Land-vehicle mems INS/GPS positioning during GPS signal blockage periods

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Abstract. The demand of vehicle navigation and guidance has been urgent for many years. The idea of integrating multisensor navigation systems was implemented. The most efficient multisensor configuration is the system integrating an inertial navigation system (INS) consisting of MEMS based micro sensors and a global positioning system (GPS). In such system, the GPS is used for providing position and velocity whereas the INS for providing orientation. The estimation of the system errors is performed by a Kalman filter (KF). A serious problem occurs in the INS/GPS system application that is caused by the accidental GPS signal blockages. In this paper, the main objective is to improve the accuracy of the obtained navigation parameters during periods of GPS signal outages using different methods. The overall performance of the system have been analyzed by experimentation data; and results show that these methods indeed improve the quality of the navigation and guidance systems.

1. Introduction

In the last decade, the demand for accurate land-vehicle navigation in several applications has grown rapidly [1]. With the strong growth of Micro-Electro-Mechanical-System (MEMS) technology, there appears a new trend in navigation and guidance domain: it consists of the integration of INS and GPS altogether [2]. Integrating these two navigation methods can improve the performance of the system and reduce concurrently the disadvantages of both INS and GPS. The Kalman filter (KF) is utilized to estimate the system errors in order to improve the accuracy of the overall system [3]. In the case of the GPS signal blockage, positioning is provided by the INS until GPS signals are reacquired. During such periods, navigation errors increase rapidly with time due to the time-dependent INS error behavior. For accurate positioning in these cases, some solutions should be used to improve navigation information. In this paper, a flexible configuration of KF will be used for the INS/GPS integration. The land-vehicle kinematics data set is also used with induced GPS outages. By using these methods, the results showed remarkable improvement of position errors.

2. Integration of INS and GPS using Linearized Kalman Filter

The INS system has two main advantages when comparing with other navigation system: self-contained ability and high accuracy for short term navigation. The serious problem of the INS caused

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by accumulation of gyroscope and accelerometer errors. Therefore, in long-term navigation applications, the INS works with the aid of other systems such as radio navigation systems (Loran, Tacan), satellite navigation systems (GPS, GLONASS). The important advantage of these systems is stable performance. Consequently, there is a great need for integration of INS with one of these systems. The integration of INS and GPS is considered an optimal combination. The heart of integrated system is Kalman algorithm.

The Kalman filter is a multiple input, multiple output digital filter that can optimally estimate in real time the states of the system based on its noisy outputs. Some of the most successful applications of Kalman filtering is that it can deal with non-linear measurement relationships. The principle approach in such cases is to linearize the non-linear model first and then apply the standard Kalman filter to obtain the state of the system. There are eight such states which consist of velocity errors (eV_N, eV_E, eV_D), drift terms (Gx, Gy, Gz) and attitude errors (Tn, Te). The GPS output is used as a tool to estimate the error in the INS and to correct the error as much as possible. It is called the GPS-aided INS system configuration [4]. Looking at the state space model:

$$\dot{x} = Fx + Gu \tag{1}$$

where F is the dynamic matrix (obtained by partial derivatives), x is the state vector, G is the design matrix and u is the forcing function.

Because our navigation system works in real time mode, we convert equation 1 to its discrete time form:

$$x_{k+1} = \Phi_k x_k + w_k \tag{2}$$

where Φ_k is the state transition matrix, w_k is the driven response at t_{k+1} due to the presence of input white noise during time interval (t_k, t_{k+1}).

Because this time interval is short (it means that the update rate of the INS is high), we can approximate Φ_k as:

$$\Phi_k = e^{(F\Delta t)} \approx I + F\Delta t \tag{3}$$

and the covariance matrix associated with w_k is

$$Q_k = E[w_k w_k^T] \approx \Phi_k G Q G^T \Phi_k^T \Delta t \tag{4}$$

where $Q = \text{diag}[\sigma_{ax}^2 \quad \sigma_{ay}^2 \quad \sigma_{az}^2 \quad \sigma_{\omega x}^2 \quad \sigma_{\omega x}^2 \quad \sigma_{\omega x}^2]$.

