The Aiding of MEMS INS/GPS Integration Using Artificial Intelligence for Land Vehicle Navigation

J-H. Wang and Y. Gao

Abstract—**This paper applies two Artificial Intelligence (AI) techniques, fuzzy logic and expert system, to enhance the Kalman filter-based MEMS INS/GPS integration. For better INS error control, the expert knowledge on vehicle dynamics is utilized to simplify dynamics models and to extend measurement update schemes in the velocity filter. To optimize position fusion, a fuzzy inference system is developed to provide GPS signal degradation information for modification of the innovation-based adaptive measurement covariance in the position filter. The effectiveness of the proposed AI-based enhancement methods is demonstrated through several field tests.**

Index Terms—**GPS, INS, Kalman Filter, Artificial Intelligence**

I. Introduction

Today, the Global Positioning System (GPS) has been used by most navigation systems to a wide range of applications. GPS however is still subject to severe performance degradation in the presence of signal blockage, diffraction and multipath and its application in signal-degraded environments such as urban areas remains a significant challenge. With operational characteristics complementary to GPS, the self-contained Inertial Navigation System (INS) has been widely adopted to assist GPS-based navigation systems. An INS/GPS integrated navigation system is able to provide improved navigation performance in terms of accuracy, availability, and reliability over GPS-only systems.

Kalman filtering methodology has been extensively applied for optimal fusion of data from GPS and INS sensors and the bridging of GPS outages [1][2][3][4]. As the increasing use of low-cost Micro-Electro-Mechanical System (MEMS) inertial sensors to land vehicle applications, however, the traditional Kalman filter methodology was found insufficient due to poor quality of the MEMS inertial measurements [5][6]. In MEMS INS/GPS integration, the Kalman filter processes the low-quality inertial data which have large bias variation, high noise level, and large random error due to flicker noise, random walk and etc. In this case, sensor errors are much difficult to realistically model using stochastic processes and thus the imperfect modeling resulted from mis-modeling, non-modeling and non-white properties of input data is obvious. In addition, when the navigation system operates in GPS challenging environments such as urban canyons, GPS solutions are characterized by large noise and multipath error and GPS accuracy is much difficult to assess properly [7][8]. As a result, inevitably using the inaccurate dynamics and statistical models for both system and measurement states, the Kalman filter has degraded estimation accuracy and even divergence problems.

In this paper a modified integration methodology using adaptive Kalman filtering and artificial intelligence (AI) techniques is developed to provide improved integration performance. Two cascaded Kalman filters, velocity and attitude filter and position filter, are employed separately in the loosely coupled closed-loop integration scheme. In the velocity and attitude filter we develop a dynamics knowledge aided inertial navigation algorithm to simplify filter dynamics models and to extend measurement updates. This technique provides continuous error control for INS velocity and attitude even during GPS outages. In the position filter the corrected velocity and attitude are integrated with GPS position using the innovation-based adaptive filtering technique incorporated with vehicle dynamics knowledge and a fuzzy logic rule-based GPS data classification system. Vehicle dynamics knowledge is used to identify the slowly changing GPS position error so that they wouldn't affect the integration solution. The GPS data classification system is designed to classify GPS signal degradation conditions based on GPS signal and geometry information. Correlated to GPS position performance, the identified signal degradation condition is further applied to weight the innovation-based adaptive measurement noise covariance for better characterizing GPS performance.

The designed integration algorithm has been evaluated with field tests using a van driven in downtown Calgary, Canada. The test results show that the low-cost MEMS INS/GPS system applying the proposed AI-enhanced integration algorithm can provide continuous and reliable navigation solutions with about 9 m root-mean-square (RMS) of the across-track error in urban areas. The average maximum across-track position error has been maintained within around 37 m while the GPS-only

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system suffers from the position error at a hundred-meter level.

The paper is organized as follows. Section 2 describes the AI-based methods for integration enhancement including a dynamics knowledge aided inertial navigation algorithm and a fuzzy rule-based GPS data classification system. Section 3 explains how these AI-based methods are applied to modify the Kalman filter for better INS/GPS integration. Section 4 presents the field test results and discussions. The conclusions are given finally in Section 5.

