IMPROVING THE ATTITUDE ACCURACY OF A LOW COST MEMS/GPS INTEGRATED SYSTEM USING GPS HEADING SENSORS

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ABSTRACT

Integrated GPS/INS systems provide an enhanced navigation system that has superior performance in comparison with either system operating in stand-alone mode as it can overcome each of their limitations. The high cost and government regulations prevent the wider inclusion of high quality IMUs to augment GPS as a commercialized navigation system in many navigation applications. The progress in MEMS technology enables complete inertial units on a chip, composed of multiple integrated MEMS accelerometers and gyroscopes. In addition to their compact and portable size, the price of MEMS based is far less than those high quality IMUs as well, however, due to the lightweight and fabrication process, MEMS sensors have large bias instability and noise, which consequently affect the obtained accuracy from MEMS-based IMUs. Many research works have been conducted to improve the performance of low cost MEMS-based INS/GPS integrated systems. Accommodating heading measurements update using physical heading sensors (e.g. GPS heading sensors and magnetic compass) or pseudo heading sensor (e.g. derived from GPS velocities or positions) is an appropriate option to solve the problem. In this study, three approaches are implemented to obtain the headings of a moving vehicle using carrier phase DGPS measurement. Then a 21 states loosely-coupled extended Kalman filter is applied to integrate a low cost GPS/MEMS system along with the heading updates provided by the heading sensor to examine the attitude accuracy of proposed system.

1. INTRODUCTION

The GPS has become the primary source of providing navigation information for most of the present vehicular navigation applications. However, GPS technology needs line of sight signals to the GPS satellites to provide solutions with long-term stability, therefore, it is capable of providing navigation solutions continually in all situations only with uninterrupted signal reception, which is not the case for land vehicular navigation applications which suffer the impact from intermittent signal reception (i.e., forest area or urban canyon) or no signal reception (i.e., underground or tunnel). Therefore, GPS has to be integrated with other sensor to bridge periods of no signal reception to provide continuous navigation solutions. On the contrary, an INS is a self-contained positioning and attitude device that continuously measures three orthogonal linear accelerations and three angular rates to calculate the required position. The primary advantage of using an INS on outdoor land vehicles is that acceleration, angular rotation and attitude data are provided at high update rates. Thus the velocity and position of the vehicle can also be provided with abundant dynamic information and excellent short term performance. However, the error of accelerometers will be double integrated and cause position error that accumulate with time; the error of gyro will generate attitude errors (i.e. the horizontal platform misalignments), which causes gravity to project into the horizontal axes and disturb the acceleration measurement to the vehicles. Both errors grow as a function of time; therefore, an INS is only accurate for a limited time if without external aiding. Integrated systems provide an enhanced navigation system that has superior performance in comparison with either a stand-alone GPS or INS as it can overcome each of their limitations. However, those improvements come with the price.
The high cost and government regulations prevent the wider inclusion of those high quality IMUs to augment GPS as a commercialized navigation system in land vehicular applications until now with the introduction of MEMS-based inertial system. The progress in MEMS technology enables complete inertial units on a chip, composed of multiple integrated MEMS accelerometers and gyroscopes. In addition to their compact and portable size, the price of MEMS-based IMUs is far less than those high quality IMUs as well, however, the performance of current MEMS-based IMUs does not meet the requirement of tactical grade IMU due to their noisy measurements and poor stability. Therefore, such devices are not usable as sole navigation system. In a decentralized Kalman filter configuration, there are two filters working independently: an INS filter and a GPS filter. The INS filter is the main one in the configuration and uses the output of the INS mechanization to estimate the states (i.e., positions, velocities and attitudes) along the trajectory. The output of the GPS filter (i.e., positions and velocities) is then used to update the main filter. In other words, position and velocity update modes are the standard procedures to provide measurement updates for a decentralized Kalman filter. With the aiding information provided by GPS, those inertial error states can be estimated through the coupling relationships between them. For example, accurate estimation of the velocity error states (provided by GPS) will not only improve the accuracy of velocity computation directly but also the accuracy of the computed pitch and roll.

