Development of an Intelligent and Hybrid Scheme for Rapid INS Alignment

*Yun-Wen Huang[1], Kai-Wei Chiang[2]

[1]Department of Geomatics, National Cheng Kung Univ.(E-mail: p6694101@mail.ncku.edu.tw)
[2] Department of Geomatics, National Cheng Kung Univ. (E-mail: kwchiang@ mail.ncku.edu.tw)

Abstract

This article propose a new idea of developing a hybrid scheme to achieve faster INS alignment with higher accuracy using a novel procedure to estimate the initial attitude angles that combines a Kalman filter and Adaptive Neuro-Fuzzy Inference System architecture. A tactical grade inertial measurement unit was applied to verify the performance of proposed scheme in this study. The preliminary results indicated the outstanding improvements in both time consumption for fine alignment process and accuracy of estimated attitude angles, especially in heading angles. In general, the improvement in terms of time consumption and the accuracy of estimated attitude estimated accuracy reached 80% and 70% respectively during alignment process after compensating the attitude angles estimated by an extended Kalman filter with 15 states using proposed approach. It is worth mentioned that the proposed approach can be implemented in general real time navigation applications.

Keywords: INS, alignment, Kalman filter, fuzzy logic.

1. Introduction

In order to provide navigation solutions (i.e., position, velocity, and attitude) using the specific forces and angular rate provided by an IMU, an INS mechanization which consists of the orientation of the IMU with respect to the navigation frame is needed. The relationship between navigation frame and body frame is described using the transformation matrix R_b^n . However, the transformation matrix needs to be updated continuously since it works on a moving platform. The accuracy of those navigation parameters depends on the initial value of the transformation matrix R_b^n . The process of computing the initial value of R_b^n is known as the alignment of an IMU [El-Sheimy et al., 2004]. Alignment is accomplished with coarse alignment (CA), and fine alignment (FA). The CA process provide a quick orientation of the platform with respect to the navigation frame using the accelerations and angular rates obtained directly from the sensors without consideration of their errors [Jekeli, 2001]. For the strapdown system, a course alignment can be done in a similar way, though strictly in analytical and numerical way. On the other hand, FA provides optimal estimate algorithm to estimate the error of inertial systems.

The purpose of the CA is the determination of approximate values of the attitude angles (roll, pitch, and heading) between the body frame and navigation frame. The FA, then, refines the CA estimated attitudes using an iterative optimal estimation technique [Savage, 2000]. However, the obtained accuracy from alignment process depends mainly on the performance of the inertial sensors, i.e., sensor biases and output noise [Salychev, 1998]. Due to the relatively large measurement noise of the inertial sensors, especially for gyroscopes, usually need more time for the KF to converge [El-Sheimy et al., 2004]. Measurement errors, especially gyro bias, would extend the time needed to perform an accurate alignment. Since a key benchmark figure for many INS based navigation systems is the amount of time the INS needs to achieve readiness for navigation, considerable effort goes into devising fast, but accurate alignment and initialization procedure [Jekeli, 2001]. Recently, some of the alternative techniques have been developed to improve the accuracy of estimated by the Kalman filter; for example, El-Sheimy et al., [2004] incorporated wavelet denoising technique with Kalman filter to accelerate the alignment process with improved accuracy.

On the other hand, Artificial Intelligence (AI) techniques have been applied to develop alternative INS/GPS integration schemes to overcome the limitations of Kalman filter and improve the positional accuracy of a vehicular navigation system during GPS signal blockages successfully [Chiang, 2004]. However, utilizing AI techniques to improve the accuracy of the alignment are still not active research works in authority aspects. Therefore, this article will focus on two objectives: (1) construct a hybrid alignment scheme using a Kalman filter and Adaptive Neuro-Fuzzy Inference System (ANFIS) to achieve faster alignment with higher accuracy in comparison with a conventional scheme that uses a Kalman filter and (2) verify the performance of proposed scheme using several field test data that were collected independently.