II. AI-Based Methods for Integration Enhancement

In reasoning about a system, the precision inherent in our models of the system depends on the degree of complexity (uncertainty) of the system and the understanding about the problem (precision of measurement) [9]. For the complex systems with only ambiguous or imprecise information available, the AI-based methods provide a nonlinear, adaptive, and knowledge-based approach to understand the system's behavior by using human reasoning and intelligence. AI technologies, such as expert systems, fuzzy logic and neural networks, have found successful applications in a wide variety of fields such as nonlinear mapping, data classification, and decision analysis [10][11][12]. AI methods can be seen as the advanced versions of the estimation, the classification, and the inference methods [13]. As mentioned previously, the major limitation of using the model-based Kalman filter for low-cost MEMS INS/GPS integration lies on the processing of the low-quality INS and corrupted GPS data. Thus, with the advantages of processing ambiguous or imprecise data and the capabilities of formulating human intelligence, AI methods are applied in this research to enhance the Kalman filter-based data fusion by adding functionalities of navigation error compensation, data quality assessment, and fusion scheme optimization.

A. *Dynamics Knowledge Aided Inertial Navigation Algorithm*

The first AI-based enhancement method is to apply expert knowledge on vehicle dynamics into inertial navigation algorithm so that the simplified dynamics model and the extended measurement update scheme can be used in the Kalman filter to reduce INS error drift. The first vehicle dynamics knowledge adopted is the use of the vehicle motion constraints proposed by Brandt and Gardner (1998). In a normal driving condition, the vehicle can be assumed with no motion along the transverse direction and the direction normal to the road surface [14]. These vehicle motion constraints can be applied to simplify the mechanization equations and reduce the navigation errors. The constrained motion model describing how to obtain the vehicle velocity and position in the navigation frame (north-east-down) from accelerometer and gyro measurements of the body frame (forward-transverse-vertical) is defined as follows [14]:

$$\dot{\phi} = \omega_{Bx} + \sin\phi \tan\theta\,\omega_{By} + \cos\phi \tan\theta\,\omega_{Bz} \tag{1}$$

$$\dot{\theta} = \cos\phi\,\omega_{By} - \sin\phi\,\omega_{Bz} \tag{2}$$

$$\dot{\psi} = \frac{\sin\phi}{\cos\theta}\omega_{By} + \frac{\cos\phi}{\cos\theta}\omega_{Bz} \tag{3}$$

$$\dot{V}_f = A_{Bx} - g\sin\theta \tag{4}$$

$$V_f\,\omega_{Bz} = A_{By} + g\sin\phi\cos\theta \tag{5}$$

$$V_f\,\omega_{By} = -A_{Bz} - g\cos\phi\cos\theta \tag{6}$$

$$\dot{P}_N = V_f \cos\theta\cos\psi \tag{7}$$

$$\dot{P}_E = V_f \cos\theta\sin\psi \tag{8}$$

where ω_{Bx}, ω_{By} and ω_{Bz} are angular velocities of the body frame measured by gyros. 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 in the body frame, respectively. V_f is the vehicle forward velocity. A_{Bx}, A_{By} and A_{Bz} are the body frame accelerations measured by accelerometers. P_N and P_E are the vehicle coordinates in the north and east direction in the navigation frame.

The second benefit from vehicle dynamics knowledge is the ability to directly estimate some navigation states under some specific dynamics based on the specific physical characteristics of inertial sensors. These dynamics-derived estimates can be used as the virtual measurement updates for the INS Kalman filter to control and correct the stand-alone navigation error. The specific vehicle dynamics and the corresponding dynamics dependent estimation can be categorized as: stationary mode, straight-line motion mode, and cornering motion mode.

