Research Article

The Integration of Rotary MEMS INS and GNSS with Artificial Neural Networks

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The rotary INS (inertial navigation system) has been applied to compensate the navigation errors of the MEMS (micro-electro-mechanical-systems) INS recently. In such system, the PVA (position, velocity, and attitude) errors can be compensated through IMU (inertial measurement unit) carouseling. However, the navigation errors are only partially compensated due to the intrinsic property of the inertial system and the randomness of the IMU errors. In this paper, we present an integrated rotary MEMS INS/GNSS (global navigation satellite systems) system based on the ANN (artificial neural networks) technique. The ANFIS (adaptive neuro-fuzzy inference system) is applied to eliminate the residual PV (position and velocity) errors of the rotary MEMS INS during GNSS outages. A cascaded velocity-position structure is designed to recognize the pattern of the rotary MEMS INS PV errors and to reduce them of the rotary inertial system in standalone mode. The road tests are conducted with artificial GNSS outages to evaluate the ability of the integrated system to predict the PV errors. Compared to the position errors of the integrated rotary INS/GNSS system based on an EKF (extended Kalman filtering), they are reduced by 79.98% in the proposed system.

1. Introduction

Nowadays, the MEMS (micro-electro-mechanical-systems) inertial sensors are already widely applied to the automotive applications, in spite of their significant sensor errors [1–3]. The PVA (position, velocity, and attitude) errors grow dramatically for a MEMS INS (inertial navigation system). Although the GNSS (global navigation satellite systems) was usually integrated with the INS to eliminate its navigation error accumulation, the navigation solutions still drift away during the GNSS outages [4]. The accumulated PVA errors of an inertial system remain as one of the main challenges for the land vehicle navigation.

In the past years, the rotary INS has been proposed to eliminate the navigation errors. In such approach, the IMU (inertial measurement unit) is installed on a carouseling platform or device, as shown in Figure 1 [5]. Then, the PVA errors are automatically reduced as the inertial sensor errors are modulated through certain IMU carouseling. In the early

studies, the rotary INS was mainly applied to high-end inertial system, such as the FOG (Fiber Optical Gyro) and RLG (Ring Laser Gyro), and different single-axis and multiaxis IMU carouseling schemes were proposed to eliminate the PVA error accumulations [6, 7]. Recently, such approach has raised attentions from MEMS INS navigation community and the single-axis rotation system was proposed for the land vehicle navigation. The theoretical error analysis for different types of accelerometer and gyro errors were firstly conducted with IMU carouseling about each axis, and then the real rotated tests conducted in the lab environment was used to verify the navigation error mitigations. The effect of the IMU rotation rate on PVA errors were also analysed [8]. The investigations on the application of rotary MEMS INS to the land vehicle navigation under dynamic environments were also conducted [9]. It was found that the navigation errors are more efficiently compensated with the inertial sensors that contain mainly the time-correlated (low-frequency) noise. Given the advantages

FIGURE 1: Structure of the rotary INS.

in dealing with the low-frequency noise in MEMS inertial sensors, the rotary MEMS INS was loosely integrated with GNSS based on an EKF (extended Kalman filtering) to bridge the GNSS outages [10]. Although the IMU rotation hardly affects the PVA solutions when GNSS measurements are available, it greatly reduces the PVA errors during GNSS outages. Existing research has proved that the IMU rotation compensates the PVA errors in the rotary MEMS INS; however, it does not alter its intrinsic property as a DR (dead-reckoning) system. As a result, the navigation errors still accumulate over time. For example, the position errors accumulate to hundreds of meters in minutes [9, 10]. To further eliminate the residual PVA errors of the rotary MEMS INS in the standalone mode (the PVA errors are partially compensated by IMU rotations), and other methodologies are required to be studied.