Looking at the observation equation:

$$z_k = H_k x_k + v_k \tag{5}$$

where $R_k = E[v_k v_k^T] = \text{diag}[\sigma_\lambda^2 \quad \sigma_\mu^2 \quad \sigma_h^2]$ is the covariance matrix for v_k.

In this system, we assume that the process noise w_k and the measurement noise v_k are uncorrelated.
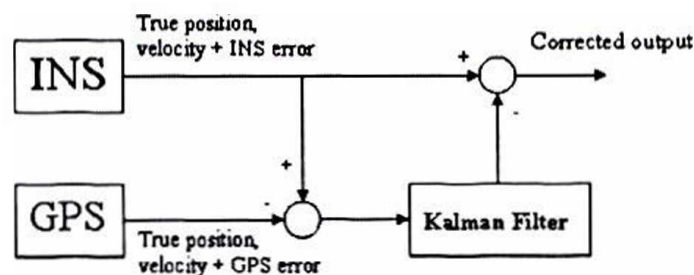

Fig. 1. Feedforward (open-loop) configuration.

Fig. 1 illustrates an open loop (or feedforward) configuration. Its advantage is that provides a rapid filter response. Alternatively, the configuration in Fig. 2 is a closed loop one. This configuration is more complex than the open loop one but it can provide better performance in the existance of nonlinear effects.
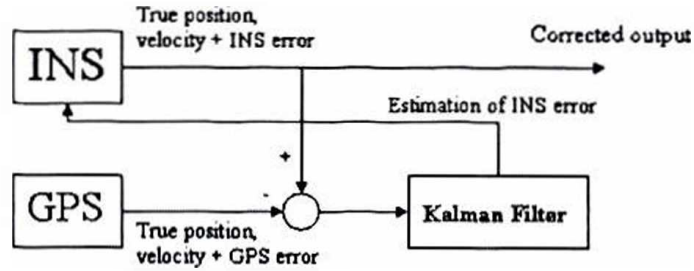

Fig. 2. Feedback (closed-loop) configuration.

3. Vehicle Motion Constraints

It is obvious that the performance of the INS will degrade in the absence of GPS signal. 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.

3.1 Velocity Constraints

We have to make sure that the vehicle does not slip on the road and not jump of the ground. Then, the velocity of the vehicle in the direction perpendicular to the movement of the vehicle would be zero as shown in Fig. 3.
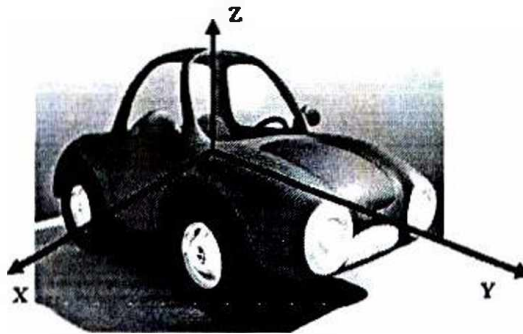

Fig. 3. Land vehicle velocity constraints.

The constraints are:

$$V_x^b(t) = 0$$
$$V_z^b(t) = 0$$

(6)

Eq. 6 can be transformed to the navigation frame:

$$\begin{vmatrix} V_N \\ V_E \\ V_D \end{vmatrix} = C_b^n \begin{vmatrix} V_x^b \\ V_y^b \\ V_z^b \end{vmatrix} \tag{7}$$

This equation can provide the virtual velocity measurements to aid the IMU. When a GPS signal is lost, a complementary Kalman filter is used to combine the INS and virtual velocity measurements in order to reduce the position and velocity errors (see Fig. 4).
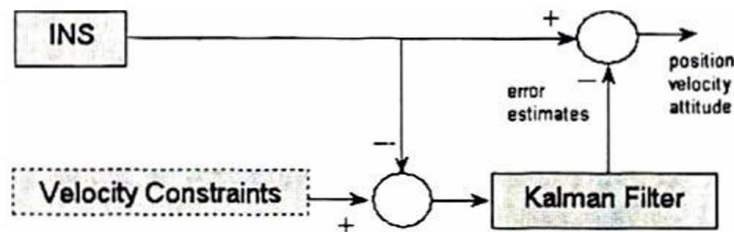

Fig. 4. Velocity constrained navigation block.