When a vehicle is static, accelerometer measurements containing only the local gravity field can be used to directly derive vehicle pitch and roll angles as follows:

$$\theta = \sin^{-1}\left(\frac{A_{Bx}}{g}\right) \tag{9}$$

$$\phi = -\sin^{-1}\left(\frac{A_{By}}{g}\right) \tag{10}$$

According to (9) and (10), no integration is required and therefore the tilt estimation error will not increase with time. Compared to the gyro-derived tilt with high error drift rates, the accelerometer-derived tilt is accurate enough to provide direct tilt error control. Another observation available during stationary periods is the constant heading constraint. Since the vehicle is not moving, the vehicle heading can be considered unchanged. The forth direct measurement during stationary periods is the well-known zero velocity update (ZUPT). ZUPT provides a very accurate velocity observation, as the vehicle is static. The last benefit from the stationary mode is the availability of gyro bias estimation. For automotive-grade MEMS INS, the stationary outputs of gyroscopes themselves can be considered as biases [15]. This is because the earth rotation is at the senor noise level for automotive-grade MEMS

INS and thus the true angular rate of the body frame during stationary periods can be assumed as zero. By averaging all gyro measurements during stationary periods, we can remove the noise effects and use this average value as the gyro bias estimate.

When a vehicle is moving straight, no significant motion acceleration along the transverse direction exists. Thus, mostly containing the local gravity field, the accelerometer output along the transverse direction can be used to determine the approximate roll angle. Although the approximation errors induced by sideslip or vibration may exit, they can be mostly reduced by moving average. When a vehicle is making a turn, the cornering motion with strong dynamics in transverse acceleration and yawing provides another occurrence for direct estimation of the vehicle velocity. Rearranging (5), the forward velocity of the vehicle can be directly estimated as follow:

$$V_f = \frac{1}{\omega_{Bz}}\left(A_{By} + g\sin\phi\cos\theta\right) \tag{11}$$

It should be noted that the vehicle motion types need to be correctly identified in order to provide the aforementioned dynamics-dependent observations and estimates. Based on our previous studies, a fuzzy expert system can be utilized to provide correct vehicle dynamics identification. Readers are referred to Wang et al. (2005) for details about the design of the fuzzy expert vehicle dynamics identification system [16].

B. *Fuzzy Logic Rule-based GPS Data Classification*

The second AI-based enhancement method is to classify GPS data based on the signal and geometry information using fuzzy reasoning so that GPS solutions can be more properly weighted in the Kalman filter. The basic idea behind this approach is that GPS positioning is based on the tracking of more than four line-of-slight satellite signals and its performance is affected by signal and geometry conditions. Based on our previous studies in [17], the signal and geometry conditions are characterized by two geo-signal degradation measures, the average fading C/N0 in the horizontal f_H and the fading satellite ratio FR, derived from fading carrier-to-noise-ratio and satellite geometry matrix. Shown in Fig. 1 is the distribution of the geo-signal degradation measures under different GPS environments. The black marks indicate the mean of the geo-signal degradation measures for each 24-hour static test. It can be seen that the signal-degraded conditions could be classified based on the clustering feature of the geo-signal degradation measures. However, there is an overlap of the input feature vectors between different classes because the signal degradation condition is changing with time according to the user-to-satellite geometry relative to the around-receiver obstacles. In addition, there is a dilemma of using fading C/N0 to indicate the magnitude of multipath errors [17]. Thus, the input data contain uncertain and imprecise terms. This motivates the application of fuzzy inference systems for GPS data classification.

Shown in Fig. 2 is the architecture of the proposed fuzzy inference system for GPS data classification. The output of the fuzzy inference system is a numeric quality rating (QR) between 0 and 1. The QR value, which describes the degree of signal plus geometry degradation, is further applied to classify GPS data. A higher rating value indicates a higher likelihood of having a poor GPS solution. Because GPS receivers use the internal filter to smooth position solutions, GPS position performance is less sensitive to the short-term or transient changing of signal degradation. To consider this filtering effect, we use the moving average of the geo-signal degradation measures as the system input variables so that the QR value can reflect the performance of GPS position more appropriately. The size of moving average window is empirically chosen as eight seconds.

