Fuzzy Logic Expert Rule-based Multi-Sensor Data Fusion for Land Vehicle Attitude Estimation

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BIOGRAPHY

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ABSTRACT

In Inertial Navigation System (INS) attitude estimation dominates the accuracy of velocity and position estimation. Traditional gyro-based attitude estimation assisted with Kalman filtering is subject to unbound error growth with time especially as using low-cost Micro-Electro-Mechanical System-based (MEMS-based) sensors for land vehicle application. Thus, in recent years a low-cost INS is still limited to provide an acceptable navigation solution. This paper introduces a new fuzzy expert system to fuse multi-sensor data from MEMS accelerometers, MEMS gyroscopes and a digital compass based on their complementary characteristics related to the corresponding motion status. Field test results have shown the drift-free and smooth attitude estimation have been achieved by using our multi-sensor data fusion algorithm. The improvement of velocity and position estimation by our proposed method is significant, showing an applicable solution to land vehicle navigation using low-cost dead-reckoning sensors.

INTRODUCTION

The Global Positioning System (GPS) has found widely applications in land vehicle navigation, as it can provide position solutions not only cost-effective but also with long-term accuracy and availability (Parkinson and Spilker, 1996). However due to the signal fading in urban area, it requires aids from other enabling sensors. A popular solution to this problem is to integrate GPS with complementary navigation sensors such as INS, which is based on dead-reckoning methodology to obtain the position state. For land vehicle application, MEMS-based inertial sensors with low cost and small size are the

affordable option. But the trade-off is the poorer performance of relatively high instrument bias, drift and noise.
Based on INS mechanization, the error of velocity and position estimations will be mainly governed by the accuracy of the estimated attitude (Titterton and Weston, 1997). In traditional approach, only gyroscopes are used for attitude determination and attitude errors are compensated by Kalman filter method. But the Kalman filter is model-dependent and a priori the model parameters need to be known (Brown and Hwang, 1997). For a low-cost sensor, the behaviors of noisy and imprecise measurements are hard to model properly and the sensor biases and scale factors are dynamic and difficult to be estimated accurately. While Kalman filter is working in prediction step without measurement updates, the estimated errors are accumulating with time due to the nature of the recursive process in error state equations. Thus, a Kalman filter-based attitude estimation using low-cost gyroscopes only would result in unreliable solutions over long-term prediction.

In this paper, we integrate three low-cost sensors, MEMS accelerometers, MEMS gyroscopes and a magnetometer for attitude estimation. A magnetometer with complementary characteristics to gyroscopes can provide absolute heading information relative to the magnetic north without time-accumulated error. For tilt sensing, when vehicle is static, the accelerometer measurement containing gravity field only can directly derive pitch and roll angle without time-accumulated errors. Based on the physical characteristics of each sensor, the accuracy of attitude estimation of each sensor is related to vehicle dynamics. Therefore, a fuzzy logic expert rule-based system is designed to identify the status of vehicle motion and fuse the data from these different sensor modalities. The proposed system can bound the attitude errors and reduce error growth when vehicle stop is available. Field tests using a van driven on a road are performed to examine the accuracy of vehicle attitude estimated by the proposed system. The performance improvement in velocity and position domains using the fused attitude is also discussed.

ATTITUDE ESTIMATION BY MULTI-SENSORS

The principle of inertial navigation is to derive the attitude, velocity and position of a moving body by measuring its dynamics based on Newton's Law. To sense the dynamics of the vehicle, the IMU is aligned with the body frame consisting of three orthogonal axes where x is in the direction of forward motion of the vehicle and y is in the direction of transverse motion of the vehicle. In land vehicle navigation, the motion of a vehicle on the earth surface is mostly represented in the navigation frame of which the axes are aligned to the local north (n), east (e) and down (d). The transformation between the navigation frame and the body frame can be accomplished by a sequence of elementary rotations about the attitude angles. Therefore, the vehicle velocity and position in the navigation frame can be obtained when the vehicle attitude and the acceleration measured in the body frame are determined.

The attitude of the vehicle is represented by three Euler angles, roll (φ), pitch (θ), and yaw (ψ), which are the rotation angles about the x, y and z axes, respectively. The changes of Euler angles, called Euler rates, are relative to the rotation rates of the body frame which can be measured by gyroscopes directly in the following manner:

$$\dot{\varphi} = \omega_{Bx} + \sin\varphi \tan\theta \omega_{By} + \cos\varphi \tan\theta \omega_{Bz} \quad (1)$$

$$\dot{\theta} = \cos\varphi \omega_{By} - \sin\varphi \omega_{Bz} \quad (2)$$

$$\dot{\psi} = \frac{\sin\varphi}{\cos\theta}\omega_{By} + \frac{\cos\varphi}{\cos\theta}\omega_{Bz} \quad (3)$$

where ω_{Bx}, ω_{By}, and ω_{Bz} are angular velocity of the body frame measured by gyroscopes.

