

Article

A New Position Prediction Method Based on ANFIS for MINS/GNSS Integrated Navigation System During GNSS Outages

Tongxu Xu ^{1,*} , Xiang Xu ² , Hualong Ye ¹ and Lingling Zhang ¹

¹ School of Electronic and Information Engineering, Suzhou University of Technology, Suzhou 215506, China; yehualong930912@sina.com (H.Y.); 18506254573@163.com (L.Z.)

² School of Automation, Nanjing University of Science and Technology, Nanjing 210014, China; hsianghsu@163.com

* Correspondence: xutx_cslg@163.com

Abstract

Global navigation satellite system (GNSS) has the characteristics of high-precision positioning, which makes it an essential part of mobile terminal positioning. In urban environments, satellite signals are easily blocked and reflected, which affects the positioning results. In this case, inertial sensors manufactured by Micro Electromechanical Systems (MEMS) technology become the key to achieving continuous positioning. Although the integration of a micro inertial system (MINS) and GNSS provides the continuous output of position information, the position error will increase with time. This paper proposes a prediction model based on an adaptive neuro-fuzzy inference system (ANFIS) and a method to obtain model parameters. The model takes the position error δP^b of the carrier system as the output, and the rejection time (the time when GNSS positioning information remains unavailable), accelerometer data, and gyroscope data as the model inputs. Aiming at the model parameters, the consequent parameters acquisition method based on the least squares method and the antecedent parameters acquisition method based on a genetic algorithm are proposed. When GNSS outages last for 60 s, the maximum value of horizontal positioning error is reduced by 80% in six outage sections. Therefore, the proposed method in this paper is a potential method to predict the positioning error of a MINS/GNSS integrated navigation system.

Keywords: integrated navigation; MINS; ANFIS; error prediction; GNSS outage; least squares



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1. Introduction

Under the trend of intelligence, mobile terminals [1,2] such as unmanned aerial vehicles have been widely used, and their accurate positioning is a current research hotspot. The global navigation satellite positioning system, as a real-time positioning system, is an indispensable part of mobile terminal positioning systems [3,4]. However, in complex urban environments, GNSS signals are easily blocked by tall buildings and tunnels [5–7], resulting in positioning failures. This is detrimental to the positioning of intelligent mobile terminals. The navigation positioning system composed of inertial sensors is the key to achieving sustainable positioning when GNSS is denied [7]. With the advancement of MEMS technology, MEMS sensors have developed rapidly. Among them, MEMS inertial sensors, due to their low cost, small size, and high precision, have been applied in naviga-

tion positioning systems of intelligent mobile terminals, such as unmanned aircraft and unmanned vehicles [8–10].

Currently, in the navigation and positioning of mobile terminals such as low-altitude aircraft and unmanned vehicles, improving the sustainable positioning accuracy of the MINS/GNSS integrated system when GNSS outages appear is one of the research hotspots [7]. Regarding this research, it can be divided into three directions. The first direction is to improve the measurement accuracy of MEMS inertial sensors. The static bias, non-orthogonal error, scale factor error, and temperature drift of MEMS inertial sensor parameters [11–13] are the main factors affecting their measurement accuracy. Among these error items, calibration methods under constant temperature have been widely studied, and effective parameters can be obtained. For example, the least squares method and systematic calibration methods. For the drift error under temperature changes, studies usually take the calibration results of multi-point constant temperature as the basis and combine fitting methods and interpolation methods to obtain the drift curve of the parameters. However, the results of multi-point constant temperature rely on expensive temperature control turntables. Therefore, for most MEMS inertial sensors, their temperature drift error has not been estimated and compensated, thus affecting the sustainable positioning accuracy of the MINS/GNSS integrated system.

The second direction involves adding additional sensors to the integrated system [14], thereby providing more measurement information. In such studies, the fusion positioning system assisted by an odometer can provide incremental distance information or forward speed constraints, effectively reducing the positioning error of the system when GNSS positioning is unavailable. Research using magnetometers as an aid provides heading information that can constrain the divergent heading angles. In vehicle navigation and positioning, visual information is used to calculate the distance and obtain the forward speed, which constrains the divergent speed of the vehicle, thereby improving the positioning accuracy of the vehicle. In these studies, the divergent positioning errors have been suppressed to a certain extent, but the additional sensors increase the cost of the navigation and positioning system.