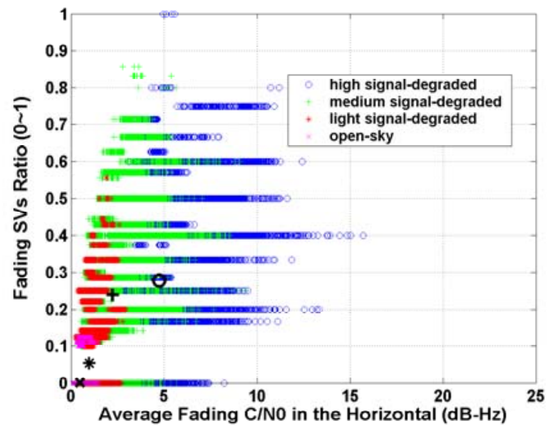

Fig. 1. Distribution of the geo-signal degradation measures in various signal degradation environments.

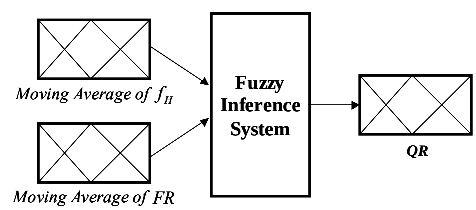

Fig. 2. Architecture of the fuzzy inference system.

For the purpose of computational simplicity, the triangle membership functions are used in the fuzzy inference system. Three membership functions are used for each input variable to categorize the geo-signal measures under low, medium and high signal-degraded conditions, respectively. The parameters of input membership functions are determined based on the results of the various environment tests shown in Fig. 1. The mean of the geo-signal degradation measures under each signal degradation condition is assigned to the core values of the corresponding membership function. These mean values are well representative of data clustering centers since they were calculated from large amount of sampling data. For the output membership functions, three triangles with even overlaps between sets and even segmentation from zero to one are used because in this study GPS data are intentionally classified into three classes. Based on the results of the various environment tests shown in Fig. 1, the design of the fuzzy rules describing the relationship between the input and the output is quite straightforward. For example, the GPS positioning solution would be poor (QR is large) if the fading satellite ratio and the average fading C/N0 in the horizontal are high.

After membership functions and fuzzy if-then rules are defined, an inference procedure is applied to derive the output fuzzy set. In this research, the Mamdani type fuzzy inference system with max-min composition, which is considered as the most commonly seen fuzzy methodology, is used [18]. Then the centroid of area defuzzification is applied to extract a crisp value from the output fuzzy set as a representative value of the final fuzzy output. This crisp value in a range between 0.25 and 0.75 is further used for data classification. For example, if the value of quality rating is smaller than 3.75 (the medium between the core value of the 'Small' and 'Medium' output membership functions), data are classified as low signal-degraded data.

III. AI-ENHANCED INTEGRATION ALGORITHM

The architecture of the AI-enhanced integration algorithm employed in the loosely coupled closed-loop integration scheme is shown in Fig. 3. The INS and the GPS receiver operate as independent systems and process data parallelly. INS raw measurements (acceleration and angular velocity) are processed in the INS mechanization to derive INS attitude, velocity and position. GPS raw observations (code, Doppler and phase) are processed in the GPS Kalman filter to derive GPS velocity and position. Then, in the integration Kalman filter the differences between the INS and GPS velocities and positions are utilized as measurements and the INS error equations are used as the system model. When GPS is available, the integration Kalman filter estimates all observable INS sensor and navigation errors to compensate system outputs. When GPS is unavailable, the INS sensor and navigation errors will be predicted based on the system model and corrected by dynamics-derived measurements.

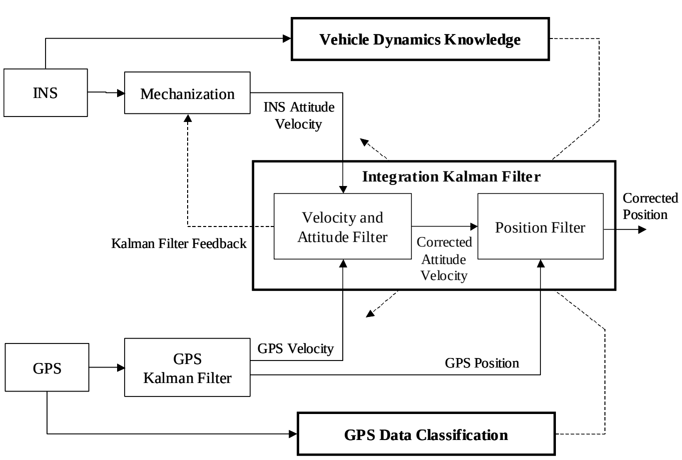

Fig. 3. Architecture of AI-enhanced integration algorithm.