The shortcoming of using gyroscopes to estimate attitude is the error accumulation due to the integration process. Even small amounts of gyro bias will result in substantial error growth of attitude without bound. Especially for low-cost sensors, attitude estimation would become unreliable since sensor errors are dynamic and much difficult to model.

In contrast to gyroscopes, accelerometers can be used to directly derive vehicle pitch and roll angles while vehicle is static or moving linearly at constant speed. Under these condition vehicle pitch and roll angles can be calculated as follows.

$$\varphi = -\sin^{-1}\left(\frac{A_{By}}{g}\right) \quad (4)$$

$$\theta = \sin^{-1}\left(\frac{A_{Bx}}{g}\right) \quad (5)$$

where A_{Bx} and A_{By} are acceleration of the body frame measured by accelerometers and g is the local gravity field.

According to equation (4) and (5), no integration is required and therefore tilt estimation error will not increase with time. The accuracy of tilt estimation mainly governed by the accelerometer bias to gravity field ratio is much better than gyro-based estimation. Thus, accelerometers can be used to bound and reset the tilt information calculated by the gyroscopes when the vehicle is not moving. (Ojeda et al., 2002)

For vehicle heading determination, a magnetometer is able to provide absolute heading information relative to the magnetic north without time-accumulated errors (Caruso, 1997). But the compass measurements are still subject to the influence of nearby ferrous effects and interference. In land vehicle application, the nearby ferrous effects are mainly generated by the vehicle itself and have a weak time-variant characteristic. On the other hand, the interference is the result of magnetic disturbances from environment such as power line and it has a strong time-variant characteristic. In addition to these environmental magnetic effects, the declination angles must be determined to correct for true north. Thus, we can model the nearby ferrous effects and declination angles as the combination of bias and scale factor as follows.

$$\psi = \hat{\psi} + b_{\psi} + S_{\psi}\hat{\psi} + n_{\psi} \quad (6)$$

where ψ is the true heading, $\hat{\psi}$ is the heading provided by magnetometer, b_ψ is the sensor bias, S_ψ is the scale factor, and n_ψ is the noise and disturbance. After sufficient data of measurement and true value are available, the biases and scale factors can be estimated by using least squares method (Wang, 2004).

It should be noticed that in land vehicle application the magnetometer is not always confined to a level plane in which the earth magnetic field stands. Thus, the tilt angles should be determined for heading corrections (Caruso, 1997). Since the tilt information is very difficult to be accurately estimated using low cost sensors when vehicle is moving, we only apply tilt compensation when vehicle is static. Thus, we can use magnetometer heading to bound and reset the heading information calculated by the gyroscopes when vehicle is not moving.

Once vehicle attitude is determined, vehicle velocity and position in the navigation frame can be derived from accelerometer measurements based on vehicle dynamics model. In this paper we applied the constrained motion model proposed by Brandt and Gardner, 1998. The extra information of vehicle motion constraints can be used to reduce the navigation errors. The constrained motion model is defined as fellows.

$$\dot{V}_f = A_{Bx} - g\sin\theta \tag{7}$$

$$\dot{x}_t = V_f \cos\theta \cos\psi \tag{8}$$

$$\dot{y}_t = V_f \cos\theta \sin\psi \tag{9}$$

where V_f is the vehicle forward velocity. x_t and y_t are the vehicle coordinate in the XY plane of the earth-fixed tangent frame.

Based on equation (7) to (9), the accuracy of the estimated velocity and position are mainly dominated by pitch and heading errors. Thus, in this study we only assess the accuracy of the estimated pitch and heading information.

FUZZY EXPERT SYSTEM FOR MULTI-SENSOR DATA FUSION

As mentioned in previous section, the performance and characteristics of each sensor are related to vehicle dynamics. Based on the knowledge of specific physical shortcomings and strengths of each sensor modality in the corresponding status of vehicle motion, vehicle attitude information can be derived from multi-sensor data. Thus, the association between raw measurements and vehicle dynamics should be investigated and identified. In this paper, we apply a fuzzy expert system for the identification of vehicle dynamics. Then, according to vehicle motion status we use the most suitable sensor to estimate vehicle attitude. In the meantime, the errors of the unused sensors are also estimated based on the statistics of observations. More specifically, we use the accelerometers and the magnetometers to derive tilt and heading information and estimate gyro drift using least squares method when vehicle is static. When vehicle is moving, we estimate vehicle attitude using compensated gyro measurements. The block diagram of our fuzzy expert system is shown in Figure 1.