3.2 Height Constraints

This constraint is derived from the fact that the height does not change much in land vehicular situation, especially in short time periods. It not only improves the height solution, but also the overall horizontal solution accuracy during GPS outage. However, a realistic measurement uncertainty value must be chosen for these measurements, because any errors in the height solution will ultimately skew the horizontal solution.

4. External Heading Aiding

To take the in-motion alignment of the navigation system, we use the heading from GPS or the external heading measurements such as magnetometer into the attitude computations. The heading error is an importance parameter because of its relation to the system error states. The heading error is derived based on the following heading computation equation which can be transformed to the navigation frame:

$$\hat{\psi} = \tan^{-1}\left(\frac{C_b^n(1,2)}{C_b^n(2,2)}\right) \tag{8}$$

5. Experimentation Results

In this study, as for the INS system we have used the IMU BP3010 (see Fig. 4) which consists of three ADXRS300 gyros and three heat compensated ADXL210E accelerometers. 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.
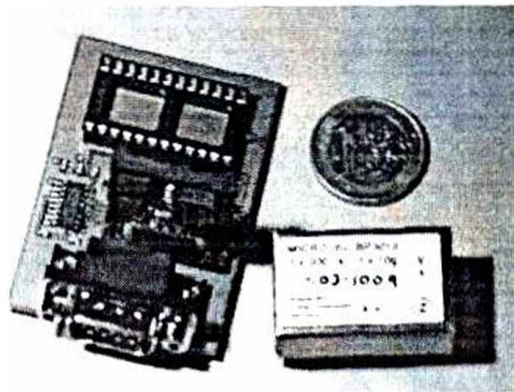
Fig. 5. The IMU BP3010 – A MEMS unit used in our INS/GPS system.

The integrated navigation system implements both open loop and closed loop configurations. The error compensation module utilizes the vehicle motion constraints and the magnetometer measurement during GPS outages. The logic switches in the VC++ software allows the filter to switch between various filter designs, depending on GPS availability.

After characterizing the IMU errors [5], 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.

To see the usefulness of the KF, look at the Fig. 6 and Fig. 7 that illustrate the heading of INS while standing still in the case without KF and with KF, respectively.
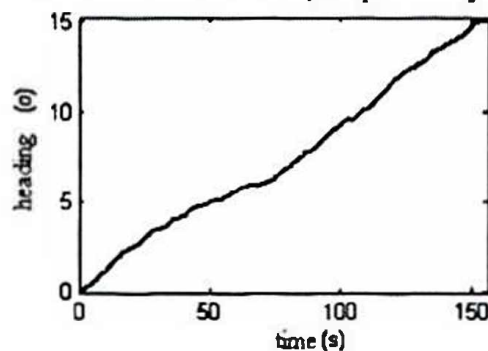

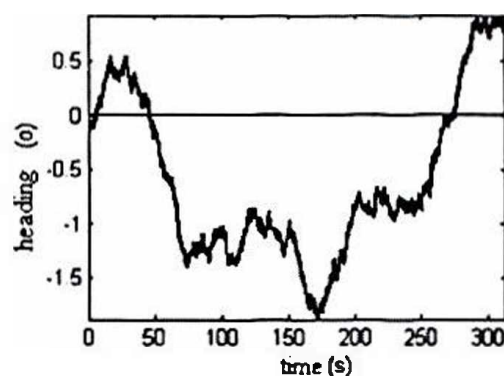Fig. 6. The drift of heading (without KF).

Fig. 7. The heading with the present of KF. Note that the
difference in scale of the graphs in Fig.6 and Fig. 7.

For the experiment of the IMU on road [6], GPS and the data acquisition system were installed in a vehicle. The vehicle was driven for 12 minutes in a 5 km trajectory. Initially the vehicle was at rest, with the engine on, for about 60 seconds in order to estimate the determined errors.

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. The field test 2-D trajectory is presented in Fig. 8.

Fig. 8. Trajectory of the experimental vehicle.

