ACCURACY ENHANCEMENT OF A LOW COST INS/GPS INTEGRATION SYSTEM FOR LAND APPLICATIONS

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ABSTRACT: *In this paper, the design of the low cost INS/GPS integration system is addressed with good accuracy. The Strapdown INS (SINS) and Cascade Kalman filter have been tested to ensure that the system can be operated flexibly between feed forward and feedback modes due to various GPS conditions. The vehicle motion constraints are also utilized to reduce the INS error degradation during the periods of GPS unavailability. The experiment results shown that the INS/GPS system can be applied to land applications in challenging GPS environments.*

1.INTRODUCTION

The demand for positioning applications in recent years has made various researches towards the development of navigation systems. The Inertial navigation System (INS) has been widely used thanks to the strong growth of Micro Electronic Mechanical System (MEMS) technology. The Global Positioning System (GPS) also experience the great demand. However, both systems have limitations in many applications. The INS can provide us the position, velocity and attitude of the vehicle but it is suffering from errors caused by inertial sensors [1, 2]. By integrating the sensor measurements, these errors will be accumulated, leading to significant drift in the position and velocity outputs. Navigation data from GPS can be used for the INS error compensation. However, the quality of GPS degrades in harsh environments such as urban and forest areas. Further more, the GPS receiver can not provide attitude data. To overcome these limitations, one the most efficient method is the combination of INS and GPS using Kalman filter. We can estimate the errors of both the INS and GPS in order to give the better information.

The contribution of this paper is development of a special scheme for INS/GPS integration that can be used in various GPS conditions. Since there is a lack of research devoted to the integration of an IMU with GPS in different surroundings, the intent of this research is to develop the flexible integration system based on three Kalman filters. The INS/GPS system can switch between feedforward and feedback schemes depends on GPS environments. In this system, the input is the difference between the noisy INS output and the noisy GPS output; the output of KF is finally introduced into the unaided INS system. INS errors are compensated by a feedforward and a feedback loop.

Initially the simulation of the whole navigation would be done on a computer, where given the initial state of the aircraft and regular updates from the sensors and the GPS, the program would return the estimated information of the vehicle. Eventually this simulated model would be implemented on real-time hardware.

2. INS/GPS INTEGRATION

Unlike the GPS receiver, the INS can provide navigation information at a relatively high rate. The data rate of GPS measurements in this study is 1 Hz, while the INS data rate is 64 Hz. Another important advantage of an INS is the ability to provide not only position and velocity data but also attitude information. However, the stand-alone INS degrades due to gyro drifts and accelerometer biases, while GPS errors are smaller and is time independent. The combination of GPS and INS can tremendously improves accuracies compared to the GPS and INS when operating alone as individual navigation systems. The heart of integrated system is Kalman Filter (KF) [3, 4]. The Kalman filter is a set of mathematical equations that provides estimations of past, present, and future states. Moreover, it can do that even when the modeled system is unknown.

In this study, as for the INS system we have used the IMU BP3010 which consists of three ADXRS300 gyros and three heat compensated ADXL210E accelerometers [5] (see Fig. 1). The measurements are realized by IMU's micro-controllers and transmitted out via RS232 interface. The unit transmits output data as angular incremental and velocity incremental data in serial frames of 16 bytes at the frequency of 64 Hz.

Figure 1. The IMU BP3010 – an Inertial Measurement Unit (IMU)

Standalone GPS provides the vehicle position and velocity data. Comparing this information with the data measured by the INS, we can obtain the position and velocity errors. The INS error estimation scheme is shown in Fig. 2. In this case, the position and velocity estimation is performed independently. The main reason for such separation lies in the relatively small dimensions of the filter state vectors. It can help the filter convergence time to decrease. In this paper, the INS error equations are used as a system model, and measurements that are fed to the filter are the differences between the INS and GPS positions and velocities [6]. When GPS data is not available, the Kalman filter works in prediction mode and the INS/GPS system switch to feedforward scheme.