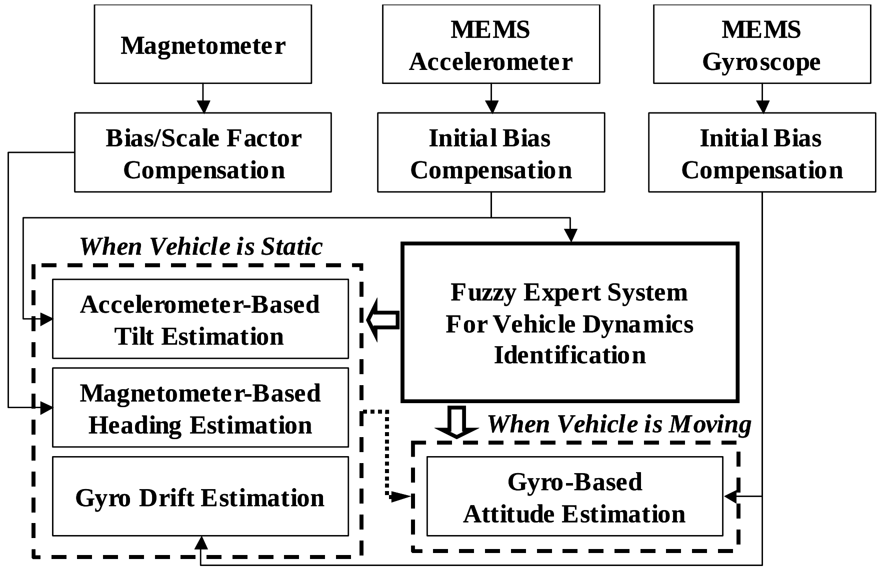

Figure 1: System Block Diagram

To correctly identify vehicle dynamics (static/moving) based on low-cost sensor measurements, the identification system must have the capacity of dealing with uncertainty and imprecision due to the noisy measurements and vehicle vibration effects. Both of probability-based and fuzzy set theories can handle the uncertainty and imprecision of data. However, the failings of probability in situations where little or no a priori information is known provide an arena for the use of fuzzy expert system (Kandel, 1992). Fuzzy expert system is an expert system which incorporates fuzzy sets and/or fuzzy logic into its reasoning process and/or knowledge representation scheme. Fuzzy set theory provides a natural method for dealing with linguistic term which is a very effective knowledge representation format for imprecise and uncertain information (Kandel, 1992). Described in the following is the development of a fuzzy expert system for land vehicle dynamics identification.

Shown in Figure 2 is the architecture of the fuzzy logic-based vehicle dynamics identification system. In this research, the Mamdani type fuzzy inference system, which is considered as the most commonly seen fuzzy methodology, has been used (Mamdani and Assilian, 1975). The input variables for the system are the accumulated jerk magnitude in x, y, and z direction of body frame to interpret the degree of vehicle motion. The definition of the accumulated jerk magnitude is described as follows.

$$AJ_x = \sum_{i=k-d}^{k} \left| (Jerk_x)_i \right| \tag{10}$$

$$AJ_y = \sum_{i=k-d}^{k} \left| (Jerk_y)_i \right| \tag{11}$$

$$AJ_z = \sum_{i=k-d}^{k} \left| (Jerk_z)_i \right| \tag{12}$$

where the subscript k indicates the present measurement index and d is the backward accumulation quantity. After taking the summation of jerk, the vibration and noise effect on observations are diluted and the accumulated jerk difference between stop and move can become more significant. The output of the fuzzy inference system is a numeric rating between 0.05 and 0.95 to describe vehicle dynamics grade. A lower rating value indicates a higher likelihood of having vehicle static.

