicator in row cropped agricultural applications is to minimize the cross track error of the tractor. This is defined as the deviation of the centre of the rear of the tractor from the desired path and for low value crops accuracies of approximately 55 mm are required to improve performance compared to a human operator.

INITIAL ALIGNMENT

An initial alignment procedure is needed to initialize the INS. Through the subsequent integration of IMU acceleration and angular velocity measurements, it is possible to then obtain vehicle position, velocity and attitude. So, it is crucial to have an accurate initial alignment in order to implement an integration navigation system.

The Direction Cosine Matrix (DCM) from the body frame to the navigation frame can be defined as

$$C_b^n = \begin{bmatrix} \cos\theta\sin\psi & \sin\gamma\sin\theta\sin\psi + \cos\phi\cos\psi & \cos\gamma\sin\theta\sin\psi - \sin\gamma\cos\psi \\ \cos\theta\cos\psi & \sin\gamma\sin\theta\cos\psi - \cos\gamma\sin\psi & \cos\gamma\sin\theta\cos\psi + \sin\gamma\sin\psi \\ \sin\theta & -\sin\gamma\cos\theta & -\cos\gamma\cos\theta \end{bmatrix} \tag{1}$$

Where θ is the pitch angle, γ is the roll angle, and ψ is the heading of the vehicle.

When the vehicle is stationary, the measurement from the three accelerometers is

$$f^b = C_n^b \begin{bmatrix} 0 \\ 0 \\ g \end{bmatrix} = \begin{bmatrix} g\sin\theta \\ -g\sin\gamma\cos\theta \\ -g\cos\gamma\cos\theta \end{bmatrix} \tag{2}$$

Hence, the pitch and roll can easily be estimated as

$$\theta = \sin^{-1}\left(\frac{f_x}{g}\right) \tag{3}$$

$$\gamma = \tan^{-1}\left(\frac{f_y}{f_z}\right) \tag{4}$$

Because the bias of the MEMS gyro used is too large to measure the earth rotation rate, it is impossible to perform the azimuth alignment without using an external aid.

When the vehicle starts moving, the azimuth can be obtained by GPS velocity information

$$\psi = \tan^{-1}\left(\frac{v_E}{v_N}\right) \tag{5}$$

When the vehicle is static, the outputs of the gyros can be considered to be measurement biases. This is because the Earth rotation can not be measured by our gyros and the true angular rate of the body frame during the stationary periods can be assumed to be zero. By averaging all gyro measurements during the stationary periods, we can remove the noise effects and use this average value as the gyro bias estimate. So we have

$$\varepsilon_g = mean(\omega_{ib}^b) \tag{6}$$

VEHICLE DYNAMIC MODEL

The inertial sensors that were used cannot guarantee a steady heading or pitch reading, so the GPS information was used to provide azimuth and pitch information

$$\psi = \tan^{-1}(\frac{v_E}{v_N}) \tag{7}$$

$$\theta = \tan^{-1}(\frac{v_U}{\sqrt{v_E^2 + v_N^2}}) \tag{8}$$

The GPS can only give the position information such as latitude, longitude and height, and the acceleration and velocity of GPS can not be obtained directly from the GPS observation. So a Kalman filter is needed to estimate the accurate velocities from GPS. A dynamic model is set up as a 12-state vector as shown below.

$$x = [L \quad \lambda \quad h \quad v_N \quad v_E \quad v_U \quad a_N \quad a_E \quad a_U \quad k_N \quad k_E \quad k_U]^T \tag{9}$$

Where

L, λ, h - are latitude, longitude and height, respectively

v_N, v_E, v_U - are north, east and up velocities, respectively

a_N, a_E, a_U - are north, east and up accelerations, respectively

k_N, k_E, k_U - are north, east and up jerks, respectively

The dynamic model of the state vector in equation (9) is

$$\begin{bmatrix} \dot{L} \\ \dot{\lambda} \\ \dot{h} \\ \dot{v}_N \\ \dot{v}_E \\ \dot{v}_U \\ \dot{a}_N \\ \dot{a}_E \\ \dot{a}_U \\ \dot{k}_N \\ \dot{k}_E \\ \dot{k}_U \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & 1/R_m & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1/R_n \cos L & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} L \\ \lambda \\ h \\ v_N \\ v_E \\ v_U \\ a_N \\ a_E \\ a_U \\ k_N \\ k_E \\ k_U \end{bmatrix} \tag{10}$$