In the case that the GPS loses its signal as in an experiment in Fig. 9, the INS continues to compute the position during the period of lost GPS signal (from the 400th to the 470th seconds, in the trajectory in Fig. 9). It can be seen that the INS/GPS trajectory (solid curve) supported by KF follows the GPS one (dot curve) with small error for quite a long trip. In this combined structure, the closed loop KF is utilized when the GPS signal is available and the open loop KF is applied when GPS is outage. We note that 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.
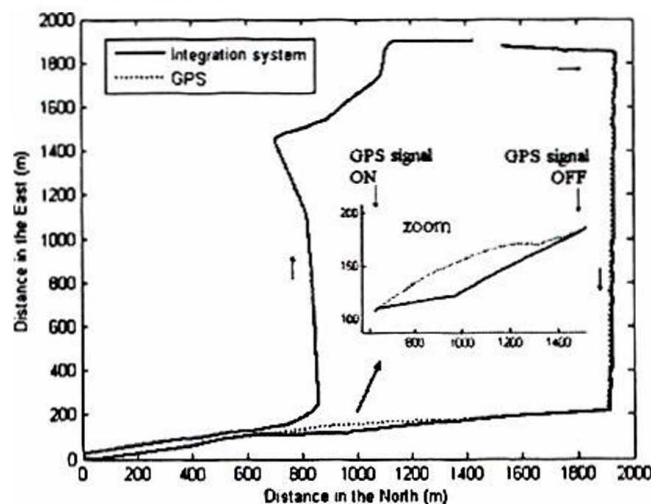

Fig. 9. Trajectory of the land vehicle in the case of GPS outage. The insert shows the time time interval where the GPS signal is blockaged.

Fig. 10.a and 10.b show the East and North velocities of the integrated system. It can be seen that the INS/GPS velocities supported by KF (solid curve) follows the GPS one (dot curve) with small error for quite a long trip. In case of the GPS signal outtage, the accuracy is affected as we can see from the graphs. But once the new GPS values are read by the program, the KF takes very less time to settle down towards the actual values.
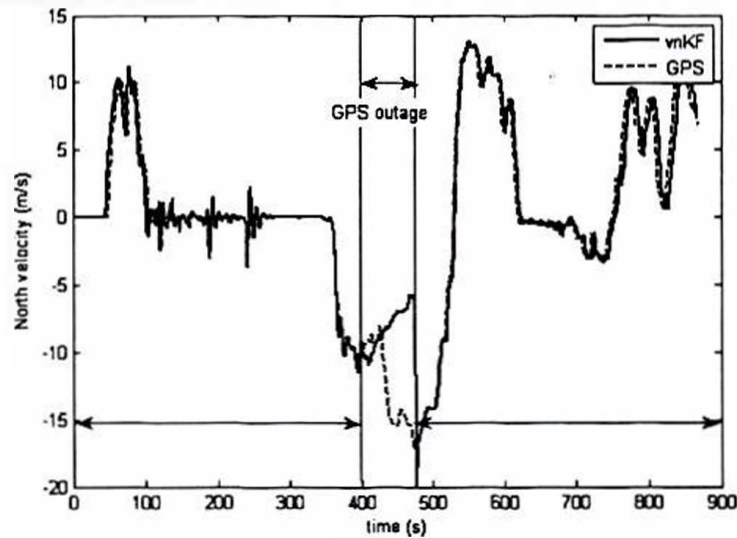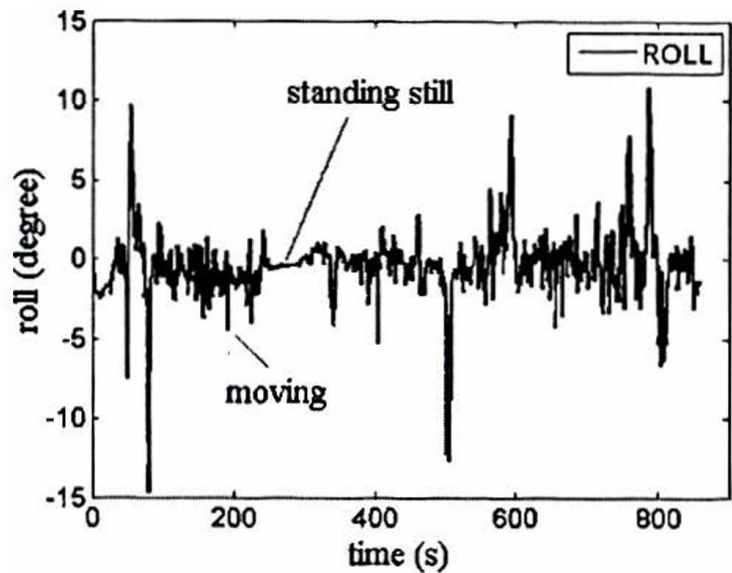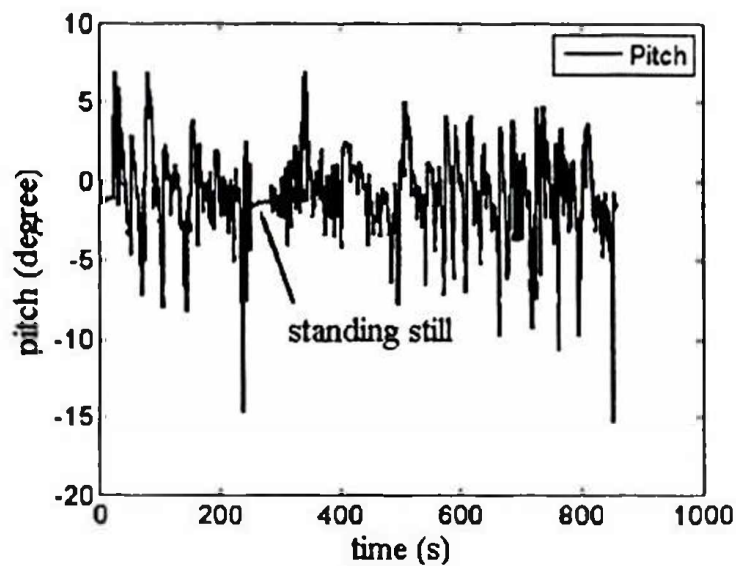