2. Mechanization and Optimal Estimation of INS

The convergence time and accuracy of the conventional alignment algorithm, i.e. CA + FA, are mainly depending on the fine alignment. Since the only signals during stationary alignment process that can affect the inertial sensors are the Earth's gravity and the Earth's rotation rate, the autonomous alignment method can be done only when the gyro bias is smaller than the value of the Earth's rotation rate [El-Sheimy et al., 2004]. Fine alignment use the INS mechanization and the navigation KF (with some simplification sometimes) but only applying the measurement updates of zero velocity and the Earth rate, which are available in the static mode. So the key parts of the fine alignment are actually the navigation algorithm.

2.1. INS Mechanization Equations

The essential process implemented in any inertial navigation algorithm is the INS mechanization process. The INS mechanization equations integrate the accelerations and angular rates provided by the inertial sensors (accelerometers and gyroscopes) to compute the position, velocity, and attitude (PVA) of the vehicle [Wong, 1988]. The algorithm takes into account the earth rotation rate and gravity. These mechanization equations can be simply presented as follows:

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

where r^l is the position vector, v^l is the velocity vector, R_b^l is the transformation matrix from the IMU body to local level frame as a function of attitude components, g^l is the gravity vector in the local level frame, $\Omega_{ib}^b, \Omega_{il}^b$ are the skew-symmetric matrices of the angular velocity vectors $\omega_{ib}^b, \omega_{il}^b$ respectively, and D^{-1} is a 3x3 matrix whose non zero elements are functions of the user's latitude and ellipsoidal height.

For further details of solution and numerical implementation 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 these 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].

2.2 Kalman Filtering

The dynamic error model used in a 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. In addition to the nine navigation elements in (equation 2), states of the dynamic model include the sensor errors (three accelerometer biases and three gyro drifts). It is a common tend to model the stochastic part of these sensor errors as first order Gauss Markov process. The state space representation of dynamic error model is of the form:

$$\dot{x} = Fx + Gw \quad (2)$$

where x is the error state vector of inertial navigation containing the following 15 states, F is the dynamic matrix, a detail element expression of the matrix is proven in [Mohinder and Angus, 2001], and w in equation (2) is a zero-mean Gaussian white noise vector.

Kalman filtering can be used to optimally estimate these elements using a form of feedback control at the current epoch. For this purpose, the statistical properties of the system should be well defined. In a Kalman filter, the final state estimates are based on a combination of predicted states and the actual measurements. Basically, the equations of KF are divided into two groups [El-Sheimy, 2002]; 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 time prediction equations are [Gelb, 1974]:

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

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

where $\hat{x}$ and P are the optimally estimated state vector and its variance-covariance matrix of inertia states, Q is the system noise covariance matrix, $(-)$ denotes the estimated value after prediction, and $(+)$ denotes the estimated value after updating. The measurement update equations utilize new measurements into the a priori state estimate to obtain an optimized a posteriori state estimate.

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

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

$$P_k(+) = P_k(-) - K_k H_k^T P_k(-) \quad (7)$$

The measurement update equations are given from equation (5) to (7) where the Kalman gain matrix is K, z is the vector of updating measurements of position and velocity, and R is the measurements variance-covariance matrix.

For the case of fine alignment, the measurement vector (i.e. z) is normally consists of only the velocity (which is zero for stationary alignment). Sometimes the earth rate is also included as an additional update.

3. Concepts of Fuzzy Logic and ANFIS

Fuzzy logic systems have been considered as an alternative approach which is able to cope with uncertain information and to provide a framework for handling uncertainty and imprecision in real-world application. It is able to simultaneously handle numerical data and linguistic knowledge. It is also a nonlinear mapping of an input data (feature) vector into scalar output, in other words, it maps numbers into numbers [Mendel, 1995]. Fuzzy logic algorithms accomplish this by allowing computers to simulate human reasoning with less bias, but, in the process, to behave with less analytical precision and logic than traditional computing methods [Turban and Aronson, 2000].

Unlike the traditional hard computing, soft computing strives to model the pervasive imprecision of the real world. Solutions derived from soft computing are generally more robust, flexible, and economical than those provided by hard computing [Malhotra and Malhotra, 1999]. Moreover, fuzzy logic with neural networks and probabilistic reasoning constitute the three cornerstones of soft computing, a trend that is growing in visibility [Zadeh, 1994].