The heading error dA, is therefore, playing an important role in determining the long-term positioning accuracy [El-Sheimy, 2002]. Since it is modulated by the velocity components Vn or Ve, the effect of azimuth error becomes particularly significant at high velocities. However, there is no strong coupling between the velocity errors and the heading error, which is mainly affected by gyro bias. As a result, the positional errors of a low cost MEMS IMU will deteriorate rapidly during GPS signal outages.

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Therefore, it would be beneficial for a low cost MEMS/GPS integrated system to have direct heading measurement update using a pseudo GPS heading sensor utilizing only one GPS receiver or physical heading sensors such as GPS heading sensor that has two GPS receivers or magnetic compass. In fact, magnetic compasses have been applied as a standard option for the early version of dead reckoning navigation system [El-Sheimy, 2002]. However, the problems with magnetic compasses are the calibration of magnetic field and the derivation of proper model to compensate for the disturbance of the magnetic field [El-Sheimy, 2002]. Such problems become more complicated in typical land vehicular environments.

On the other hand, Chiang [2004] implemented a pseudo GPS heading algorithm that combines the GPS headings provided by a GPS receiver and INS headings provided by the mechanization to provide the stable headings of a moving vehicle. In addition, Shin [2005] implemented the extended Kalman filter that has 21 states (e.g,3 position sates, 3 velocity states, 3 attitude states, 3 accelerometer bias/scale factor states, and 3 gyro drift/scale factor states) with the ability to accommodate direct heading update provided by a pseudo GPS heading sensor derived by GPS positions using a GPS receiver. The results presented in the Shin [2005] do show the enhancement of the attitude accuracy when the direct heading measurement updates are applied.

Therefore, the objectives of this study are to: (1) develop a physical GPS heading sensor using two GPS receivers along with the proper algorithm to obtain GPS heading (2) compare the performance of the proposed GPS heading aided low cost INS/GPS integrated system with an unaided INS/GPS integrated system.

2. KALMAN FILTERING

To estimate an optimal navigation solution, the output of the INS mechanization needs to be integrated with the position and velocity solutions derived from GPS. The extended Kalman filter (EKF) is the most popular estimation technique for such integration. A simple form of the mechanization equations can be written as follows [Schwarz and Wei, 2001]:

$$\begin{bmatrix} \dot{r}^l \\ \dot{v}^l \\ \dot{R}_b^l \end{bmatrix} = \begin{bmatrix} D^{-1} v^l \\ R_b^l f^b - \left(2\Omega_{ie}^l + \Omega_{el}^l\right) v^l + g^l \\ R_b^l \left(\Omega_{ib}^b - \Omega_{il}^b\right) \end{bmatrix} \tag{1}$$

where

r^l	is the position vector (latitude, longitude, height),
v^l	is the velocity vector (e, n, u),
R_b^l	is the transformation matrix from the IMU body to local frame as a function of attitude components,
g^l	is the gravity vector in the local level frame,
Ω_{ib}^b & Ω_{il}^b	are the skew-symmetric matrices of the angular velocity vectors w_{ib}^b 、 w_{il}^b respectively,
D^{-1}	is a 3x3 matrix whose non zero elements are functions of the user's latitude and ellipsoidal height

For further discussions concerning the solutions and numerical implementations of the above differential equation, see El-Sheimy [2002]. An INS mechanization algorithm by itself is seldom in good performance due to the inertial sensor biases and the fixed-step integration errors, and those errors will cause the PVA solution to diverge quickly. The navigation software must have some approach to account for these error sources to correct the estimated PVA [El-Sheimy et al., 2004].

The dynamic error model used in the KF for the navigation parameters (position, velocity and attitude) can be determined through the linearization of the INS mechanization equations and by neglecting insignificant terms in the resultant linear model. A simplified form is then obtained as[Bar-Itzhack and Berman, 1988]:

$$\begin{aligned} \delta\dot{r}^l &= D^{-1}\delta v^l \\ \delta\dot{v}^l &= -(2\Omega_{ie}^l + \Omega_{el}^l)\times\delta v^l - \delta R_b^l f^b + R_b^l \delta f^b + \delta g^l \\ \delta\dot{A}^l &= E\delta v^l + R_b^l \delta\omega^b \\ \delta f^b &= b_a + diag(f^b)s_a \\ \delta\omega^b &= b_g + diag(\omega^b)s_g \end{aligned} \tag{2}$$

where

δr^l	is the position error state vector in the local level frame
δv^l	is the velocity error state vector in the local level frame,
δA^l	is the attitude error state vector in the local level frame,
δg^l	is the error in the computed gravity vector in the local level frame,
$\delta f^b \& \delta\omega^b$	are accelerometer bias and gyro drift vectors in the body frame respectively, and
$S_a \& S_g$	are scale factor of accelerometers and gyros respectively, and
E	is a 3x3 matrix whose non-zero elements are a function of the vehicle's latitude and the Earth's radii of curvatures.