The ANNs (artificial neural networks) were widely employed to mimic the error pattern of the INS during GNSS outages in recent years, due to their ability for the nonlinear mapping between inputs and outputs without the predefined mathematical model [11]. Different ANNs, such as MLP (multilayer perceptron) [12], RBF (radial basis function) [13, 14], and ANFIS (adaptive neuro-fuzzy inference system) [15, 16], were investigated for navigations in previous studies, and they have been proved to be able to reduce the navigation errors. The limitation of MLP is that it is time-consuming to obtain the optimal number for the hidden layer and neurons [12]. In contrast, the RBF could dynamically generate the best internal structure due to its dynamic property [13]. The ANFIS provides superior performance in dealing with the randomness of the inputs [16]. Regarding the architectures for the INS/GNSS integration, the $P - \delta P$ model (or $V - \delta V$ model) is commonly employed [17]. The input and outputs of the ANN are the INS position (or velocity) and the INS position (or velocity) error, and the GNSS position (or velocity) is considered as the true value, which is used for training sessions. Such model has proved to be able to recognize the error behavior in the INS position and velocity during GNSS outages. Other architectures, such as the PUA (position update architecture) [18, 19], and hybrid approaches combine both ANN and EKF [20, 21], which were also well studied.

With the objective to further eliminate the residual navigation errors in the system with carouseling IMU, we

proposed to apply the ANN for the integration of the rotary MEMS INS and GNSS in this study. In the proposed system, the ANFIS is employed due to its superior ability to deal with the stochastic errors in the inertial data. Based on the $P - \delta P$ model, a cascaded velocity-position structure is designed to recognize the pattern of the rotary MEMS INS PV errors and then to predict them of the integrated system in the standalone mode. A nonoverlap window scheme is used for the GNSS and rotary inertial data processing [17]. The road tests are conducted with artificial GNSS outages to investigate the positioning accuracy of the integrated system. Compared to the position errors of the integrated rotary INS/GNSS system based on an EKF, they are reduced by 79.98% in the proposed system with the predicted error components from the ANFIS. To the author's best knowledge, the ANN techniques are applied for the first time for the integration of rotary INS with GNSS, though they have been widely employed for the nonrotary INS/GNSS system. In this paper, the rotary INS is referred to the inertial system with IMU carouseling, while the nonrotary INS is referred to the one with static IMU.

Adding the rotational device would nullify the typical advantage of MEMS accelerometers and gyros, namely, extreme compactness, low cost, and low power consumptions, as the rotation platforms are usually cumbersome. However, the low-cost MEMS IMUs can be installed on the centre of the wheel for the land vehicles. The rotation of IMU can improve the system observability and therefore result in lower estimation errors for certain error states. It is well known that the system observability of an inertial system is poor without manoeuvres and certain error state cannot be accurately estimated. As the observability of some error states are related to the IMU poses, proper IMU rotations can provide redundant observations which improve their observability.

In Section 2, the mechanization algorithm for the rotary MEMS INS, the carouseling effect on the sensor errors, and the proposed calibration procedure are given. Then, Section 3 presents the integration architecture based on ANFIS modules for the rotary MEMS INS and GNSS. The conducted road tests as well as the positioning error analysis are given in Section 4, and finally the conclusions are summarized in Section 5.

2. Rotary MEMS Inertial System

2.1. Mechanization Algorithm. In this paper, the body frame is defined as the RFU (right-forward-upward) coordinate frame. For the carouseling IMU, the accelerometer and gyro data are collected in the IMU frame, whose axes are usually defined as the sensitive axes of the IMU [5]. The navigation frame is defined as the ENU (east-north-upward) coordinate frame. The body, navigation, and IMU frames are referred as the B-frame, N-frame, and S-frame, respectively. In this study, the IMU carouseling scheme is defined that the IMU is rotating about its Z-axis, while the X- and Y-axes are aligned to the right and forward axes of the B-frame, respectively. Such carouseling scheme has been proved to be able to effectively reduce the horizontal PVA errors [5, 9, 10].