As shown in Fig. 3, two cascaded filters, the velocity and attitude filter and the position filter, are employed separately in the integration Kalman filter. This is because for land vehicle applications in GPS challenging environments, the Doppler-derived velocity is more reliable than the code-derived position because multipath and signal degradation have much more impact on pseudorange measurements than Doppler measurements. In this condition, the Doppler-derived velocity is more useful for updating the inertial system while the code-derived position would not benefit but deteriorate velocity and attitude estimation.

The velocity and attitude filter is designed to estimate INS sensor errors as well as velocity and attitude errors based on INS error dynamics and GPS velocity updates. To improve estimation performance, system dynamics and measurement models are modified based on the dynamics knowledge aided inertial navigation algorithm. The simplified system models are derived from the land vehicle motion models shown in (1) through (4) using perturbation techniques. The extended measurement update schemes, which have been described in the previous section, are used here to correct the INS velocity and attitude states continuously. Then, the corrected velocity and attitude will be integrated with GPS position in the position filter to output an optimal position estimate. Because only horizontal position is interested in land vehicle applications, position and velocity in the north and east directions are modeled as the system states in the position filter. Obviously, the state of position is the integration of velocity and the state of velocity is the integration of acceleration. For simplicity, we model the vehicle velocity as a constant with an input noise driven by the vehicle acceleration. Therefore, the system model for the INS position filter is defined as follow:

$$\underbrace{\begin{bmatrix} \dot{P}_N \\ \dot{P}_E \\ \dot{V}_N \\ \dot{V}_E \end{bmatrix}}_{\dot{\mathbf{x}}} = \underbrace{\begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}}_{\mathbf{F}} \underbrace{\begin{bmatrix} P_N \\ P_E \\ V_N \\ V_E \end{bmatrix}}_{\mathbf{x}} + \underbrace{\begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix}}_{\mathbf{G}} \underbrace{\begin{bmatrix} w_{V_N} \\ w_{V_E} \end{bmatrix}}_{\mathbf{u}} \tag{12}$$

where P_{Nn} and P_{Ne} are the north and east position states; V_{Nn} and V_{Ne} are the north and east velocity states; and w_{V_n} and w_{V_E} are the driving noise for the north and east velocity states.

Based on the above dynamics model, the position filter is actually performing a linear combination between GPS position and the corrected INS velocity using the Kalman gain weighting. To compute the correct Kalman gain, GPS position error must be modeled properly. For land vehicle applications under various signal degradation conditions, however, GPS measurement is likely corrupted by multipath and high code noise so that GPS position error is changing quickly with environments and the accurate estimation of a priori knowledge about the position errors and noise statistics becomes a challenge. To model GPS position error more appropriately, an innovation-based adaptive filtering algorithm with unknown measurement noise covariance, a fuzzy logic rule-based GPS data classification system and vehicle dynamics knowledge are integrated here to adapt the covariance of GPS position error.

More specifically, for each channel, we decrease the innovation-based adaptive measurement noise covariance to the power of 0.5 and 0.75 when GPS position is obtained under low and medium signal-degraded conditions. Therefore, when good GPS position is available, the adaptive measurement noise covariance is reduced to better characterize the real GPS performance. When vehicle is stationary, the vehicle position should be unchanged but GPS position may drift and change slowly over time due to the smoothing feature provided by the in-receiver filter. To prevent the drift effect on the filter position, we assign an extremely large measurement noise covariance for GPS position when vehicle is stationary. Table 1 lists the AI-based modification of the adaptive measurement noise covariance for GPS positions based on signal degradation condition and vehicle dynamics. $\hat{\mathbf{R}}_k$ denotes the innovation-based adaptive measurement noise covariance. Details about the innovation-based adaptive Kalman filter can be found in [19].