3.1 Fuzzy Inference Systems

Fuzzy inference systems (FIS) have recently gained reputation as well established means of utilizing human intelligence machines. There are three types of fuzzy inference systems, which are used in several aspects of engineering applications: the Tagaki-Sugeno-Kang (also known as Sugeno), the Mamdani FIS or the TSK-FIS and the Tsukamoto fuzzy inference systems (TS-FIS) [Sugeno 1985, Jang et al. 1997 and Cordón et al. 2001]. They are different in their methods of fuzzification of the input space, defuzzification to the output space and aggregation [Reda Taha et al., 2003], while all FIS use similar logic. In this article, TSK-FIS shall be used for modeling unknown process.

A fuzzy inference system is composed of five components, as shown in the Figure (1). A rule base containing a number of fuzzy if-then rules which are capable of describing the desire system behaviors, and a database defines the membership functions of the fuzzy sets used in the fuzzy rules. Usually, the rule base and the database are jointly referred to as the knowledge base [Jang, 1993]. Decision-making unit performs the inference operations on the rules. Fuzzification is defined as the process of mapping numerical inputs to the fuzzy domain of the model which ranges between zero and one using membership functions. These membership functions define how much each data point belongs to each data set or cluster in the input space. On the other hand, defuzzification is regard as the process of transferring the aggregated fuzzy sets at the output space to a single value that represents the membership of the output parameter to the aggregated fuzzy set [Reda Taha,. et al., 2003]. The defuzzification process is usually done using the centroid function in Mamdani systems [Mamdani and Assilian, 1975] and the weighted average in Tagaki-Sugeno-Kang (TSK) systems [Sugeno, 1985].

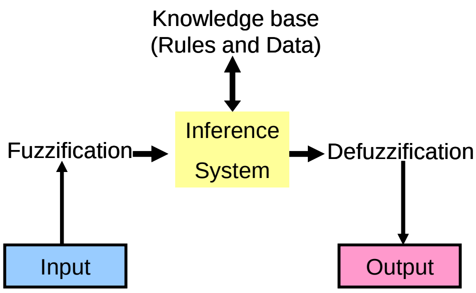

Figure 1. Fuzzy inference system

3.2 ANFIS Architecture

Normally, an approximate fuzzy model is first initiated by the system, and then improved through an iterative adaptive learning process. The training algorithm was developed by Jang [1993] and is referred to as the ANFIS or Adaptive Neuro-Fuzzy Inference System. ANFIS was proposed in order to combine the advantages of both neural networks and fuzzy inference systems [Jang et al. 1997].

Figure (2) illustrates a possible architecture of ANFIS for two-input one-output system. Input X is assumed to have three membership functions and two membership functions for input Y. Fuzzification process is done at layer 1. The fuzzified inputs which mean weights are normalized using a T-norm operator at layer 2. At layer 3, the ratio of every rule's firing strength of the sum of all rules' firing strength is calculated, and the fuzzy rules are applied at layer 4. Finally, the output Z in layer 5 is gained by the sum of the weighted outputs of all fuzzy rules.

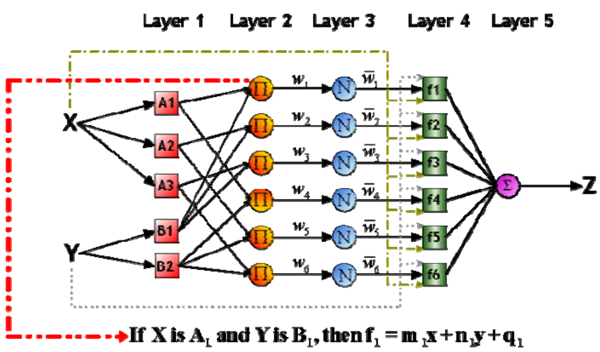

Figure 2. A general ANFIS architecture

ANFIS algorithm is basically a technique which provides a method for fuzzy modeling procedure to learn information about a given data set to compute the membership function parameters that best allow the associated fuzzy inference system to track the input/output data. This learning method is quite similar to the training of neural networks and combines back-propagation and least mean square optimization algorithm. In addition, the membership functions are tuned with gradient decent method to determine the premise parameters. Training won't stop until the preset epoch number or error rate is obtained. Neuro-fuzzy systems have been proven as efficient modeling techniques for mapping non-linear systems.