The unmodulated gyro errors in the Z-axis lead to accumulated azimuth errors and horizontal velocity and position errors related to vehicle dynamics. Eliminating those errors usually requires additional rotation about X- or Y-axis; however, they are not feasible for the single-axis system. In fact, the accumulated position and velocity error would be modelled and compensated by using ANFIS in this paper. More details will be given in Section 3. Although the PV in the navigation frame can be still computed through the traditional INS mechanization for the nonrotary INS, the rotation matrix from the B-frame to the N-frame, C_B^N , requires a transformation process as follows:

$$C_B^N = C_S^N C_B^S, \quad (1)$$

where $C_{K_1}^{K_2}$ is the rotation matrix from the K_1 frame to the K_2 frame and N, B, and S represent the navigation frame, body frame, and sensor frame, respectively. According to the definition of the rotation matrix, C_B^S can be calculated as

$$C_B^S = \begin{bmatrix} \cos \alpha & -\sin \alpha & 0 \\ \sin \alpha & \cos \alpha & 0 \\ 0 & 0 & 1 \end{bmatrix} \text{ for the designate rotation scheme,}$$

and α represents the IMU rotation angle, which is usually recorded by the rotation platform.

2.2. Carouseling Effect on Sensor Errors. The following present the IMU carouseling effects on the gyro biases, scale factors, and nonorthogonality errors. The effects on the accelerometer errors are similar [5, 9].

When the IMU rotates at a constant rate of ω , the gyro bias in the B-frame can be calculated, as shown in equation (2). If biases are constants, the errors in X- and Y-axes are modulated into periodic signals. Therefore, the resulted attitude errors are automatically removed after the rotation cycle. In contrast, the attitude errors caused by the bias in the Z-axis remains the same as the nonrotary INS because of the unmodulated bias in the Z-axis (rotation axis). Although biases usually are considered to be slow-varying errors (or time-correlated random errors), the resulted navigation errors can still be partially compensated. As the biases in the Z-axis cannot be modulated, only horizontal position and velocity are considered in the single-axis rotary INS mechanization [9]:

$$\eta^B = C_S^B \eta^S = \begin{bmatrix} \eta_x^S \cos \omega t + \eta_y^S \sin \omega t \\ -\eta_x^S \sin \omega t + \eta_y^S \cos \omega t \\ \eta_z^S \end{bmatrix}, \quad (2)$$

where η is the gyro bias vector, η_x , η_y , and η_z represent the gyro bias in the X-, Y-, and Z-axes of the coordinate frame, and the superscript B and S mean the vector or scalar is expressed in the B-frame and S-frame, respectively. The

rotation matrix C_S^B can be calculated as $\begin{bmatrix} \cos \omega t & \sin \omega t & 0 \\ -\sin \omega t & \cos \omega t & 0 \\ 0 & 0 & 1 \end{bmatrix}$, and t represents the time.

The MEMS IMU scale factor and nonorthogonality errors are treated as constants in this study, though they usually vary with the temperature. According to the IMU error model [22], the scale factors S_g and nonorthogonality errors N_g are described by equations (3) and (4), respectively:

$$S_g = \begin{bmatrix} \xi_x & 0 & 0 \\ 0 & \xi_y & 0 \\ 0 & 0 & \xi_z \end{bmatrix}, \quad (3)$$

$$N_g = \begin{bmatrix} 0 & \zeta_{xy} & \zeta_{xz} \\ \zeta_{yx} & 0 & \zeta_{yz} \\ \zeta_{zx} & \zeta_{zy} & 0 \end{bmatrix}, \quad (4)$$

where ξ_i represents the gyro scale factor along i -axis ($i = x, y, z$) and ζ_{ij} represents the nonorthogonality error between i -axis and j -axis ($i, j = x, y, z$).