In the EKF, the INS errors are updated by the difference between GPS and INS solutions. The EKF applied in this study has 21 state vectors [Shin and El-Sheimy, 2004] :

$$[\delta p_{1\times3} \quad \delta v_{1\times3} \quad \delta A_{1\times3} \quad b_{a,1\times3} \quad b_{g,1\times3} \quad s_{a,1\times3} \quad s_{g,1\times3}]^T$$

The dynamic error model used in the KF for the navigation parameters (position, velocity and attitude) can be determined through the linearization of the INS mechanization equations and by neglecting insignificant terms in the resultant linear model. The equations of the KF are divided into two groups of equations; prediction and update. The time prediction equations are responsible for the forward time transition of the current epoch (k-1) states to the next epoch (k) states. The prediction equations are

$$\hat{x}_k\left(-\right) = \Phi_k \hat{x}_{k-1}\left(+\right) \tag{3}$$

$$P_k(-) = \Phi_k P_{k-1}(+)\Phi_k^T + Q_{k-1} \tag{4}$$

P is the estimated variance-covariance matrix of inertial states,
Q is the system noise matrix,
(-) denotes the estimated value after prediction,
(+) denotes the estimated value after updating,

The measurement update equations utilize new measurements into the a priori state estimate to obtain an optimized an optimized a posteriori state estimate. The measurement update equations are given as:

$$K_k = P_k(-)H_k^T\left[H_k P_k(-)H_k^T + R_k\right]^{-1} \tag{5}$$

$$\hat{x}_k(+) = \hat{x}_k(-) + K_k\left(Z_k - H_k\hat{x}_k(-)\right) \tag{6}$$

$$P_k(+) = P_k(-) - K_k H_k^T P_k(-) \tag{7}$$

where
K is the Kalman gain matrix,
Z is the vector of updating measurements of position and velocity,
R is the measurements variance-covariance matrix

The Kalman update engine is triggered at every GPS measurement using the difference between GPS and INS solutions as input. Hence, the KF generates an updated estimate for reducing the INS errors using measurement update equations. Whenever a GPS measurement is unavailable, the KF works in time prediction mode to estimate the error state vector. In this case, the KF equations need the statistical properties of the system to be stationary and well defined which cannot be guaranteed, specially, with a MEMS-based IMU implemented in kinematic or dynamic environments [El-Sheimy, 2002].

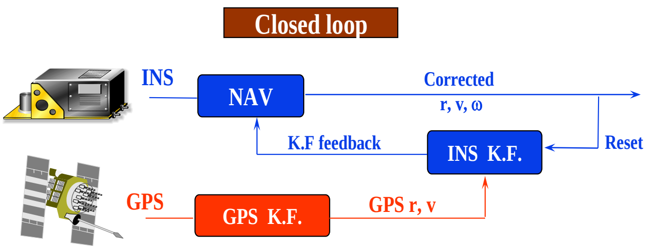


Figure 1: A standard INS/GPS loosely coupled integration scheme

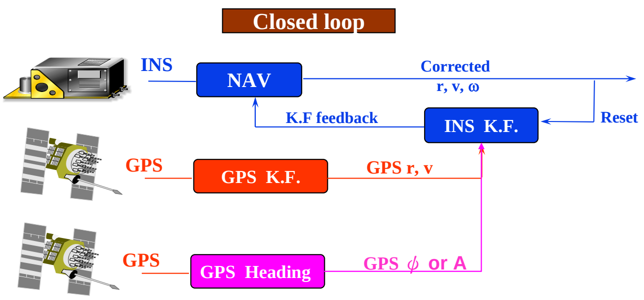


Figure 2: Modified INS/GPS integration scheme with GPS heading update

For a standard loosely coupled INS/GPS integrated architecture, GPS position and velocity information are applied to provide measurements update, as shown in the Figure(1). In this study, the GPS heading information can be applied as additional measurements update thus the modified loosely coupled INS/GPS integrated architecture implemented in this study is given in the Figure(2).