4. Proposed Hybrid Scheme

The Kalman filter (KF) is utilized to optimally estimate the initial attitude errors as well as the sensor biases and compensate for their effect. This process usually requires about 10 to 15 minutes of static data for tactical-grade IMUs. The observations (updates) for .the KF, in this case, are Zero Velocity Updates (ZUPTs).

4.1 Training of the ANFIS-KF Intelligent Scheme

In order to accelerate the INS alignment process and obtain those initial attitude angels with higher accuracy, an intelligent compensation method can be implemented to predict the error in fine alignment procedure. During the alignment process, the outputs of Kalman filter might contain the errors that can not be estimated well due to the limitations mentioned in Chiang [2004]. Consequently, the overall accuracy of estimated attitude angles can be deteriorated. In addition, Kalman filter requires more time to converge. Therefore, an algorithm that can predetermine the error behavior of Kalman filter is needed. Hence, an ANFIS-KF integrated algorithm is delivered to do so. Once it has been trained well, The ANFIS is expected to work efficiently to compensate the errors of predicted by the KF used.

As indicated in Figure (3), the errors of roll, pitch, and heading estimated by Kalman filter are used as the desired output or target values during the learning process of three different ANFIS architectures, respectively. It is decided to use three separated architectures instead of one because the error behaviors of roll, pitch, and heading vary. In addition, the roll, pitch and heading angles along with the time information in each scenario are used as the inputs for those architectures, respectively.

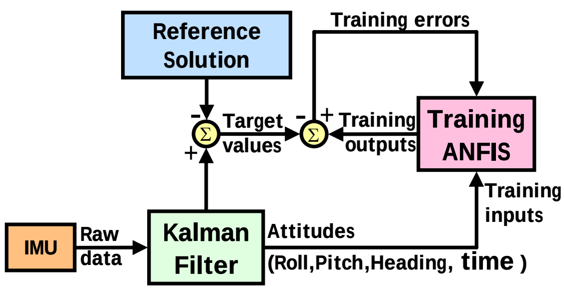

Figure 3. An ANFIS training architecture

In this article, the target values, the initial attitudes errors of the Kalman filter, were obtained with respect to reference solution which is generate by the post mission process (e.g. smoothing algorithm) using a high-accuracy navigation grade IMU. The parameters of membership functions of the ANFIS are then tuned epoch-by-epoch according to the training error. The training process terminates after the training errors reach the error threshold. This process can be regarded as the training mode of the proposed hybrid scheme.

4.2 Predicting Errors Using ANFIS-KF Architecture

After being well trained, the proposed ANFIS architectures can then be utilized in compensation or prediction mode when the new measurements provided by an IMU in alignment mode are applied. Similar to the training mode, the hybrid architecture first receives raw data from an IMU then uses a 15 states Kalman filter in ZUTPs mode to estimate initial attitude angles, meanwhile, the estimated attitude angles are sent to proposed ANFIS architectures along with time information in each scenario to generate predicted errors for compensating the estimated angles provided by the Kalman filter simultaneously. Errors of three attitude angles are predicted with three different ANFIS architectures, and the correction would be completed after the predicted errors have been removed from the outputs of KF. A prediction process is illustrated in the Figure (4). It is worth mentioning that the proposed architectures can be operated in real time for compensating those initial attitude errors.

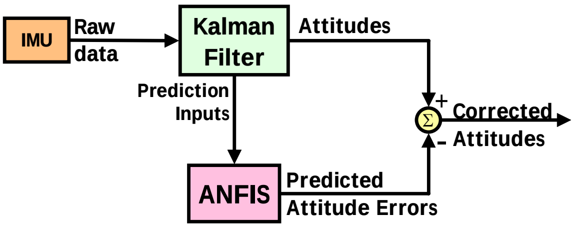

Figure 4. ANFIS prediction architecture

5. Experimental Result of Proposed Scheme

5.1 The Platform

In order to evaluate the effectiveness of the proposed ANFIS-KF model, three field test data (provided by the MMSS group at the Department of Geomatics Engineering, the University of Calgary) incorporating a tactical-grade IMU, LN200 (Litton) and navigation-grade IMU, CIMU (Honeywell).