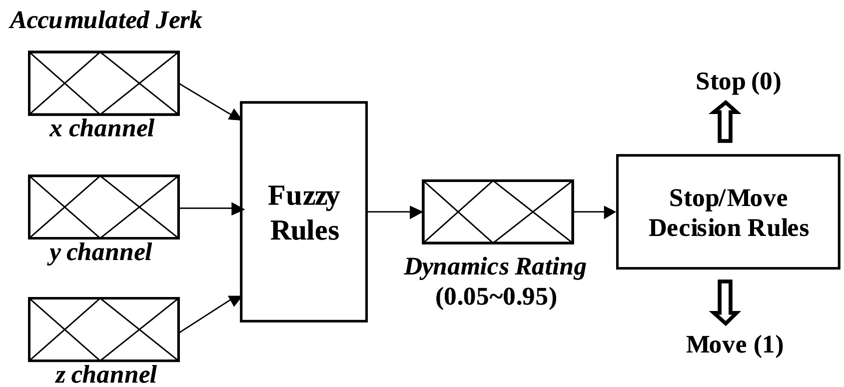

Figure 2: Fuzzy Logic-based Vehicle Dynamics Identification System

Once the inputs and output are defined for the system, the membership functions are further designed to define the quantity of the linguistic terms such as stop, uncertainty and move for fuzzy output. In this research, the design of the membership functions is based on our personal experience and knowledge gained from the field test data. At the same time, a set of rules is developed to describe the relationship between the input and the output. The rules are established basically based on common sense reasoning and further modified through processing the field test data. The final tuned membership functions and rules are shown in Figure 3 and Table 1. Then, the output fuzzy set is defuzzied into a crisp value using the center of the area method. It should be noticed that the design of fuzzy system is vehicle dependent and varies with the location of sensor installation.

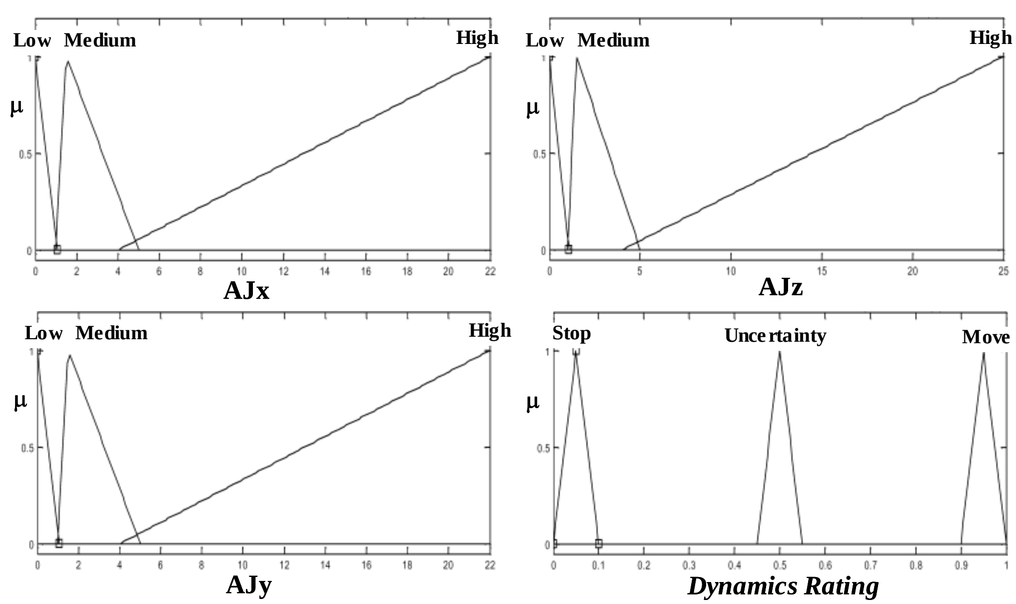

Figure 3: Membership Functions used in Fuzzy Expert System

Table 1: Rules used in Fuzzy Expert System

Rule No.	AJx	AJy	AJz	*Dynamics Rating*
1	High			Move
2		High		Move
3			High	Move
4	Medium	Medium	Medium	Move
5	Medium	Medium	Low	Uncertainty
6	Medium	Low	Medium	Uncertainty
7	Medium	Low	Low	Uncertainty
8	Low	Medium	Medium	Uncertainty
9	Low	Medium	Low	Uncertainty
10	Low	Low	Medium	Uncertainty
11	Low	Low	Low	Stop

To identify the stop or move of a vehicle based on the fuzzy output values, a set of decision making rules is designed as shown in Figure 4. The rule 1, 2, and 3 work as a classifier to transfer the continuous numeric rating values into a Boolean value to distinguish stop and move of vehicle. The rule 4 is useful to instantly detect the movement of vehicle to avoid the detection delay due to the use of the accumulated jerk as our fuzzy input.