3. DEVELPEMENT OF GPS HEADING SENSOR

In this study, several methods are provided to compute redundant heading information utilizing GPS antennas. Carrier phase measurements are processed in kinematic DGPS mode to obtain high accuracy positions and velocities solutions. Therefore, these solutions could be used to compute the heading or azimuth of a vehicle except for GPS outages. Meanwhile, those computed headings can be used to provide measurement updates to the Kalman filter applied to improve the performance of the low cost INS/GPS integrated system used in this study.

The first approach used to obtain heading information of a vehicle is based on the positional differences between two GPS antennas. As shown in the Figure (3), the positions of antenna ***A*** and ***B*** are obtained through the used of kinematic carrier phase DGPS processing with superior accuracy. The position difference can then be obtained and headings are derived by following equation:

$$\theta_{DGPS,P}(t) = \tan^{-1}\left(\frac{E_{A,DGPS}(t) - E_{B,DGPS}(t)}{N_{A,DGPS}(t) - N_{B,DGPS}(t)}\right) + C = \tan^{-1}\left(\frac{\Delta E(t)}{\Delta N(t)}\right) + C \tag{8}$$

where

N_i, E_i are the coordinates of GPS antennas under local level frame
C is a constant that depends on the quadrant in which point ***B*** lies

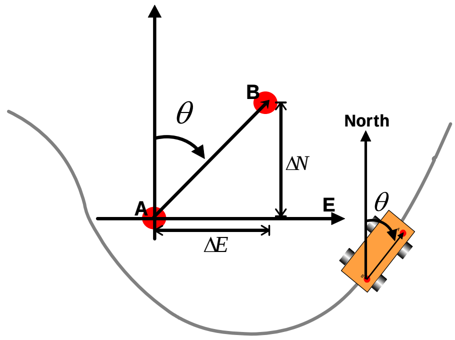
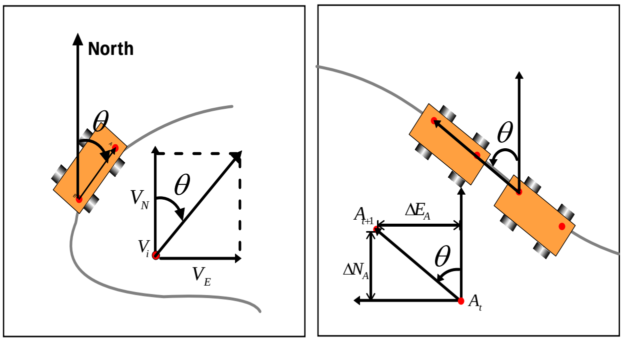


Figure 3: Obtaining GPS heading from the positional differences of two antennas

A calculated example is shown in the Figure 5(a). As mentioned previously, the combination of two GPS antennas can be regarded as the physical GPS heading sensor.

The second approach used to calculate GPS heading is through the use of the velocities information provided by a GPS receiver. A simple illustration is shown in the Figure 4(a). The instantaneous velocities of a GPS antenna can be regards as vectors to describe the directions of a moving vehicle. The equation is given as follow [Chiang, 2004]:

$$\theta(t)_{DGPS,V} = \tan^{-1}\left(\frac{V_{E,DGPS}(t)}{V_{N,DGPS}(t)}\right) + C \tag{9}$$



(a) (b)

Figure 4: Computing heading form the velocities and position displacement

Figure 5(b) shows the headings derived through the velocities of a GPS receiver which are obtained through the use of kinematic carrier phase DGPS processing with superior accuracy. However, the headings derived from DGPS velocities become unstable when the denominator approaches zero (e.g. during ZUPT or for low (ϕ_1, ϕ_2, ϕ_3), as shown in the Figure 5(b).