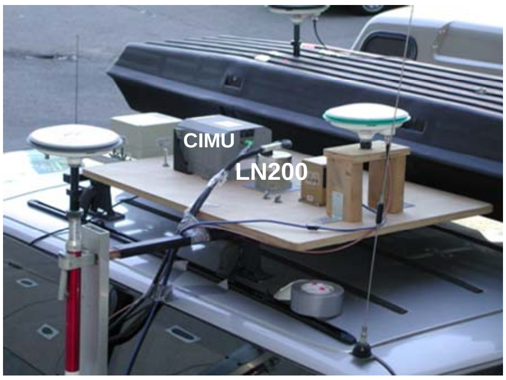

Figure 5. Setting of LN200 and CIMU

Three field data were collected under different environment and time. Therefore, these filed data can be considered independent from each other. The setting of LN200 and CIMU is shown in Figure (5). The axes of LN200 are basically aligned together with the axes CIMU of in order to provide reference solutions. The reference solutions were generated in post-mission mode using a navigation grade IMU, CIMU.

5.2 Training Result

The first test data was utilized as the training data. The length of this data set is 300 seconds. Since the ANFIS was trained by 1st test data, it learnt the estimated error behaviors of the attitude angles provided by the Kalman filter using the same data set very well. As indicated in the Figure (6), the estimated attitude errors were almost removed through compensation process using the proposed scheme. In addition the Root Mean Square (RMS) errors of proposed scheme and Kalman filter are listed in Table 1. As stated previously, since the training data set was utilized as test data set in this scenario, the attitude errors estimated by Kalman filter were compensated well.

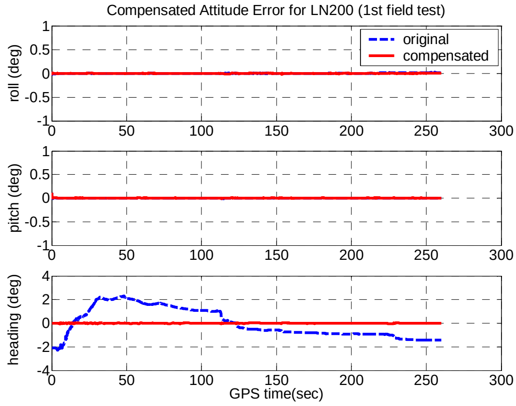

Figure 6. Compensated attitude errors (1st data set)

5.2 Testing Result

To examine the performance of proposed scheme in prediction mode, two field test data sets that were collected independently from the training data set were applied as the test data sets. The time spans of those data sets are 300 seconds and 70 seconds, respectively. Figures (7) and (8) demonstrate the enhancement after applying compensation scheme. As indicated in both figures, there are no significant improvements after applying proposed scheme for compensating roll and pitch errors as those errors are well estimated using Kalman filter. However, the heading errors in both scenarios are well compensated in term of the magnitude of the heading error as well as the time span for convergence. The significant improvement in heading errors in accuracy and time after applying compensation scheme are listed in Tables 1 and 2.

Table.1: RMS value enhancement after compensation

Field test	Attitude Angle	RMS value (degree)		Improvement (%)
		original	compensated	
1^{st}	roll	0.0068	0.0030	56%
	pitch	0.0039	0.0037	5%
	heading	1.2532	0.0149	98.8%
2^{nd}	roll	0.0094	0.0080	14.9%
	pitch	0.0022	0.0023	-4.5%
	heading	0.7923	0.0448	**94.4%**
3^{rd}	roll	0.0117	0.0088	24%
	pitch	0.0039	0.0042	-7.7%
	heading	0.2964	0.0913	**69.2%**

Table.2. Alignment time enhancement after correction

Field test	Alignment time of heading(sec)		Improvement (%)
	original	compensated	
2nd	185	20	89.1%
3rd	253	27	89.3%

As indicated, the time epochs for convergence in heading errors are indicated by arrows in the Figures (7) and (8). The significant improvement in heading errors in accuracy and time after applying compensation scheme are listed in Tables 1 and 2. As presented in Table 1, the improvements in heading errors after applying compensation scheme reach 94.7% and 69.2%, respectively. In addition, Table 2 verifies the improvement in convergent time to be 89.1% and 89.3%, respectively. In other words, based on the field test data sets applied in this article, the proposed scheme is able to provide a faster alignment procedure with superior accuracy in compensating heading error, which is the most difficult element to estimate during normal alignment process.