(a)
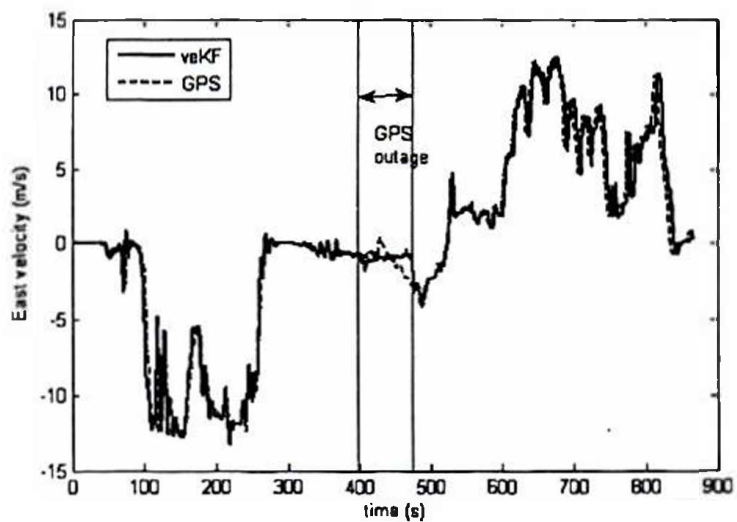
(b)

Figure 10. Velocities in the navigation frame: in the North (a) and in the East (b).

Fig. 11.a and 11.b show the roll and pitch of the navigation system. These results seem to be quite reasonable for a system was on to a land vehicle.

(a)

(b)

Figure 11. Roll (a) and pitch (b) angles of the integrated navigation system.

6. Conclusions

In this paper, an eight state Kalman filter was proposed to be used in order to enhance the quality of a combined GPS and INS system. The vehicle motion constraints and magnetometer measurements are utilized to reduce the INS error degradation during the periods of GPS unavailability. The experimental results have shown that the initial calibration and alignment is accurate enough to allow navigation with IMU sensors for extended period of time with low dead reckoning errors. In fact, the Kalman filter tremendously improves accuracies compared to the GPS and INS when operating alone as individual navigation systems. The accuracy of estimated parameters

is improved by increasing the dimension of the systems' states space. Obviously, by its simplicity, this model can be embedded easily into a real time system. Future work will investigate in-flight calibration and alignment algorithms extending the error models of the INS system.

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