The measurement model can be expressed as

$$z = Hx + v \tag{11}$$

Where

$$H = [I_{3\times3} \quad 0_{3\times3} \quad 0_{3\times3} \quad 0_{3\times3}]$$

KALMAN FILTER

Basically, the Kalman filtering estimation algorithm comprises two steps, namely, the prediction step to provide the apriori state vector and the update step with external measurements. The main Kalman filtering equations are given below:

Prediction:

$$\hat{x}_{k/k-1} = \phi_{k/k-1}\hat{x}_{k-1} \tag{12}$$

$$P_{k/k-1} = \phi_{k/k-1}P_{k-1}\phi_{k/k-1}^T + Q_{k-1} \tag{13}$$

Updating:

$$K_k = P_{k/k-1}H_k^T[H_k P_{k/k-1} H_k + R_k]^{-1} \tag{14}$$

$$\hat{x}_k = \hat{x}_{k/k-1} + K_k[z_k - H_k\hat{x}_{k/k-1}] \tag{15}$$

$$P_k = (I - K_k H_k)P_{k/k-1} \tag{16}$$

where $\hat{x}_{k/k-1}$ is the predicted state vector; $P_{k/k-1}$ is the variance matrix for $\hat{x}_{k/k-1}$; K_k is the gain matrix; $\hat{x}_k$ is the estimated state vector; and P_k is its variance matrix.

Due to the difficulty in determining an accurate value for both the system noise covariance and the measurement noise covariance, a novel adaptive fading Kalman filter is used to estimate the velocity accurately. (Yanrui Geng, etc, 2004)

ADAPTIVE KALMAN FILTER

The Kalman filtering estimation at epoch k can be considered as a 'weighted' adjustment between the new measurements (observation model) and the predicted state vector based on the dynamic model and all previous measurements. If too much 'weight' were put on the dynamic model component, the estimation would ignore the information received from the measurements and this would cause the divergence of the filtering process. Fagin (1964) initiated a method to limit the memory of the KF by using an exponential fading of past data via a forgetting factor s. The equations describing the fading Kalman filter are identical to those of the normal Kalman filter in equations (13) except the forgetting factor s in the covariance equation.

$$P_{k/k-1} = \phi_{k,k-1}(sP_{k-1/k-1})\phi_{k,k-1}^T + Q_{k-1} \qquad s > 1 \quad (17)$$

The main difference between different fading memory algorithms is on how to calculate the scale factors. One approach is to assign the scale factor as a constant, s = 1.0~1.4. When S =1.0, it becomes the conventional Kalman filter. Obviously there are some drawbacks with a constant factor. For example, as the filtering progresses, the precision of the filter will decrease because the effects of the old data will reduce with time. The best method is to use a variant scale factor that will be determined based on the dynamic and observation model accuracy.

For a linear dynamic system, when a filter is stable, we have

$$v_k \sim N(0, H_k P_{k/k-1} H_k^T + R_k) \quad (18)$$

where

$$v_k = z_k - H_k \hat{X}_{k/k-1} \quad (19)$$

When the filter is unstable, a scale factor S≥1 is introduced to the predicted covariance matrix

$$P_{k/k-1} = \phi_{k,k-1}(sP_{k-1/k-1})\phi_{k,k-1}^T + Q_{k-1} \qquad s > 1 \quad (20)$$

Then

$$\mathrm{var}(v_k) = H_k(\phi_{k/k-1} s P_{k-1} \phi_{k/k-1}^T + Q_{k-1})H_k^T + R_k \quad (21)$$

We can construct a statistic:

$$v_k^T [H_k(\phi_{k/k-1} s P_{k-1} \phi_{k/k-1}^T + Q_{k-1})H_k^T + R_k]^{-1} v_k \quad (22)$$

which has such an attribute as follows:

$$\gamma_k = v_k^T [H_k(\phi_{k/k-1} s P_{k-1} \phi_{k/k-1}^T + Q_{k-1})H_k^T + R_k]^{-1} v_k \sim \chi^2(m) \quad (23)$$

γ_k is then submitted to the chi-square distribution with m freedom. Then we have the following test criteria:

$$\zeta = \frac{\gamma_k}{\varepsilon} = \begin{cases} \geq 1 & \textit{abnormal} \quad \textit{filtering} \\ < 1 & \textit{normal} \quad \textit{filtering} \end{cases} \quad (24)$$

Where the scale factor for the statistical test is ζ and ε is the threshold value according to the chi-square distribution table at the given reliability.