Table 1. AI-enhanced adaptive measurement noise covariance for GPS position

Vehicle dynamics	Non-stationary			Stationary
Signal degradation condition	Low	Medium	High	All
Measurement covariance	$\hat{\mathbf{R}}_k^{0.5}$	$\hat{\mathbf{R}}_k^{0.75}$	$\hat{\mathbf{R}}_k$	10^6

IV. Experimental Results

To examine the AI-enhanced integration algorithm, several road tests in downtown Calgary, Canada have been performed. A low-cost Xsens MT9 MEMS inertial sensor and a SiRF Star II GPS receiver were mount on a land vehicle for road tests. The MT9 is a miniature inertial measurement unit providing serial digital output of 3D acceleration, 3D rate of turn and 3D earth-magnetic field data with the sensor specifications shown in Table 2. The SiRF GPS receiver is a low-cost single-frequency 12-channel receiver which provides code-based single point positioning solutions. The data output rate of the MEMS inertial sensor and GPS receiver was chosen as 20 Hz and 1 Hz, respectively.

The test route was chosen to have a variety of spatial urban characteristics as shown in Fig. 4. Four data collection runs on the route were performed, each starting in a nearly open-sky area to obtain good GPS position fix. Then the vehicle moved into the core of downtown areas and took about 10 minutes to finish a loop of about 2 km in length. During the test the vehicle frequently stopped on the traffic lights and had the speed varied from 0-40 km/h. A digital map of downtown Calgary provided by the city of Calgary was used as reference for position accuracy analysis. The map provides the coordinates of a road centerline with several meters accuracy.

Shown in Fig. 5 are GPS positions and fuzzy data classification results obtained from a sample run. GPS positions are marked with different colors and symbols according to the data classification results. As shown, GPS position accuracy degraded in the core of downtown areas. GPS position performance is inconsistent and unstable, i.e., some on the track and some off the track by a hundred-meter level. Using fuzzy data classification, we have identified the erroneous GPS positions as the high signal-degraded data. In addition, more accurate and stable position solutions have been identified as the low or medium signal-degraded data as shown in Fig.5

Table 2. MT9 specifications

Parameter	Gyro	Accelerometer	Magnetometer
Unit	deg/s	m/s^2	mGauss
Operating range	+/- 900	+/- 20	+/- 750
Linearity	0.1	0.2	1
Bias stability (1σ)	5	0.02	0.5
Noise (RMS)	0.7	0.01	4.5

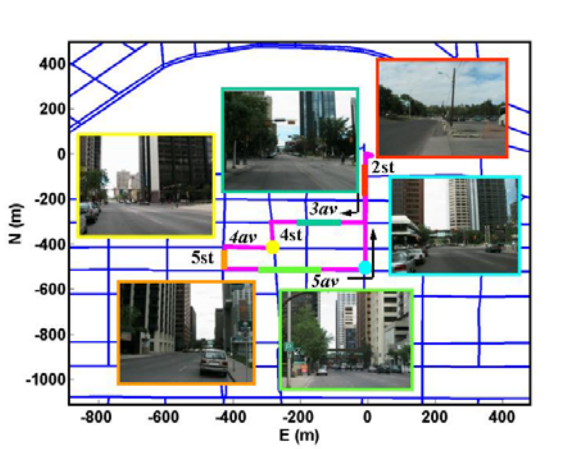

Fig. 4. Downtown test route

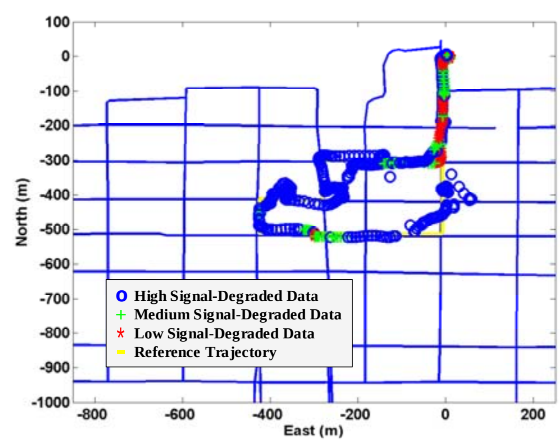

Fig. 5. GPS positions and classification results.