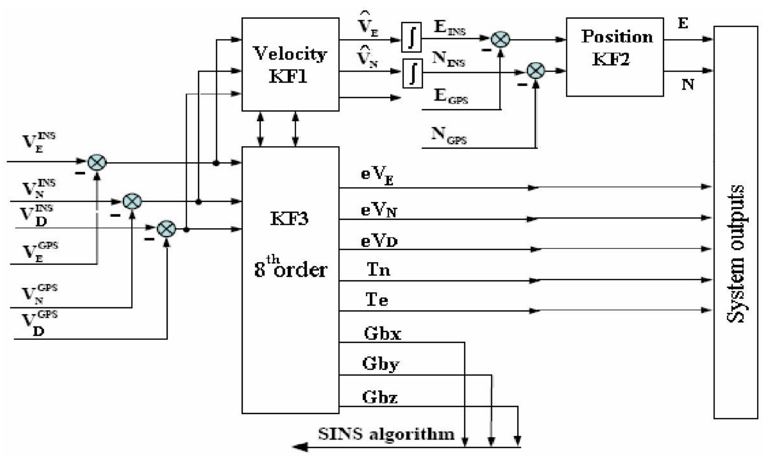

Fig 2. The integration configuration

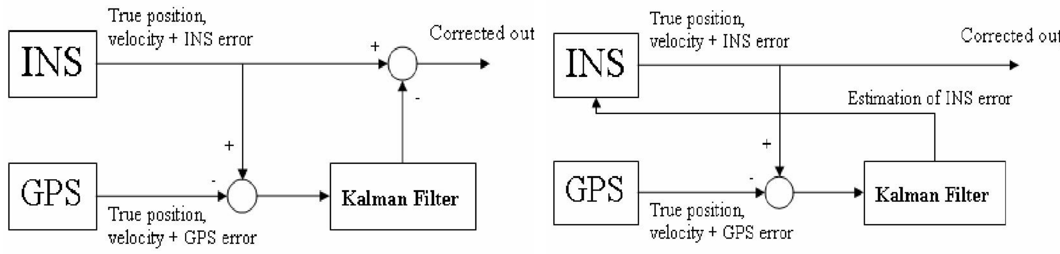

Fig 3. Feedforward (a) and feedback (b) configurations

In discrete form, any linear system can be described as:

$$x_k = A_{k,k-1}x_{k-1} + G_{k,k-1}w_{k-1} \tag{1}$$

Where $A_{k,k-1}$ is a (n x n) transition matrix, $G_{k,k-1}$ is an (n x r) input matrix, and w_{k-1} is (r x 1) input noise. We can derived these matrix based on the INS error equations.

And the measurement model:

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

Where z_k is a (m x 1) measurement vector, H_k is a (m x n) design matrix, and v_k is (m x 1) measurement noise.

In the first block (KF1), a conventional Kalman filter with a reduced system model is utilized for the INS velocity error estimation. In the KF2, the INS position increments in the East and North directions, E_{INS} and N_{INS}, are determined via integration of the East and North velocities, which are already corrected for major errors. The differences between the INS and GPS position increments are considered as the INS position error in the East and North directions. These measurements are fed into the coordinate KF. Estimated INS position and velocity errors are compensated in the system output. In the KF3, the estimation of INS errors is performed in order to improve estimation accuracy. There are eight such states (x_k) which consist of attitude errors (T_n, T_e), velocity errors (e_{VN}, e_{VE}, e_{VD}), and drift terms (Gb_x, Gb_y, Gb_z). The transition matrix is:

$$A_{k,k-1} = I + \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & h_N C_{11} & h_N C_{12} & h_N C_{13} \\ 0 & 0 & 0 & 0 & 0 & h_N C_{21} & h_N C_{22} & h_N C_{23} \\ 0 & -Dvd & 0 & 0 & 0 & 0 & 0 & 0 \\ Dvd & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & -h_N\beta & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & -h_N\beta & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & -h_N\beta \end{bmatrix} \tag{3}$$

Where *Dvd* is the velocity increment in Down direction of the navigation frame (north, east, down), β is one of parameters of the correlation function, and hN here is 0.015625s.