Table 2: Rules used for Stop Identification

Rule 1	If *Dynamics Rating* equal 0.95, Then vehicle is moving.
Rule 2	If *Dynamics Rating* equal 0.05, Then vehicle is stop.
Rule 3	If *Dynamics Rating* is larger than 0.05 and smaller than 0.95, Then the present motion status equal the previous motion status.
Rule 4	If the present motion status is stop and the jerk magnitude in forward direction is larger than a criterion value, Then vehicle is moving.

As mentioned early, when the stop of vehicle is detected, we can use the accelerometers and the magnetometers to derive tilt and heading information and estimate gyro drift. Under this condition, we can average the tilt and heading estimations to remove the noise effects since vehicle attitude would remain static. On the other hand, the random walk of gyro measurement and gyro bias can be monitored. In this research, we use least squares method to estimate the gyro noise and bias effects in attitude domain, that is, the estimated attitude errors over time. The role of the least squares estimation is to determine the attitude errors rate in a statistical sense. The least squares problem can be described by a linear equation as fellows.

$$L = AX \tag{13}$$

The observation, L, is the difference between the gyro-derived attitude at each epoch and its mean value during stop periods. This value indicates the divergence of the gyro-derived attitude at each epoch. The design matrix, A, consists of the accumulated time from stop at each epoch. The unknown parameter, X, is the attitude errors rate to be estimated. Once vehicle starts to move, the attitude errors rate is estimated based on the collected information during stop periods. Therefore, in every stop the attitude drift error using gyro measurements can be controlled and the dynamic gyro noise and bias effects in attitude domain can be estimated.

When vehicle is moving, attitude information would be determined by this compensated gyro measurement based on equation (1) to (3). In general driving conditions of land vehicle, the roll angle is small and the rotation rate in z-axis is much larger than y-axis. In addition, the roll estimation is very difficult to be accurate using a lost-cost gyro. Thus, for yaw rate estimation we ignore the effects of y-axis rotation and for pitch estimation we consider the effects of z-axis rotation only when vehicle is making a turn. Based on the vehicle dynamics constraint, no lateral motion is allowed. Thus, the y-axis accelerometer measurement only contains gravity field which can be used to derive roll angle while vehicle isn't making any turn. In this research we simply derive the roll information during turning by interpolating the accelerometer-derived roll angle before and after turning. However, the drawback of this method is the time delay of estimation output when vehicle is making a turn

TEST RESULTS AND DISCUSSIONS

Filed tests were performed to examine the performance of our proposed system. A low-cost MEMS-based inertial sensor, namely MT9 made by Xsens Inc., was used in the experiments. The MT9 is a digital inertial measurement unit that measures 3D rate-of-turn, acceleration and earth-magnetic field. The data output rate was chosen as 20 Hz which is high enough to sample vehicle dynamics. In the meantime, two Javad Legacy GPS receivers were used to provide 1 Hz carrier phase DGPS solutions for reference position, velocity and heading. All of the sensors were mounted in a van and their outputs were logged and synchronized with computer time for subsequent analysis. The test was performed in a parking lot at the University of Calgary. The trajectories of the tests are shown in Figure 4. The van stopped four times during the test and took about 6 minutes to complete the trail.

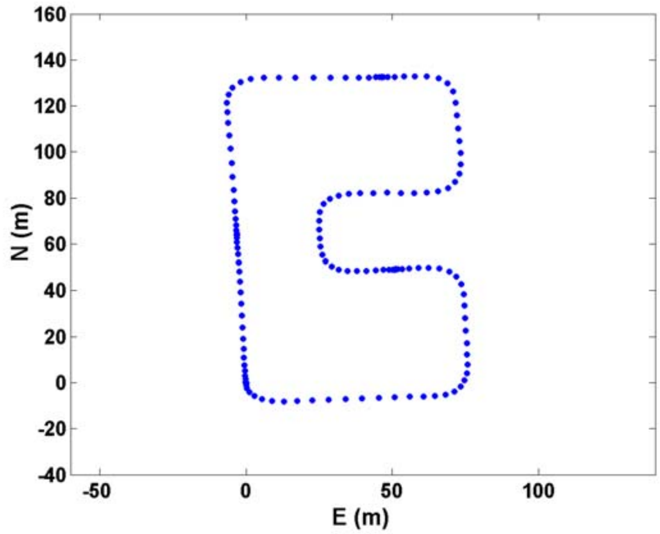

Figure 4: Test Trajectory

Figure 5 to 7 show the raw data including 3-axis acceleration, angular rate, and magnetic field measured by MT9. It has shown that the accelerometer and magnetometer measurement keep quite stable when vehicle is stop. The accelerometer measurement profiles also imply the diversity of vehicle jerk between stop and move. For gyro measurement, vehicle rotation dynamics in z-axis is much larger than noise level. By contrast, the dynamics of pitching and rolling of a land vehicle is much lower than yawing and gyro measurements in x-axis and y-axis are much noisy due to vehicle vibration and road raggedness.