Shown in Fig. 6 is the MT9/GPS integration result obtained from the same sample run. The trajectories derived from the integration of the dynamics-aided velocity filter outputs with GPS positions using the conventional adaptive Kalman filter

(AKF) and using the AI-enhanced adaptive Kalman filter (AI+AKF) are marked with cyan squares and pink diamonds, respectively. As shown, the AI+AKF solution keeps on the reference trajectory quite well while the AKF solution has some position drifts away from the track. This demonstrates the advantage of the AI-enhanced AKF in terms of better characterizing the real GPS performance and separating the slowly changing GPS position error.

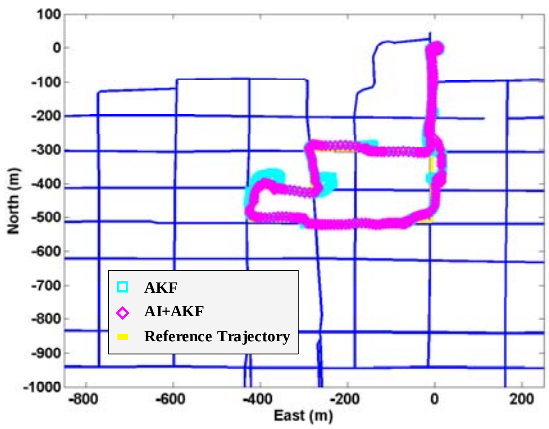

Fig. 6. MT9/GPS integrated positions.

Table 3 lists the obtainable position accuracy of the integrated solutions versus GPS solutions from four-run tests. Because in our test the digital map is the only available reference, the across-track errors are computed for position accuracy analysis. As shown, the AI-enhanced integrated solution provides the best position accuracy. Compared to the stand-alone GPS solution, the average maximum across-track error is reduced from a hundred-meter level to about 37 meters. Compared to the conventional adaptive position filter, the AI-enhanced adaptive position filter provides about 11%, 20% and 26% improvement in the average maximum, mean and RMS of the across-track error, respectively.

Table 3. Integrated MT9/GPS vs. GPS position accuracy.

Across-Track Errors		Test Run #				Average
		1	2	3	4	
GPS	MAX (m)	48.62	216.80	105.55	80.18	112.79
	Mean (m)	7.00	20.91	10.72	12.06	12.67
	RMS (m)	10.21	45.37	20.29	22.16	24.51
AKF	MAX (m)	35.54	50.23	51.53	31.37	42.17
	Mean (m)	6.32	10.63	9.37	7.34	8.42
	RMS (m)	9.08	15.62	15.10	10.51	12.58
AI+AKF	MAX (m)	34.72	33.02	42.58	39.75	37.52
	Mean (m)	4.05	7.49	8.36	6.79	6.67
	RMS (m)	5.73	9.64	12.14	9.73	9.31

V. Conclusion

The traditional Kalman filter methodology was found insufficient for low-cost MEMS INS/GPS integration due the difficulty of controlling INS error drift and charactering the corrupted GPS data. This paper has applied the expert knowledge of vehicle dynamics to simplify filter dynamics models and to extend measurement update schemes so that the INS error can be reduced and well controlled. In addition, a fuzzy system has been developed to identify GPS signal degradation conditions so that GPS performance can be better characterized. Incorporating these two AI-based methods with adaptive Kalman filter, an enhanced integration algorithm has been developed and implemented to a low-cost MEMS INS/GPS integrated system. The results of road tests in urban areas have shown that the proposed AI-based methods can better characterize the real GPS performance and identify the slowly changing GPS position error. The AI-enhanced integrated system can provide continuous and reliable navigation solutions with about 9 m RMS of the across-track error for land vehicle applications in urban areas.