We have two matrices as follows:

$$A_k = H_k \phi_{k/k-1} P_{k-1} \phi_{k/k-1}^T H_k^T \quad (25)$$

$$B_k = H_k Q_{k-1} H_k^T + R_k \quad (26)$$

Written

$$J_k = sA_k + B_k = H_k(\phi_{k/k-1} s P_{k-1} \phi_{k/k-1}^T + Q_{k-1})H_k^T + R_k \quad (27)$$

Where A_k and B_k are both symmetrical positive-defined matrices.
When the filter is in steady state processing, we have

$$v_k^T [sA_k + B_k]^{-1} v_k \leq \chi_\alpha^2 \quad (28)$$

Each element of v_k satisfies

$$\gamma_k(i) = \frac{[v_k(i)]^2}{J_k(ii)} \sim \chi(1) \quad (29)$$

Where $v_k(i)$ is the i th element of v_k, $J_k(ii)$ is the i th diagonal element of matrix J_k .We also have

$$J_k(ii) = sA_k(ii) + B_k(ii) \quad (30)$$

With the same test criteria, when a filter is stable, we can further obtain that

$$\frac{[v_k(i)]^2}{J_k(ii)} / \varepsilon(i) < 1 \quad (31)$$

With equation (30), we can have

$$s(i) > \frac{[v_k(i)]^2}{A_k(ii)\varepsilon(i)} - \frac{B_k(ii)}{A_k(ii)} \qquad (i = 1,2,\cdots,m) \quad (32)$$

Written

$$s = max\{1, s(1), s(2), \cdots, s(m)\} \tag{33}$$

Finally we can calculate the fading factor s adaptively.

INTEGRATED GPS/MEMS INS

A basic set of system parameters in the Kalman filter for the GPS/INS system normally only include the navigation parameters, the accelerometer and gyroscope error states such as follows:

$$\begin{aligned} X = [&\phi_E, \phi_N, \phi_U, \delta V_E, \delta V_N, \delta V_U, \delta L, \delta\lambda, \delta h, \\ &\varepsilon_{bx}, \varepsilon_{by}, \varepsilon_{bz}, \varepsilon_{rx}, \varepsilon_{ry}, \varepsilon_{rz}, \nabla_x, \nabla_y, \nabla_z]^T \end{aligned} \tag{34}$$

Where ϕ_E, ϕ_N, ϕ_U gives the attitude errors; $\delta v_E, \delta v_N, \delta v_U$ the velocity errors; $\delta L, \delta\lambda, \delta h$ the position errors; $\varepsilon_{bx}, \varepsilon_{by}, \varepsilon_{bz}$ the gyro constant drifts. $\varepsilon_{rx}, \varepsilon_{ry}, \varepsilon_{rz}$ the first-order Markov process and $\nabla_x, \nabla_y, \nabla_z$ the accelerometer biases.

The error state equation is then

$$\dot{X}(t) = F(t)X(t) + G(t)W(t)$$

and the measurement equation is:

$$Z = HX + V$$

Where

$$Z = [\delta\theta \quad \delta\psi \quad \delta L \quad \delta\lambda \quad \delta h]^T$$

$$H = \begin{bmatrix} -\cos\psi & \sin\psi & 0 & 0 & 0 & 0 & 0_{3\times9} \\ -\dfrac{\sin\theta\sin\psi}{\cos\theta} & -\dfrac{\sin\theta\cos\psi}{\cos\theta} & 1 & 0 & 0 & 0 & 0_{3\times9} \\ 0 & 0 & 0 & 1 & 0 & 0 & 0_{3\times9} \\ 0 & 0 & 0 & 0 & 1 & 0 & 0_{3\times9} \\ 0 & 0 & 0 & 0 & 0 & 1 & 0_{3\times9} \end{bmatrix}$$

SYSTEM DESIGN AND TEST

This section introduces the GPS and INS measurement systems for field test on a typical mid-sized agricultural tractor. The test tractor is a Challenger 865 tractor which is shown in figure 1 and the IMU is mounted in the device shown in figure 2 which also houses the GPS receivers and mounts in the radio slot onboard the tractor. Four GPS antenna, which were used to determine accurate roll, pitch and heading, were amounted on the roof of the tractor as a benchmark, the height and geometry of the antennas was kept as even as possible.