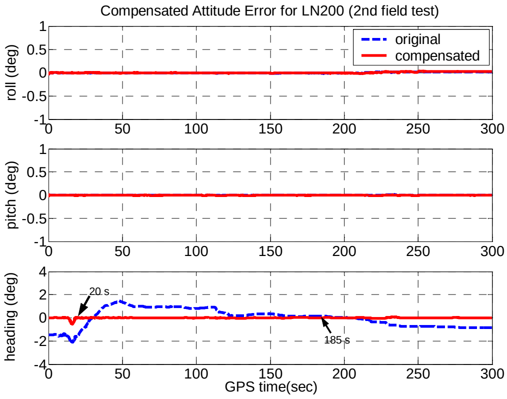

Figure 7. Compensated attitude errors (2nd data set)

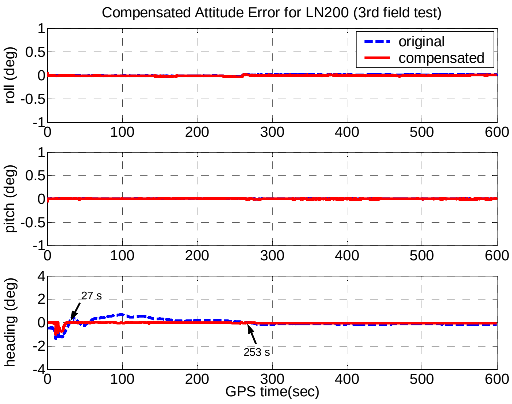

Figure 8. Compensated attitude errors (3rd data set)

This is the template to produce the proceedings for IAIN/GNSS 2006. The paper should be submitted surely after author's confirmation if there is no error because it will be published as it is.

6. Conclusion

The idea of developing a hybrid scheme to reach faster IMU alignment with higher accuracy using a novel procedure that combines an ANFIS architecture and Kalman filter is presented in this article. The ANFIS architectures were first trained to learn the residual error of Kalman filter using the field data set gathered with a tactical grade IMU (LN200). Then the proposed architectures were evaluated in terms of the accuracy and time using two field test data sets that were collected independently from the training data set using the same system.

The preliminarily results presented in this article indicate the improvement of saving the time consumption of alignment process by 89.1% and 89.3%, respectively. In addition, the compensation schemes were able to improve in heading errors after applying compensation scheme reached 94.4% and 69.2%, respectively. In other words, based on the field test data sets applied, the proposed scheme in this article has a better performance that accelerate alignment procedure with superior accuracy in compensating heading error, which is much difficult to estimate than the other two attitude angles during normal alignment process.

Acknowledgement

The author would like to thank the financial support by NSC funds (95-2221-E-006-001-). Dr Naser El-Sheimy and Dr. Xiaoji Niu from the MMSS group at the Department of Geomatics engineering, the University of Calgary are acknowledged by providing the field test data sets applied in this research along with their knowledge about alignment process.

Reference

1. Bar-Itzhack, I.Y. and Berman, N., "Control Theoretic Approach to Inertial Navigation System," AIAA Journal of Guidance, Control & Dynamics, vol. 11, 1988,pp. 237-245.

2. Chae, M. J. and Abraham, D. M., "Neuro-Fuzzy Approached for Sanitary Sewer Pipeline Condition Assessment," Journal of Computing in Civil Engineering, ASCE, 2001, Vol. 15, No. 1, pp. 4-14.

3. Chiang, K.W., "INS/GPS Integration Using Neural Networks for Land Vehicular Navigation Applications", UCGE Report 20209, Department of Geomatics Engineering, The University of Calgary, Calgary, Canada, 2004.

4. Cordón, O., Herrera, F., Hoffmann, F. and Magdalena, L., "Genetic Fuzzy Systems: Evolutionary Tuning and Learning of Fuzzy Knowledge Bases. Advances in Fuzzy Systems- Applications and Theory," World Scientific, Singapore, 2001.