Different from the biases, the scale factors motivate additional errors with carouseling IMU. According to equations (5) and (6), the scale factor of the rotation axis, ξ_z , is coupled with ω and motivates accumulated attitude errors in the rotation axis [5, 9]. Similarly, nonorthogonality errors also induce additional errors with IMU rotating as follows:

$$\begin{aligned} \delta \omega_{SF}^B &= C_S^B \delta \omega_{SF}^S \\ &= \begin{bmatrix} (\xi_x - \xi_y) \omega_{ie} \cos \varphi \sin \omega t \cos \omega t \\ (\xi_x \sin^2 \omega t + \xi_y \cos^2 \omega t) \omega_{ie} \cos \varphi \\ \xi_z (\omega_{ie} \sin \varphi + \omega) \end{bmatrix}, \end{aligned} \quad (5)$$

$$\int_0^T \delta \omega_{SF}^B dt = \begin{bmatrix} 0 \\ \frac{T \omega_{ie} \cos \varphi (\xi_x + \xi_y)}{2} \\ \xi_z (\omega_{ie} \sin \varphi + \omega) T \end{bmatrix}, \quad (6)$$

$$\begin{aligned} \delta \omega_N^S &= N_g \omega_{IS}^S \\ &= \begin{bmatrix} \zeta_{xy} \omega_{ie} \cos \varphi \cos \omega t + \zeta_{xz} (\omega_{ie} \sin \varphi + \omega) \\ \zeta_{yx} \omega_{ie} \cos \varphi \sin \omega t + \zeta_{yz} (\omega_{ie} \sin \varphi + \omega) \\ \zeta_{zx} \omega_{ie} \cos \varphi \sin \omega t + \zeta_{zy} \omega_{ie} \cos \varphi \cos \omega t \end{bmatrix}, \end{aligned} \quad (7)$$

$$\int_0^T \delta \omega_N^B dt = \begin{bmatrix} \frac{T \omega_{ie} \cos \varphi (\zeta_{xy} - \zeta_{yx})}{2} \\ 0 \\ 0 \end{bmatrix}, \quad (8)$$

where $\delta \omega_{SF}$ represents the motivated gyro bias vector by the scale factor during IMU carouseling, $\delta \omega_N$ represents the motivated bias vector by the nonorthogonality error, ω_{IS}

represents theoretical gyro output vector, the superscripts B and S mean the vector or scalar is expressed in the B -frame and S -frame, respectively, ω_{ie} and φ represent the Earth rotation rate, and the latitude, respectively, and T represents the time span for a complete rotation cycle.

2.3. Proposed Calibration Procedure. Based on the previous analysis, ξ_z , ζ_{xz} , and ζ_{yz} motivate navigation errors with IMU carouseling; therefore, a calibration procedure is necessary for the single-axis rotary INS. In this paper, the least square algorithm is employed to estimate the ξ_z , ζ_{xz} , and ζ_{yz} as well as the gyro biases with the gyro error model and measurement model given in equation (9)–(11). The calibration procedure can be described as follows: firstly, the IMU remains static to estimate the gyro biases; secondly, the IMU rotates with the designated rotation rate to estimate the ξ_z , ζ_{xz} , and ζ_{yz} . The calibration errors are related to the IMU static time and carouseling time, as the gyro biases are not constants but time-correlated random errors, for more details, one can refer to [9]:

$$\delta\omega_{is}^S = \begin{bmatrix} \zeta_{xz}\omega + \eta_x^S \\ \zeta_{yz}\omega + \eta_y^S \\ \xi_z\omega + \eta_z^S \end{bmatrix}, \quad (9)$$

$$Z_j = \tilde{\omega}_{is}^S - \omega_{is}^S \approx \begin{bmatrix} \tilde{\omega}_x^S \\ \tilde{\omega}_y^S \\ \tilde{\omega}_z^S - \omega_j \end{bmatrix}, \quad (10)$$