The INS errors are used to correct the quaternion and the transformation matrix C_b^N. Estimated gyro drifts are also taken into account in the SINS navigation scheme. The Kalman filter estimates of the attitude errors: Te and Tn, represent the fact that the platform frame has a small angular deviation from the navigation frame due to sensor errors. This means that in the SINS algorithm, the transformation matrix between the body frame and platform frame C_b^p is calculated, instead of transformation matrix between the body frame and the navigation frame C_b^N. In order to compensate the attitude errors, the C_b^p is corrected as following:

$$C_b^N = C_p^N C_b^p \tag{4}$$

Where C_p^N is the transformation matrix between the platform and navigation frame, which has the form:

$$C_p^N = \begin{bmatrix} 1 & 0 & Tn \\ 0 & 1 & -Te \\ -Tn & Te & 1 \end{bmatrix}$$

(5)

The gyro drifts in the projections on the body frame can be compensated not only in the raw output directly but also the quaternion of the motion.

For a land vehicle, the heading angle can be calculated by utilizing the GPS velocity components. Note that the GPS heading angle is calculated only when a vehicle has sufficient speed. Heading angle from GPS velocities can be computed as follows:

$$H^{GPS} = tg^{-1}\frac{V_E^{GPS}}{V_N^{GPS}}$$

(6)

The filters switch to prediction mode when the GPS measurements are not available or not reliable. In this case, the Kalman gain is set to zero and the Kalman equations are transformed to prediction mode. The structure of the KF is also switched from feedback to feedforward configuration. The reliability criterion is defined by the number of satellites used in the solution and the difference between GPS velocity and predicted INS velocity.

In the case of the GPS signal blockage, positioning is provided by the INS and virtual measurements until GPS signals are reacquired. During such periods, navigation errors increase rapidly with time due to the time-dependent INS error behavior. The reason is that the low cost MEMS IMUs consists of low quality sensors which provide large errors and noises. In these cases, we sometime utilized land vehicle motion attributes to prevent INS error accumulation. The equation derived from behavior of a land vehicle will compensate the GPS's measurement. In this paper, we mention to velocity and height constraints. They can provide the virtual measurements to aid the IMU.

For a long trip, the vehicle sometime needs to stop for error updating. In this case, the linear velocity is zero. Thus, the non-zero output of the INS velocity indicates is the INS velocity error. A complete stop of a land vehicle is determined from the filtered accelerometer output and GPS velocities. Raw accelerometer data is averaged by sliding window method in several seconds. The stop criterion threshold equals to 0.05 m/s. When a vehicle stops, the velocities in the INS East and North are fed into the filters. It is different from the in-motion scenario when the differences between the INS and GPS velocities are used as measurements. To accurately estimate the component of the INS error, these static measurements should have larger Kalman gain than in-motion measurements. It can be done by choosing the measurement covariance for static mode. This choice is different from the measurement covariance for kinematics mode.

There are two kinds of noise in the INS: deterministic and stochastic errors. The deterministic noises are usually eliminated by the carefully calibration process but the stochastic noises are always difficult to treat. We have determined successfully the characteristics of the MEMS sensors' noise by analyzing the Allan variance of the experiment data. After characterizing the IMU errors, the information of these noises is applied to the KF based MEMS INS/GPS integration module in order to estimate the velocities, positions and attitude of the object [7, 8].

3. EXPERIMENTAL RESULTS

For the experiment (see Fig. 4), the system were installed in a mini vehicle [9]. The IMU is placed inside a vehicle and the GPS is placed outside the vehicle. The INS computations and its integration with the HI-204III GPS are carried out on the ADVANTECH PC box.