5. El-Sheimy, N., Nassar S., Noureldin, A., "Wavelet De-Noising for IMU Alignment," IEEE A&E Systems Magazine, 2004.

6. El-Sheimy, N., "Introduction to Inertial Navigation", ENGO 699.71 lecture notes, Geomatics department, University of Calgary, 2002.

7. El-Sheimy, N., Abdel-Hamid, W. and Lachapelle, G., "An Adaptive Neuro-Fuzzy Model for Bridging GPS Outages in MEMS-IMU/GPS Land Vehicle Navigation," ION/GNSS 17th International Technical Meeting of the Satellite Division, Long Beach, CA, 2004.

8. Gallo, S., Murino, T. and Santilllo, L. C., “Time Manufacturing Prediction: Preprocess Model in Neuro Fuzzy Expert System,” CD Proceedings of European Symposium on Intelligent Techniques, Greece, 1999, pp. 11.

9. Gelb, A., “Applied Optimal Estimation,” The Analytic Science Corporation, 1974.

10. Jang, J., “ANFIS: Adaptive-Network-Based Fuzzy Inference System,” IEEE Transactions on Systems, Man, and Cybernetics, 1993, Vol. 23, No. 3, pp. 665-685.

11. Jang, J., “Self-Learning Fuzzy Controllers Based on Temporal Back Propagation,” IEEE Transactions on Neural Networks, 1993, Vol. 3 No. 5, pp. 714-23.

12. Jang, J. -S. R., Sun, C. -T. and Mizutani, “Neuro-Fuzzy and Soft Computing, A Computational Approach to Learning and Machine Intelligence,” Prentice Hall Inc., Englewood Cliffs, N.J., USA, 1997.

13. Jekeli, C., “Inertial Navigation Systems with Geodetic Applications,” Walter De Gruyter, Berlin, New York, 2001.

14. Lin, J. W., Hwang, M. I. and Becker, J. D., “A Fuzzy Neural Network for Assessing the Risk of Fraudulent Financial Reporting,” Managerial Auditing Journal, 2003, Vo. 18, No. 8, pp. 657-665.

15. Malhotra, R. and Malhotra, D., “Fuzzy Systems and Neuro-Computing in Credit Approval,” Journal of Lending & Credit Risk Management, 1999, Vol. 81 No. 11, pp. 24-37.

16. Mamdani, E. and Assilian, S., “An Experiment in Linguistic Synthesis with a Fuzzy Logic Controller,” International Journal of Manmachine Studies, 1975, Vol. 7 No. 1, pp. 1-13.

17. Mendel, “Fuzzy Logic Systems for Engineering: A Tutorial,” IEEE, 1995.

18. Mohinder, S.G. and Angus, P.A., “Kalman Filtering: Theory and Practice Using MATLAB,” 2nd Edition, ISBN: 0-471-39254-5, Wiley Inter Science, Canada, 2001.

19. Salychev, O., “Inertial System in Navigation and Geophysics,” Bauman Moscow State Technical University Press, Moscow, Russia, 1998.

20. Savage, P. G., “Strapdown Analytics,” Part I, Strapdown Associates, Inc., Maple Plain, Minnesota, USA, 2000

21. Sugeno, M., 1985, “Industrial Applications of Fuzzy Control,” Elsevier Science Publishing Company, NY, USA.

22. Reda-Taha, M. M., Noureldin, A. and El-Sheimy, N., “Improving INS/GPS Positioning Accuracy During GPS Outages Using Fuzzy Logic,” ION GPS/GNSS 2003, Portland, OR, 2003.

23. Turban, E. and Aronson, J., “Decision Support Systems and Intelligent Systems,” 6th ed., Prentice-Hall, Englewood Cliffs, NJ, 2000.

24. Van Bronkhorst, A., ”Strapdown System Algorithms,” Strap-Down Inertial Systems,” AGARD, Agardograph, 1978, No:95.

25. Wong, R.V.C., “Development of a RLG Strapdown Inertial Navigation System,” PhD thesis, USCE Report Number 20027, Dept. of Geomatics Eng., the Univ. of Calgary, 1988.

26. Zadeh, L., “Fuzzy logic, neural networks and soft computing,” Communication of the ACM, 1994, Vol. 37 No. 3, pp. 77-84.