$$Z_j = H_j X$$

$$= \begin{bmatrix} \omega_j & 0 & 0 & 1 & 0 & 0 \\ 0 & \omega_j & 0 & 0 & 1 & 0 \\ 0 & 0 & \omega_j & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \zeta_{xz} \\ \zeta_{yz} \\ \xi_z \\ \eta_x^S \\ \eta_y^S \\ \eta_z^S \end{bmatrix}, \quad (11)$$

where $\tilde{\omega}_{is}^S$ represents the actual gyro output vector, $\tilde{\omega}_x$, $\tilde{\omega}_y$, and $\tilde{\omega}_z$ represent the gyro output in the X -, Y -, and Z -axes, respectively, Z_j is the measurement at the j^{th} epoch, the superscripts B and S mean the vector or scalar is expressed in the B -frame and S -frame, respectively, and ω_j represents the theoretical inertial sensor carouseling rate for Z_j .

Some limitations need to be clarified for the proposed calibration algorithm: (1) as the gyro errors usually varies with time, the calibration algorithm needs to be conducted before each use of the navigation system; (2) the vehicle needs to be stationary for the calibration, and such requirements prevent its use for certain applications, such as aerial or naval navigations.

The gyro outputs contain angular random walk and quantization noise, and those errors will cause the calibration errors. Usually, the integration of gyro data can greatly reduce the quantization noise level; then, the angular

random walk becomes the main source of the calibration errors. As different IMUs feature different error characteristics, the calibration accuracy can be approximately calculated based on the following equation:

$$\sigma = \frac{ARW}{\sqrt{T}}, \quad (12)$$

where σ represents the calibration accuracy, ARW is the angular random walk, and T is the calibration time.

3. Integration Strategy for Rotary MEMS INS and GNSS Based on ANFIS

Figure 2 presents the proposed cascaded velocity-position architecture for the integration of rotary MEMS INS and GNSS. The integrated system consists of the velocity and position ANFIS modules, and it works in the training and predicting modes, related to the GNSS availability. In the training mode, the velocity and position modules are trained to recognize the error pattern of velocity and position in the rotary INS with GNSS observations (usually the PV observation). More specifically, the velocity ANFIS module estimates the rotary MEMS INS velocity error with the inputs being the rotary MEMS INS velocity and time. The difference of the velocities from both the rotary MEMS INS and GNSS is treated as the target to train the velocity module. Such procedure is also known as the learning process in some literatures. The position module follows the velocity module with the inputs being the modified rotary MEMS INS position (the one corrected by the output of the velocity module) and time and the outputs being the rotary MEMS INS position errors, respectively. Similarly, the target calculated as the difference of the rotary MEMS INS modified position and the corresponding GNSS-derived position is employed to train the ANFIS position module. In the predicting mode, the trained velocity and position modules estimate the rotary MEMS INS PV errors based on the corresponding inputs during GNSS outages. The outputted errors are then removed to obtain the corrected velocity and position. As aforementioned, only the horizontal position and velocity are considered in this study. Then, the cascaded velocity-position ANFIS modules are proposed in the horizontal axes of the N -frame to predict corresponding velocity and position errors.

As a fuzzy mapping algorithm [23, 24], the ANFIS has been applied to a variety of applications, such as voice detection, classification, and navigation, just to mention a few. It is well known that the MEMS inertial sensors feature significant random errors; therefore, in this paper, it has been employed to integrate the rotary INS and GNSS because of its ability in dealing with the stochastic data. The structure of the ANFIS is illustrated in Figure 3. The P_{RINS} (or V_{RINS}) at the inputs represent the rotary MEMS INS position (or velocity), T at the inputs represents the time, and δP_{RINS} (or δV_{RINS}) at the outputs represent the rotary MEMS INS position (or velocity) errors. At the 1st and 2nd layer, the membership values are determined and the fuzzy t-Norm operator, $\prod$, is operated, respectively; at the 3rd layer, the

FIGURE 2: Velocity-position cascaded architecture based on ANFIS for integration of rotary MEMS INS and GNSS.