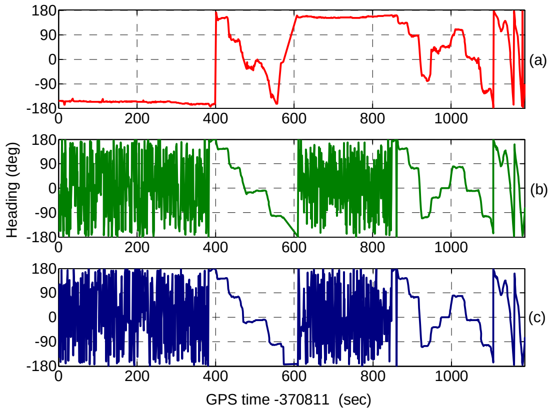


Figure 5: Three approaches to derive headings: (a) through the positional differences between two GPS antennas; (b) derived through the velocities of a GPS receiver; (c) using the displacement of a GPS antenna between two consecutive epochs

In other words, it suffers a numerical problem during low dynamics due to the nature of the inverse tangent algorithm. Consequently, the second approach does not meet the requirement to provide stable and accurate heading outputs in all conditions. Chiang [2004] developed a GPS heading constrained algorithm to overcome this issue successfully with the constrain condition introduced by INS headings and provide stable GPS velocity derived heading outputs with reasonable accuracy. However, the implementation of such criteria is not considered in this study.

The third approach used to derive headings is using the displacement of a GPS antenna between two consecutive epochs, as illustrated in the Figure 4(b). The equation of this approach is given as follows:

$$\theta_{DGPS,\Delta P}(t) = \tan^{-1}\left(\frac{E_{A,DGPS}(t+1) - E_{A,DGPS}(t)}{N_{A,DGPS}(t+1) - N_{A,DGPS}(t)}\right) + C \tag{10}$$

As indicated in the Figure 5(c), the headings derived but the third approach becomes unstable when the denominator approaches zero (e.g. during ZUPT or small $\langle w_{j,l}, W_{i,j}\rangle$). In other words, they suffer a numerical problem during low dynamics (small $b_1, b_2 = 1$) or ZUPT due to the nature of the inverse tangent algorithm. Similarly, the third approach does not meet the requirement to provide stable and accurate heading outputs in all conditions.

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In addition, the standard deviation of the headings should be estimated for providing measurement updates to Kalman filter. The standard deviation of antenna's positions can be provided by GPS processing software. Then the error propagation equation is used to calculate the standard deviation of GPS headings utilizing the following equations:

$$J = \begin{bmatrix} \frac{\partial \theta_{DGPS,P}}{\partial N_A} & \frac{\partial \theta_{DGPS,P}}{\partial E_A} & \frac{\partial \theta_{DGPS,P}}{\partial N_B} & \frac{\partial \theta_{DGPS,P}}{\partial E_B} \end{bmatrix} \tag{11}$$

$$\Sigma = diag\begin{bmatrix} \sigma_{N_A} & \sigma_{E_A} & \sigma_{N_B} & \sigma_{E_B} \end{bmatrix} \tag{12}$$

$$\sigma_h^2 = J \Sigma J^T \tag{13}$$

4. RESULTS AND DISCUSSIONS

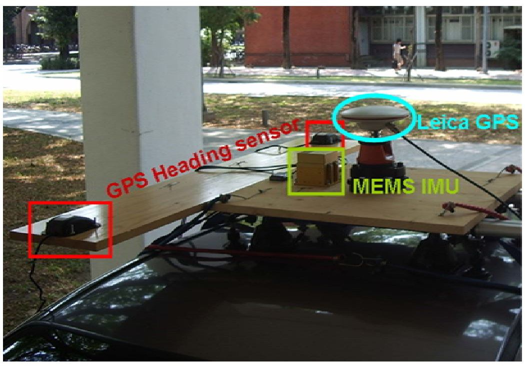

Figure 6: The experimental platform

To evaluate the performance of the proposed scheme, a field test was conducted in February 2007 by the Intelligent Multi-Sensor Geomatics System Lab of the National Cheng Kung University. The test was conducted in land vehicular environments using a low cost INS/GPS integrated system consisting of a MEMS IMU (CrossBow NAV420) and two Leica GPS System500 receivers (e.g., Rover and master station). Figure (6) shows the set up of those systems. In addition**,** two Garmin GPS35 series receivers to setup a GPS heading sensor and the baseline between them is 1.2 meters

The GPS measurements were processed using the GrafNav™ 7.0 software (Waypoint Consulting Inc.) in DGPS mode. The GPS navigation solutions along with the GPS headings were then fed into a decentralized Kalman filter of the Aided Inertial Navigation System (AINS™) Toolbox software developed by the MMSS research group at the University of Calgary, to obtain INS/DGPS integrated solutions for further analysis. The reference trajectories were generated by the INS/DGPS integrated system. The reference solutions were generated using AINS 21 states EKF and backward smoothing. The field test reference trajectory is shown in figure (7). The length of experiment is about 1000 seconds and the experimental results are shown in the Figure (8) and Table 1, respectively.