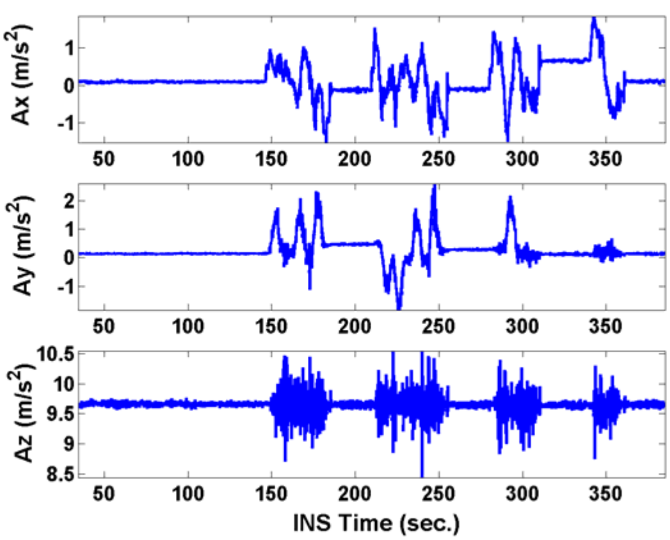

Figure 5: Raw Measurement - Accelerometer

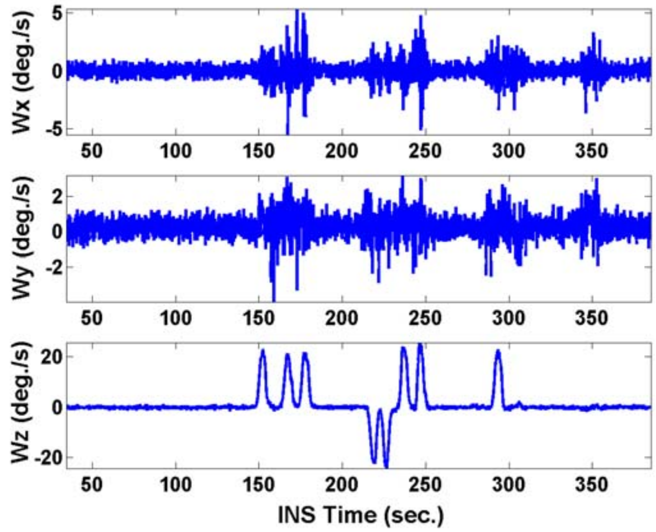

Figure 6: Raw Measurement - Gyroscope

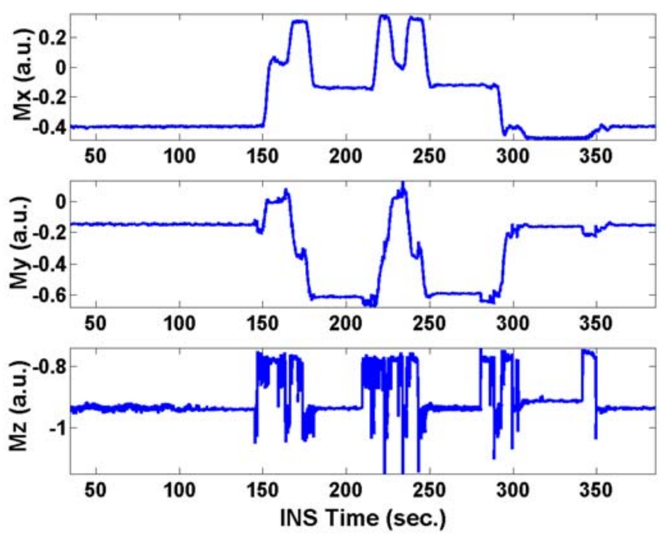

Figure 7: Raw Measurement - Magnetometer

Shown in Figure 8 is the result of vehicle dynamics identification provided by the proposed fuzzy expert system. The stop and move of vehicle are correctly distinguished. The fuzzy expert system has properly interpreted the raw measurements and successfully recognized their relationship to the vehicle dynamics.