FIGURE 3: ANFIS structure for integration of rotary MEMS INS and GNSS.

weight with respect to the i^{th} rule, $\bar{w}_i$, is calculated; and at the 4th layer, the rotary MEMS INS position or velocity error is generated with different fuzzy rules. Eventually, the module output, the position or velocity error, δP_{RINS} or δV_{RINS} is estimated in the 5th layer, as shown in Figure 3. Both feedforward propagation and backward propagation are employed in ANFIS's hybrid training methodology, for more details, one can refer to [17].

Regarding the training mode, the nonoverlapping window scheme is employed to process the rotary inertial data and GNSS data [17]. For the window size of T_w , the ANFIS modules are updated with the new collected rotary and GNSS PV components during the subsequent windows (from $t = j * T_w$ to $t = (j + 1) * T_w - 1$, for $j = 1, 2, 3, \dots$) after initialization. To ensure that the ANFIS modules have been appropriately trained with the input data and system

dynamics, the cross-validation technique is used in the training mode [17]. The window size is usually vital to the robustness and accuracy of the integrated system in the standalone mode. Generally, the large window size allows the module to be trained with more data and more vehicle dynamics, and therefore, it usually results in more robust module. However, it also results in more complicated training procedure and heavy computation burden [16]. However, for a low-cost MEMS inertial system, whose navigation errors grow dramatically, it is important to prevent, considering the inaccurate PVA information during training procedure. In this study, the proposed system with different window sizes is investigated, and the results are present in Section 4.

4. Road Tests and Positioning Accuracy Analysis

The road tests were conducted to evaluate the navigation performance of the proposed integrated system of rotary INS and GNSS. Figure 4 illustrates the employed equipment for the road test. A single-axis rotation table is employed to rotate the MTi-G, which contained a triad of low-cost MEMS accelerometer and gyroscopes. The built-in GNSS chip of MTi-G can synchronize the inertial data to GNSS time. The reference solutions are provided by a SPAN system from the NovAtel Inc. The data rate for the MTi-G and platform rotation angle data is 100 and 50 Hz, respectively. The technique specifications of the single-axis rotation table are given in Table 1, and the error characteristics of MTi-G is summarized in Table 2.

Both the rotary and nonrotary tests are conducted with the land vehicle in this study. For the rotary test, the carouseling rate is set to ten degrees per second according to the conducted lab tests [9], and a calibration process is conducted before the vehicle starts to move. For the nonrotary test, the IMU remains stationary and the S-frame is aligned to the B-frame during the whole test. For both the tests, the initial PVA information is obtained from the SPAN system, as the Earth rotate rate cannot be sensed in MTi-G. Three types of solutions are calculated based on the collected dataset. The 1st and 2nd ones are obtained by processing the nonrotary and rotary IMU data with GNSS data using the EKF in a loosely coupled mode [10]. The 3rd one is obtained by processing the rotary IMU data and GNSS data based on the proposed navigation strategy, and the nonoverlapping window of 60 s is employed. The three types of solutions are referred as the nonrotary INS/GNSS solution, rotary INS/GNSS solution, and proposed system solution, respectively. The reference solution is obtained from the SPAN system, which contains a high-end IMU and GNSS receiver; therefore, it is accurate enough to evaluate the positioning accuracy of the proposed system.

Eight GNSS outages with the length of 60 seconds (window size) are intentionally simulated for the rotary test. As shown in Table 3, the outages with different dynamics are chosen to investigate the ability of the designed cascaded ANFIS modules to estimate the rotary INS PV errors. Outages of 60 seconds corresponding to the same trajectories are also simulated for nonrotary test to demonstrate

the positioning errors of the nonrotary INS without GNSS. The time gaps between two consecutive outages are enough for the inertial sensor biases to be converged. By comparing the three types of solutions, the improvements on the positioning accuracies of the proposed strategy over other two systems can be verified.