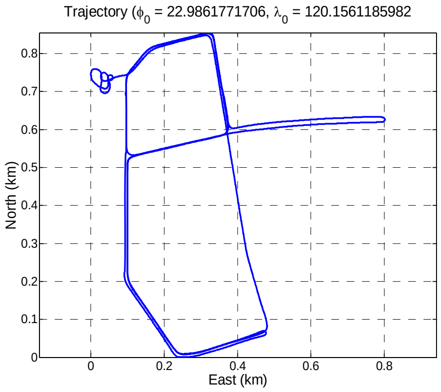

Figure 7: Field test trajectory

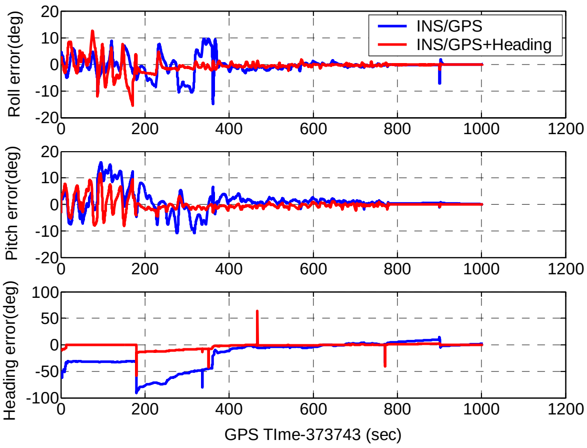

Figure 8: Attitude errors after utilizing heading sensor

As indicated in Figure (8), the GPS heading sensor have brought benefits to improve positioning accuracy on east, north and up directions. The accuracy improvement with the use proposed GPS heading sensor is illustrated in the Table 1. Based on the field test data applied in this study, the improvements of accuracy ranges from 48.1% to 90.4% in three attitudes.

As mentioned in the previous sections, a standard loosely coupled INS/GPS integration scheme combines INS measurements and GPS solutions. The error states of INS can be then estimated and corrected by the Kalman filter. The GPS solutions including positions and velocities provide long-term accurate measurement updates to the INS Kalman filter. This update procedure then improves the accuracy of estimated positions, velocities, roll and pitch based on the explicit coupling relationship between them. However, the coupling relationship between the velocity errors and the heading error is weak; in fact, it is mainly affected by the gyro bias. Hence, direct heading updates provided by a physical GPS heading sensor along with a modified loosely coupled INS/GPS integration scheme developed in this study are effective tools to enhance the performance of a low cost MEMS/GPS integrated system.

	RMS value (deg)		**Improvement (%)**
	INS/GPS	INS/GPS + heading	
Roll	3.174	1.648	48.1
Pitch	3.620	1.318	63.6
Heading	30.901	2.950	90.4

Table 1: The enhancement in attitude accuracy

5. CONCLUSIONS

This article implemented a physical GPS heading sensor to enhance the performance of a low cost MEMS/GPS integrated system. A field test data collected in land vehicular environments was utilized to verify the effectiveness and enhancement of proposed modified loosely coupled INS/GPS integration scheme in terms of the attitude accuracy.

The preliminary results presented in this article illustrate the improvement of attitude accuracy can reach 48.1% in roll, 63.6% in pitch and 90.4% in heading angle, respectively. Consequently, direct heading updates provided by a physical GPS heading sensor along with a modified loosely coupled INS/GPS integration scheme developed in this study are effective tools to enhance the performance of a low cost MEMS/GPS integrated system.

The future works of this study will collect more field test data sets to validate the performance of proposed scheme and try to improve the accuracy of heading sensor using GPS receivers that are suitable for collecting data in kinematic mode. In addition, the ultimate goal of this research is to develop a low cost positioning and orientation platform for general mobile mapping applications based on the modified scheme proposed in this study.

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