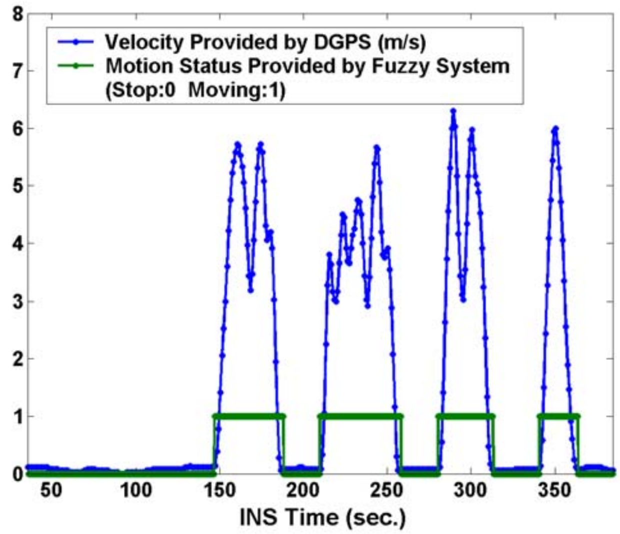

Figure 8: Vehicle Dynamics Identification

Figure 9 illustrates the heading angle derived from gyro measurements only (no aid) and modified by the fuzzy expert system, respectively. The reference heading is derived from DGPS velocity while vehicle is moving. When vehicle is static, we can adopt the previous reference heading as the present reference. Obviously, when vehicle is stop, the gyro drift errors have been controlled by magnetometer update. On the other hand, when vehicle is in motion, a smooth heading estimation that cannot be achieved by using a magnetometer because of noise and tilt effects has been accomplished by using the compensated gyro measurements.

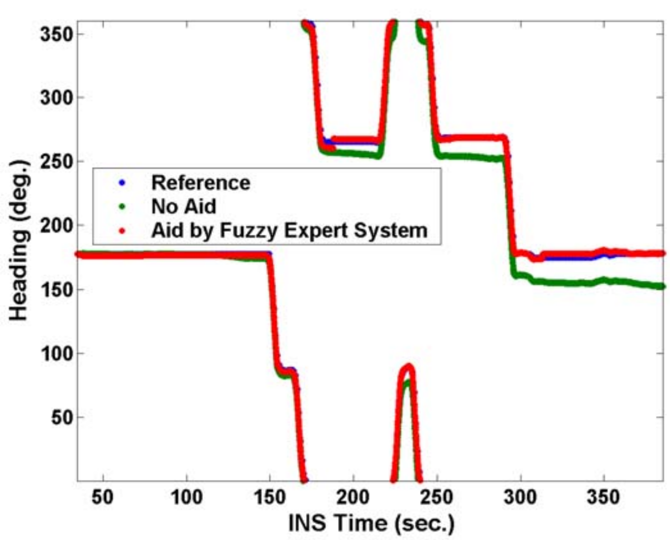

Figure 9: Heading Estimation

Figure 10 illustrates the pitch angle derived from gyro measurements only (no aid) and modified by the fuzzy expert system, respectively. With the aid of the fuzzy expert system, pitch estimation has been bound and controlled well rather than the gyro-based pitch estimation with drift. Since no reference pitch information is available in our test, we evaluate the accuracy of the estimated pitch by examining the velocity calculated by equation (7). Figure 11 shows the velocity estimation using gyro-based (no aid) and data fusion-based (aid by fuzzy expert system) pitch information, respectively. Obviously, the gyro-based one diverges quickly and cannot be used for navigation. By contract, the velocity derived from the fuzzy expert system is very close to reference velocity. Thus, the accuracy of the forward velocity estimation has been significantly improved by using the fusion-based pitch angle derived from the proposed method.