The mean of the computational time and training errors are summarized in Table 4. The training error reflects that the ANFIS velocity and position modules are accurately trained with the input data, and the training time is extracted from the MATLAB. Figure 5 illustrates the velocity errors for both the rotary INS/GNSS system and the proposed systems during outage #5 in the rotary test. The errors of the INS/GNSS system during the corresponding outage in nonrotary test are also plotted in the figure. Although the velocity errors are effectively reduced through IMU rotation, they still accumulate to about 6 m/s and 0.5 m/s in the east and north channels, respectively. With the predicted velocity errors from the ANFIS module, the velocity errors are further reduced to less than 1.3 m/s and 0.1 m/s after one minute, respectively.

As the position is calculated from the integration of the velocity in the inertial system, the accuracy of velocity during GNSS outages strongly affects the positioning errors. Beneficial from the cascaded ANFIS velocity-position modules, the reductions are also observed in the position solutions of proposed system, as shown in Figure 6. With IMU carouseling, the position errors of the rotary system are accumulated to about 180 m and 20 m in the east and north channels, respectively, while the errors are reduced to about 40 m and 2 m with the ANFIS modules.

As the position and velocity errors accumulate over time, as shown in Figures 5 and 6, the maximum errors during those outages are used to evaluate the positioning accuracy of different integrated systems. Figure 7 shows a comparison of the maximum horizontal velocity errors for the three integrated systems. Because of the sensor error modulation through IMU rotations, the velocity errors are partially compensated in rotary MEMS INS for all outages, compared to the nonrotary system. The mean of the maximum errors is reduced from 7.87 m/s to 3.39 m/s. The improvements brought by the IMU rotation can be explained from two aspects. (1) The IMU rotation can modulate the sensor errors, which reduce the navigation errors; (2) the IMU rotation can improve the system observability, which effectively improves the estimation accuracy of certain error states. With the proposed ANFIS velocity module, the velocity errors are further reduced for all outages as shown in the figure. The mean of the maximum errors is further reduced to 0.71 m/s. For all outages, the ANFIS module maintains the velocity error to be less than 1.4 m/s after one minute, as opposed to the maximum errors of 6.11 m/s for the rotary MEMS INS/GNSS system and 13.98 m/s for the nonrotary MEMS INS/GNSS system.

Figure 8 illustrates the maximum horizontal position errors of the three systems, and similar comparison results can be obtained. Beneficial from the cascaded ANFIS velocity-position modules, the smallest position errors are reached in the proposed system. Compared to the rotary

FIGURE 4: Employed equipment for the road test.

TABLE 1: Rotation table specifications.

Position precision ($^{\circ}$)	Carouseling rate precision ($^{\circ}/s$)	Maximum carouseling rate ($^{\circ}/s$)
$8e-4$	$5e-5$	± 100

TABLE 2: Error characteristics of MTi-G

	Gyros		Accelerometers
Bias instability ($^{\circ}/s$)	1	Bias instability (m/s^2)	0.02
Noise density ($^{\circ}/s/\sqrt{Hz}$)	0.05	Noise density ($m/s^2/\sqrt{Hz}$)	0.002
Alignment error ($^{\circ}$)	0.1	Alignment error ($^{\circ}$)	0.1

system, the position errors are reduced by 79.98% in terms of the mean of maximum errors in the proposed system with the predicted error components. Moreover, the results verify that the performance of the system augmented by ANFIS velocity and position modules is repeatable.