Figure 1: Test tractor for machine automation

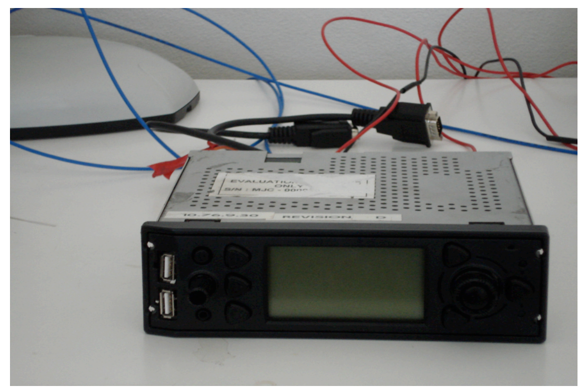


Figure 2: Radio package including IMU

During the tractor test, the data from the GPS receivers and IMU was collected via a USB stick with the USB port visible in figure 2. GPS receivers provided position and attitude data at approximately 10Hz and the IMU provided acceleration and angular data also approximately at 10Hz. However, the device does not guarantee accuracy in the sampling rates.

The position of the tractor was measured with a dual-frequency carrier-phase differential GPS receiver with a measurement error of 2-3 cm. The trajectory of the test tractor is shown in figure 3.

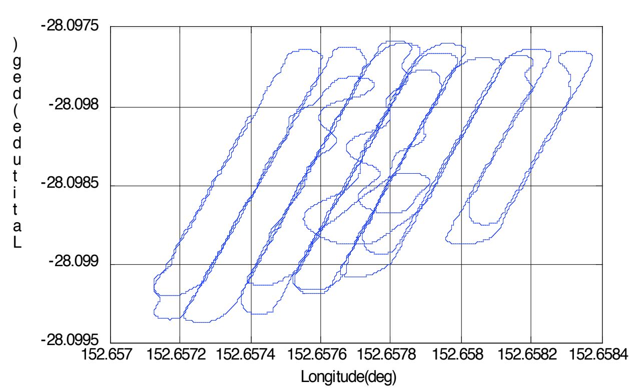


Figure 3: Trajectory of test tractor

As mentioned previously, the IMU used to measure the tractor's acceleration and angular rate was of a very low grade. Technical specifications of the gyros are provided in Table 1.

Characteristics	**Specification**
Gyro Sensitivity Error	±6%
Gyro Linearity	±0.3%
Gyro Bias Variation at Constant Temperature	±0.4 °/s
Gyro Bias Variation over Temperature	±2.5 %FSO
Gyro Bias Stability over one hour	±0.4 °/s

Table 1: Technical specifications of Gyros

While the software was implemented in C++ in order to give the capability for real time processing the first stage was post processed to test the correctness of our algorithms. The software scheme is shown in figure 4.

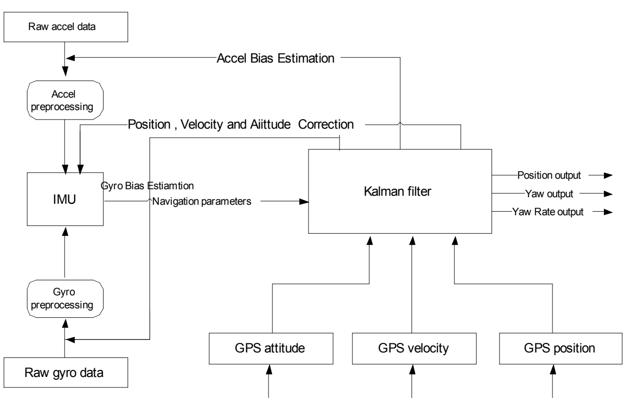
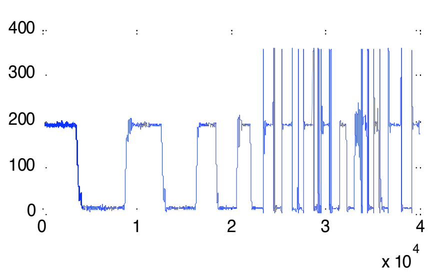


Figure 4: Scheme of GPS/MEMS integrated system for machine automation

The results of testing are shown in figure 5.