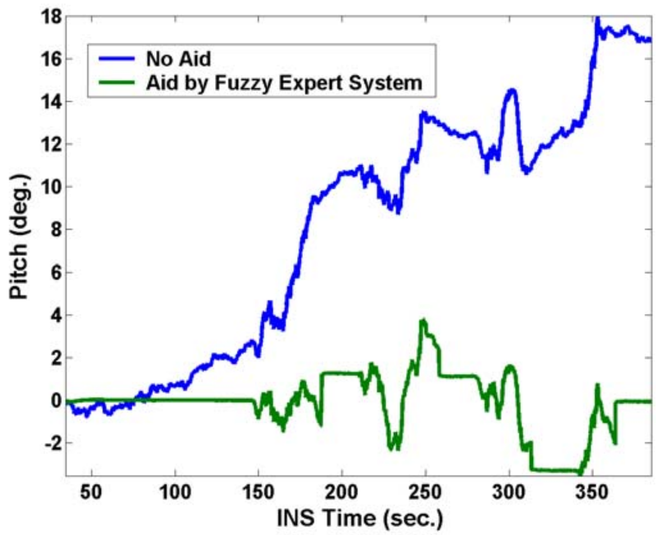

Figure 10: Pitch Estimation

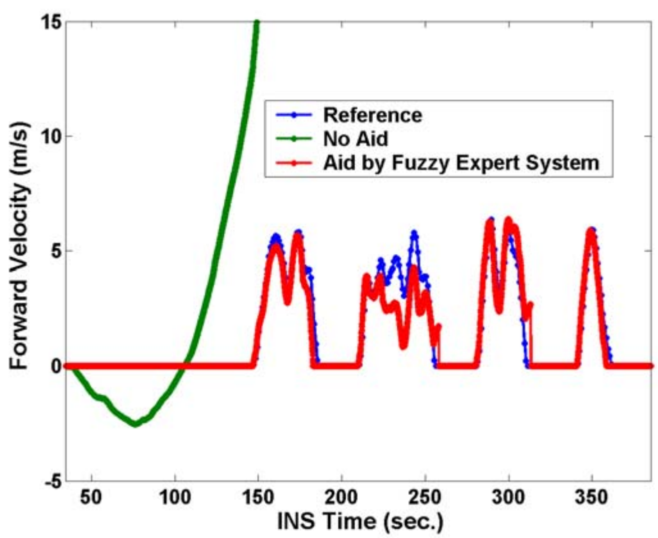

Figure 11: Velocity Estimation

For further assessing the accuracy of heading, velocity and position estimation, we compare them to the synchronized DGPS data with 1Hz down-sample rate to examine the errors. Figure 11 shows the heading, velocity and 2D position estimation errors while we apply the proposed multi-sensor data fusion algorithm. Obviously, the heading and velocity errors have been bound and controlled well during this about 6-minute drive with couple stops in-between. In statistical analysis the mean and standard deviation (std) values of heading error are –0.09 and 1.677 (degree), respectively. The mean and std values of velocity error are –0.127 and 0.639 (m/s), respectively. In terms of position domain, position error would be accumulated with time due to the integration process. The final position error over this 6-minute stand-alone navigation is about 50 meters which is far beyond the expectation provided by a low-cost MEMS-based inertial sensor.

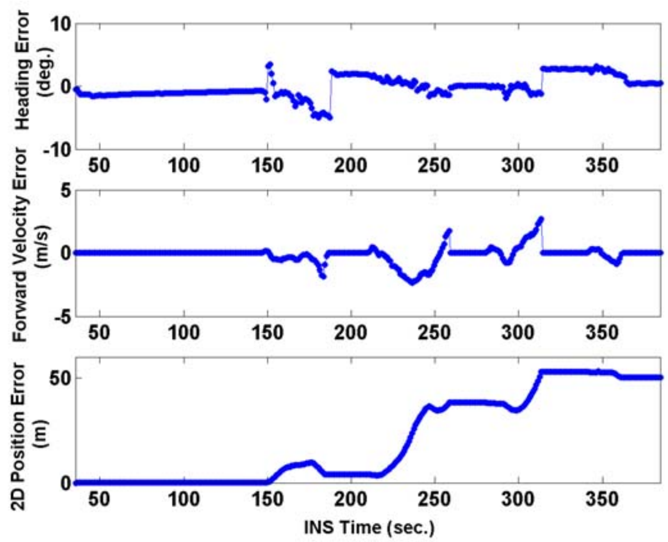

Figure 12: Heading, Velocity and Position Estimation Error

CONCULSIONS

A new multi-sensor data fusion algorithm for land vehicle attitude estimation has been developed based on a fuzzy expert system. First, we have investigated in-depth physical characteristics of each low-cost sensor and its error sources related to vehicle dynamics. Then, a fuzzy expert system has been designed to correctly identify vehicle dynamics. Finally, online error estimation and multi-sensor data fusion were implemented based on the identified motion status.

The results of the field tests have shown that the proposed method can provide adapted attitude estimation without unbound error drift and noisy disturbance. By using this fusion-based attitude, the accuracy of velocity and position estimation has been significantly improved. For further research, integration with GPS to include more error control mechanism to develop a robust land vehicle navigation system is recommended.

ACKNOWLEDGMENTS

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