As aforementioned that the windows size strongly affects the positioning errors in the proposed system. The window sizes of 30 s, 60 s, and 90 s are investigated with GNSS outages of 30 s, 60 s, and 90 s, respectively. For each type of outage, there are 8 artificial outages simulated to the trajectory. Figures 9 and 10 present the maximum horizontal position errors with different window sizes for the outage of 30 s and 60 s, respectively. Obviously, the system with the window size of 60 s outperforms the system with other two window sizes. In fact, the ANFIS modules cannot be trained with enough input data and dynamics for the small size, such as 30 s. Moreover, the cross-validation technique cannot appropriately evaluate the trained ANFIS modules. For the automotive-grade inertial systems, the PV errors grow dramatically (i.e., the position error drifts to over 300 meters in 90 s for the rotary MEMS INS according to our results). Therefore, utilizing the long window size, such as 90 s, would make the ANFIS modules be exposed to the diverged position and velocity, which will deteriorate their prediction accuracy.

Figure 11 presents the maximum horizontal position errors of the proposed system with different window sizes for the outage of 90 s. Similar comparison results are obtained, in which the system with window size of 60 s still outperforms the system with other two window sizes. As the prediction accuracy of ANFIS module degrades when the

TABLE 3: Vehicle dynamics of the artificial GNSS outages.

Outage index	Dynamics description
1	Sharp curve
2	Two sharp curves
3	Sharp curves
4	Slightly turn
5	Straight line
6	Slightly turn
7	Straight line
8	L-shape turn

length of outage exceeds double window size [17], the positioning errors corresponding to the window size of 30 s become greater than the ones corresponding to the window size of 90 s.

The obtained results from the road tests are consistent to our previous analysis that the window size affects the position errors in the proposed system in the standalone mode. As the inertial sensor error characteristics, as well as vehicle dynamics, need to be considered in choosing the window size, the obtained conclusion (the system with the window size of 60 seconds outperforms the system with other two window sizes) may not be suitable for other inertial sensors.

Generally speaking, the vehicle dynamics would affect the positioning performance. If the ANFIS has been trained with some certain vehicle dynamics (or the velocity variations), then it can properly predict the velocity errors under similar dynamics. In the contrast, if the ANFIS has not been trained with some certain vehicle dynamics, then the variation of speed would degrade the positioning performance.

TABLE 4: Training results for the ANFIS velocity and position modules.

Velocity module		Position module	
Training time (s)	Training errors (m/s)	Training time (s)	Training errors (m)
0.653	$6.9e-4$	0.556	$4.3e-4$

FIGURE 5: The horizontal velocity errors for both the rotary INS/GNSS system and the proposed systems during outage #4.

FIGURE 6: The horizontal position errors for both the rotary INS/GNSS system and the proposed systems during outage #4.

FIGURE 7: The comparison of the maximum horizontal velocity errors for the three integrated systems.

FIGURE 8: The comparison of the maximum horizontal position errors for the three integrated systems.

FIGURE 9: The comparison of the maximum horizontal position errors for the proposed integrated system with different window sizes during GNSS outage of 30 s.

FIGURE 10: The comparison of the maximum horizontal position errors for the proposed integrated system with different window sizes during GNSS outage of 60 s.

FIGURE 11: The comparison of the maximum horizontal position errors for the proposed integrated system with different window sizes during GNSS outage of 60 s.

It is also worthy to mention that, in addition to the vehicle dynamics, the random errors of the MEMS inertial system also strongly affect the positioning performance.

5. Conclusions

Although the IMU carousel compensates the navigation errors in the rotary MEMS INS, it does not alter its intrinsic property as a DR system. Therefore, the PV errors in the rotary system still accumulate over time. In this paper, we suggest an integrated rotary MEMS INS/GNSS system based on ANN techniques to further eliminate the residual PV errors in the standalone mode. The ANFIS is employed because of its superior ability to deal with the stochastic errors in the inertial data. To the authors' best knowledge, the ANN techniques are applied for the first time to the rotary inertial system. The road tests were conducted to evaluate the applicability of ANFIS to the integrated system. Compared to the position errors of the integrated rotary INS/GNSS system based on an EKF, they are reduced by 79.98% in the proposed system.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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