Fig 4. Hardware for the navigation system (a) and the trajectory of experimental vehicle (b)

To determine more precisely the quality of the navigation system, the system is examined in standing still case. Fig. 5 illustrates the comparison of the attitude between the systems with and without processing. It is clear to see that the system with processing could provide the better results. In the latter period, the attitude given by the proposed system is also seemed to be more precise.

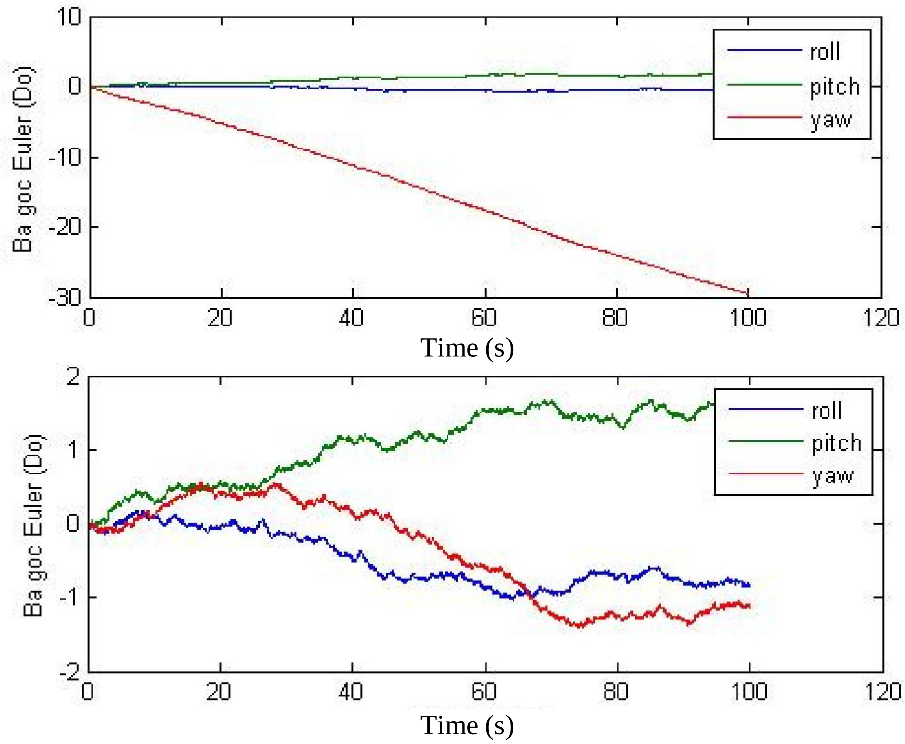

Fig 5. Attitude of the systems with (a) and without (b) processing

The graphs for velocity computed and corrected by the Kalman filter are given in Fig. 6. We can see that the un-aided INS deviates from the ideal velocity by a large quantity. If the integration system is supported by KF, the output Vn is around 0 m/s. It is mean that our KF could give the exact correction.

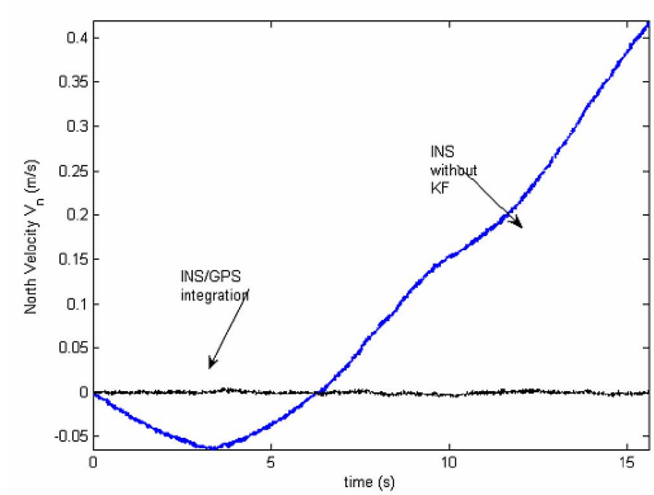

Fig 6. The north velocity of the stand still IMU in two cases: with and without KF