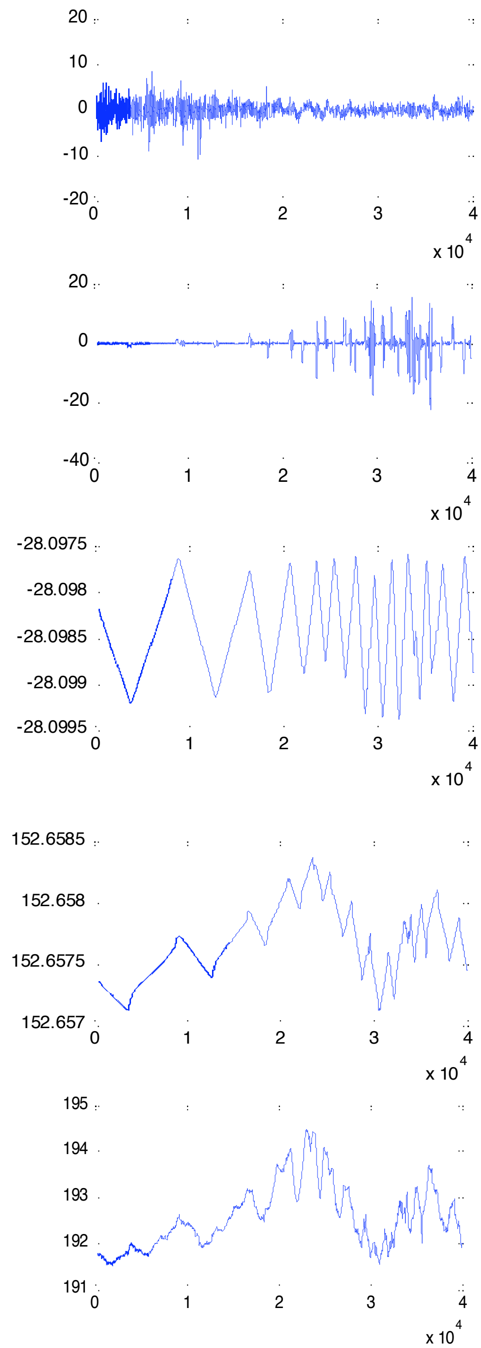


Figure 5: Test results

The expected outcomes was to determine what is an achievable accuracy by reviewing the yaw rate, the track of the x-axis of the body and heading errors over the length of the run. The cross track error, heading error and yaw rate for the first 500 seconds can be seen in figure 6.

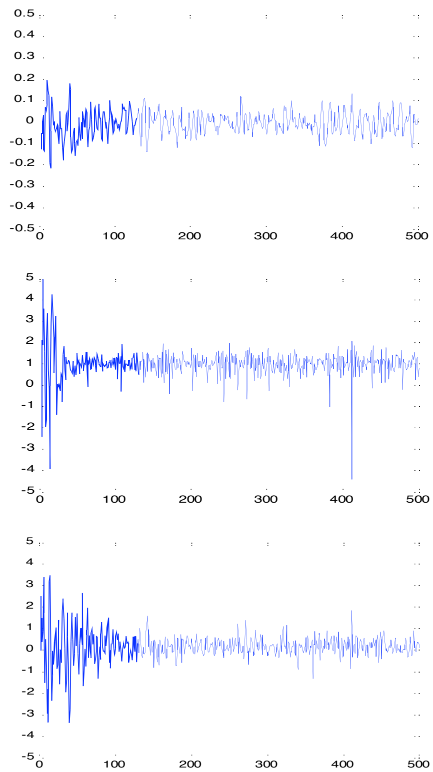


Figure 6: Results of Xtrack, Heading and Yaw rate

The statistics are shown in Table 2.

Stats	Mean	Stdev	Units
Xtrack	-0.078	0.054821	m
Heading	-0.143851	0.522923	deg
Yaw rate	0.192811	0.232130	deg/s

Table 2. Statistics results

From figure 6 and table 2, we can see that the absolute mean value of the xtrack error is less than 0.2m, the absolute value of heading error is less than 0.2deg and the value of the yaw rate error is less than 0.2 deg/s. All of the standard deviations are in the range of 0.05 m for the xtrack and 0.52 deg for the heading error. The results show that the integration of the low cost IMU and differential carrier phase GPS using this methodology provides a good position solution with an acceptable error range.

CONCLUSION AND FUTURE RESEARCH

In this paper, two Kalman filters were adopted as fusion integration methodology to develop a robust navigation system based on the sensor fusion integration with GPS and MEMS INS. An adaptive fading factor Kalman filter uses a GPS dynamic model to generate velocity and acceleration information which can be used to derive approximate pitch and heading values. Another Kalman filter is used to completely integrate position, velocity and attitude from both the IMU and GPS systems so that position and attitude can be estimated directly - due to their individual observabilities. The drift error of the inertial sensors was also well compensated as seen in the field tests. The proposed algorithm has been implemented for post-processing and has been tested in the field. The test results demonstrated that this robust MEMS/DGPS integrated system has the capability of providing continuous and reliable navigation for machine automation applications. The next stage will be to implement the algorithms in a real time implementation.

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