References

[1] M. Wei, and K. P. Schwarz, “Testing A Decentralized Filter for GPS/INS Integration,” in *Proc. IEEE PLANS 1990*, Las Vegas, NV, March 1990, pp. 429–435.
[2] O. S. Salychev, *Inertial Systems in Navigation and Geophysics.* Bauman MSTU Press, 1998.
[3] B. M. Scherzinger, “Precise Robust Positioning with Inertial/GPS RTK,” in *Proc. Institute of Navigation GPS 2000*, Salt Lake City, UT, Sept. 2000, pp. 155–162.
[4] M. G Petovello, “Real-time Integration of Tactical-Grade IMU and GPS for High-Accuracy Positioning and Navigation,” PhD dissertation, Dept. Geomatics Eng., Univ. of Calgary, Calgary, AB, 2003.
[5] A. Brown, and Y. Lu, “Performance Test Results on an Integrated GPS/MEMS Inertial Navigation Package,” in *Proc. Institute of Navigation GNSS 2004*, Long Beach, CA, Sept. 2004, pp. 825-832.
[6] R. Jaffe, S. Bonomi, and A. M. Madni, “Miniature MEMS Quartz INS/GPS Description and Performance Attributes,” in *Proc. Institute of Navigation GNSS 2004*, Long Beach, CA, Sept. 2004, pp. 852-863.
[7] G. Lachapelle, H. Kuusniemi, D. Dao, G. MacGougan, and M.E. Cannon, “HSGPS signal analysis and performance under various indoor conditions,” in *Proc. Institute of Navigation GPS 2003*, Portland, OR, Sept. 2003, pp. 1171-1184.
[8] H. Kuusniemi, G. Lachapelle, and J. Takala, “Position and velocity reliability testing in degraded GPS signal environments,” *GPS Solutions*, vol. 8, no. 4, pp. 226-237, Dec. 2004.
[9] T.J. Ross, *Fuzzy Logic with Engineering Applications*, McGraw-Hill, 1995.
[10] A. Kandel (Editors), Fuzzy Expert Systems. Boca Raton, FL: CRC Press, 1992.
[11] J-S.R. Jang, C.-T. Sun and E. Mizutani, *Neuro-Fuzzy and Soft Computing.* Upper Saddle River, NJ: Prentice Hall, 1997.
[12] S. Haykin, *Neural Networks: A Comprehensive Foundation*. Upper Saddle River, NJ: Prentice Hall, 1999.
[13] R. C. Luo., C-C. Yih, and K. L. Su “Multisensor Fusion and Integration: Approaches, Applications, and Future Research Directions,” *IEEE Sensors Journal*, vol. 2, no. 2, pp. 107-119, 2002.
[14] A. Brandt, and J.F. Gardner “Constrained Navigation Algorithms for Strapdown Inertial Navigation Systems with Reduced Set of Sensors,” in *Proc. the American Control Conference*, Philadelphia, Pennsylvania, June 1998, pp. 1848-1852.
[15] S. Sukkarieh, “Low Cost, High Integrity, Aided Inertial Navigation Systems for Autonomous Land Vehicles,” Ph.D. dissertation, Australian Centre for Field Robotics, Dept. of Mechanical and Mechatronic Eng., Univ. of Sydney, Sydney, Australia, 2000.
[16] J.-H. Wang, Y. Gao and Y. Zhang “An Intelligent MEMS IMU-Based Land Vehicle Navigation System Enhanced by Dynamics Knowledge,” in *Proc. Institute of Navigation AM 2004*, Cambridge, MA, USA, June 27-29, 2005.
[17] J-H. Wang, and Y. Gao “High Sensitivity GPS Data Classification based on Signal-Degraded Conditions,” *IEEE Trans. Vehicular Technology*, submitted for publication.

[18] E.H. Mamdani, and S. Assilian, "An experiment in linguist synthesis with fuzzy logic controller," *International Journal of Man-Machine Studies*, vol. 7, no. 1, pp. 1-13, 1975.
[19] R.K. Mehra "Approaches to adaptive filtering," *IEEE Trans. Automatic Control*, AC-17, pp. 693-698, 1972.