For the outdoor experiment, the vehicle was driven for 80 seconds to complete a closed trajectory. Initially the vehicle was at rest, with the engine on, for about 30 seconds. This stationary data was used for calibration and alignment purposes. The update from the INS was taken every 0.015625s, the GPS update was taken every 1s and the KF was run every 0.5s to achieve better accuracy. We can see that the IMU provides navigation information with high frequency in between GPS updating. At each 0.015625s, the vehicle velocity, position, attitude and quaternion are updated.

Fig 7.a and 7.b present the velocities of KF compared with the values measured with the GPS unit. It can be seen outputs of KF (solid curve) follows the GPS velocities (dot curve) with small error for 80s. There are limitations on choosing the path over which the vehicle ran. The motion of the vehicle should not have sufficiently fast changes during the test.

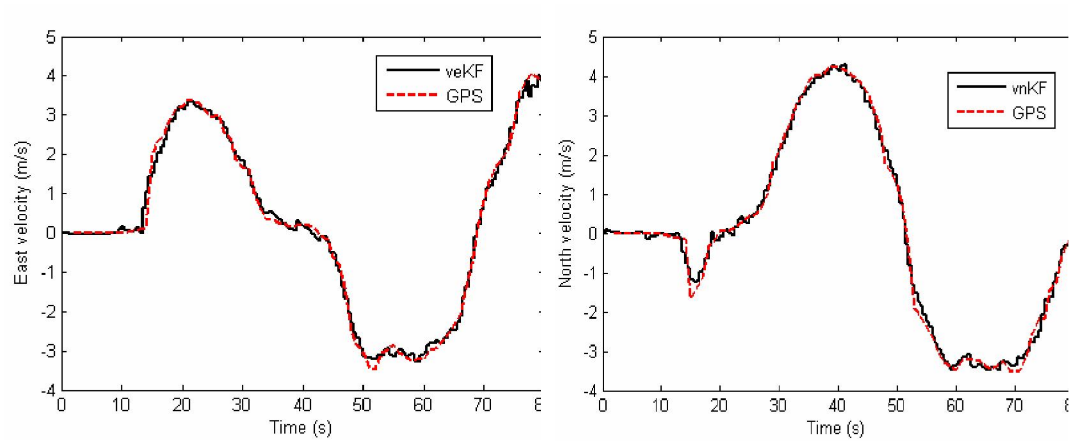

Fig 7. Comparison of East (a) and North (b) velocities

Fig. 8 shows the roll and pitch of the navigation system computed and corrected by the KF. We can not expect the KF to correct the attitude given by the INS perfectly because attitude is not a part of the measurement vector. These results seem to be quite reasonable for a system was on to a land vehicle.

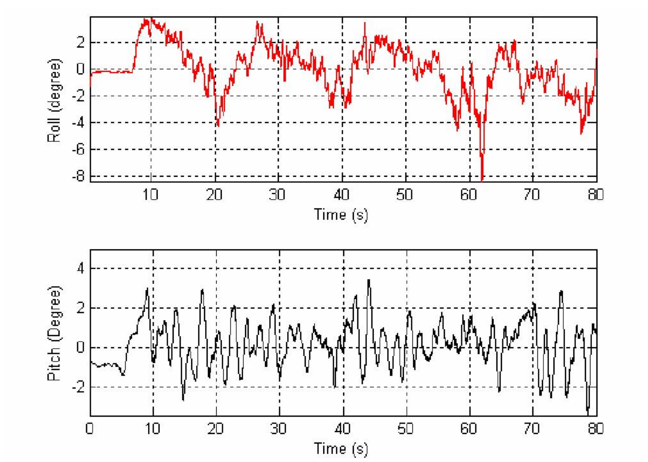

Fig 8. Roll and pitch angles of the integrated navigation system

The 2-D trajectory is presented in Fig. 9. This figure shows the position of the vehicle along North and East direction on the Earth instead of the latitude and the longitude. The reason is that we can prevent numerical instabilities in calculating the Kalman gain. It can be seen the INS/GPS trajectory supported by KF follows the GPS one (dot curve) with small error. The experimental results in this section have verified the model for low cost INS developed in this paper. These results have shown that for a low cost INS with aiding GPS information, position, velocity, and attitude accuracy can be achieved using the INS algorithms in this approach.

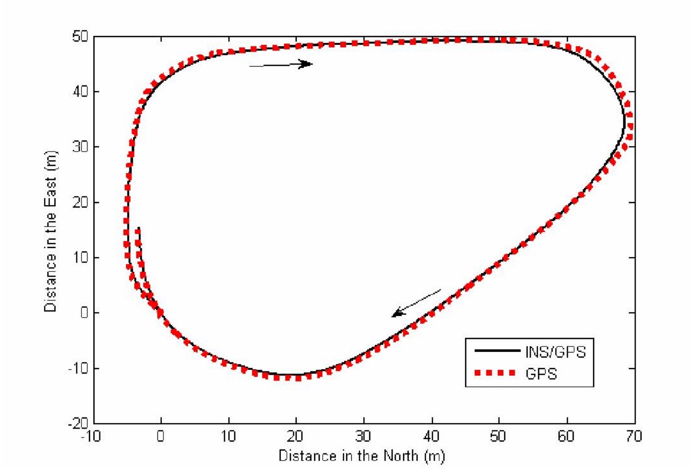

Fig 9. Comparison of trajectory

The advantages of this proposed system can be verified iteratively by not only virtual data but also experimental data. Table 1 summarized the navigation errors in three typical outdoor trajectories in order to confirm the reliability of the system.

Table 1. Navigation errors in typical trajectories

	Small round-trip trajectory (~200 m)	Medium round-trip trajectory (~ 2 km)	Straight trajectory (~ 10 km)
Attitude errors	2-3^o	2-3^o	2-3^o
Position errors (rms)	3.4 m	4.1 m	3.2 m

4.CONCLUSIONS

This paper has proposed three Kalman filters to enhance the quality and response time of a combined GPS and INS system. Vehicle kinematics is utilized in order to aid the IMU. The Zero Velocity Updates (ZUPTS) are also processes to reset the velocity of the INS. Obviously, by its simplicity, this model can be embedded easily into a real time system. The experimental results have shown that the initial calibration and alignment is accurate enough to allow navigation with IMU sensors for various GPS conditions.

NÂNG CAO CHẤT LƯỢNG CỦA HỆ THỐNG DẪN ĐƯỜNG TÍCH HỢP INS/GPS CHO CÁC ỨNG DỤNG TRÊN MẶT ĐẤT

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TÓM TẮT: *Bài báo này đề xuất tới một cấu trúc hệ thống tích hợp INS/GPS giá rẻ và độ chính xác cao. Trong hệ thống này, thuật toán dẫn đường quán tính kiểu gắn chặt (SINS) và cấu trúc lọc Kalman chồng tầng có khả năng chuyển đổi linh hoạt giữa các cấu hình vòng kín và vòng hở tuỳ thuộc vào việc tín hiệu GPS có bị mất hay không. Các ràng buộc về động học của phương tiện chuyển động trên mặt đất cũng đã được tận dụng để làm giảm bớt các sai số tích luỹ của hệ thống khi tín hiệu GPS bị gián đoạn. Các kết quả trên thực nghiệm cho thấy hệ thống tích hợp INS/GPS có thể được đưa vào áp dụng trên thực tiễn với kết quả tốt.*

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