The third direction involves using prediction models to constrain divergent errors [15–19]. Such methods have been studied to some extent; for instance, models with input and output as $P - \delta P$ [18], and prediction models based on ANFIS [6]. These studies have demonstrated the potential of error prediction, but there are inherent drawbacks, such as using position errors of the navigation coordinate system as model outputs (the error increases during turns), and the unclear and incomplete process of parameter acquisition. Moreover, whether the static bias is pre-compensated in these research results has not been explained.

After static bias compensation, to address the problem of position divergence of the MINS/GNSS integrated navigation system when GNSS information is unavailable, this paper studies a position error prediction model based on ANFIS that uses the position error of the carrier coordinate system as the model output. In short, the novelties of our work include a new prediction model with a novel output and an online training method. This model is effective compared to the results without prediction, and the maximum 2-D error was reduced by at least 31% (some outage sections were reduced by 90%).

Below, Section 2 will introduce the system model of the integrated navigation system. In Sections 3 and 4, the model and the method for obtaining the parameters studied in this paper are respectively introduced. In Section 5, the experiments and the experimental results are presented. Finally, the research summary is given in Section 6.

2. MINS/GNSS Integrated Navigation System

Currently, the fusion methods of MINS and GNSS information mainly include two types: tight integration involving the hardware of GNSS receivers and ultra-tight integration [14], as well as loose coupling [15] that does not involve the hardware of the receivers. Among them, loose coupling is more easily portable and has been widely studied. In loose coupling systems, there are two directions: position information fusion and position-velocity information fusion. In this paper, the integrated navigation system is a loose coupling system that fuses the position information of the GNSS receiver with MINS.

The MINS/GNSS integrated navigation system is based on the error equations of the inertial system (attitude error, velocity error, and position error) and takes the position error (the result of subtracting the MINS-calculated position from the GNSS position information) as the measurement to construct the system equation and the measurement equation [17,19], as shown in the following formulas:

$$\dot{\phi} = -\omega_{in}^n \times \phi - C_b^n \delta\omega_{ib}^b + \delta\omega_{in}^n \quad (1)$$

$$\delta\dot{v}^n = C_b^n \delta f^b + C_b^n \dot{\phi} \times \phi - (2\omega_{ie}^n + \omega_{en}^n) \times \delta v^n + v^n \times (2\delta\omega_{ie}^n + \delta\omega_{en}^n) + \delta g^n \quad (2)$$

$$\delta\dot{r}^n = F\delta r^n + \delta v^n \quad (3)$$

In the above equations, ϕ represents the attitude error of the MIMU, δv^n represents the velocity error of the navigation system, and δr^n represents the position error of the navigation system. $\delta\omega_{ib}^b$ is the dynamic error of the gyroscope (after removing the static bias), and δf^b is the dynamic error of the accelerometer (also after removing the static bias). These errors collectively constitute the 15-dimensional state in the system equation. During the state estimation, discrete Kalman filtering is applied as follows:

$$X_{k/k-1} = \Phi_{k/k-1} X_{k-1} \quad (4)$$

$$P_{k/k-1} = \Phi_{k/k-1} P_{k-1} \Phi_{k/k-1}^T + \Gamma_{k-1} Q_k \Gamma_{k-1}^T \quad (5)$$

$$K_k = P_{k/k-1} H_k^T (H_k P_{k/k-1} H_k^T + R_k)^{-1} \quad (6)$$

$$X_k = X_{k/k-1} + K_k (Z_k - H_k X_{k/k-1}) \quad (7)$$

$$P_k = (I - K_k H_k) P_{k/k-1} \quad (8)$$

where Z_k represents the measurement information, which is

$$Z_k = P_{ins}^n(k) - P_{gnss}^n(k) \quad (9)$$

P_{ins}^n represents the position information output from the MINS, P_{gnss}^n represents the position information from the GNSS receiver. Both are in the navigation coordinate system.

3. ANFIS-Based Prediction Method

3.1. ANFIS Model

As shown in Figure 1, this is the basic structure diagram of an ANFIS based on the Takagi-Sugeno fuzzy system model. These arrows in Figure 1 represent the direction of data flow. This ANFIS model is a two-input, three-rule ANFIS model. The ANFIS model is divided into five layers [20], namely the fuzzy layer, the rule layer, the normalization layer, the defuzzification layer, and the output layer.

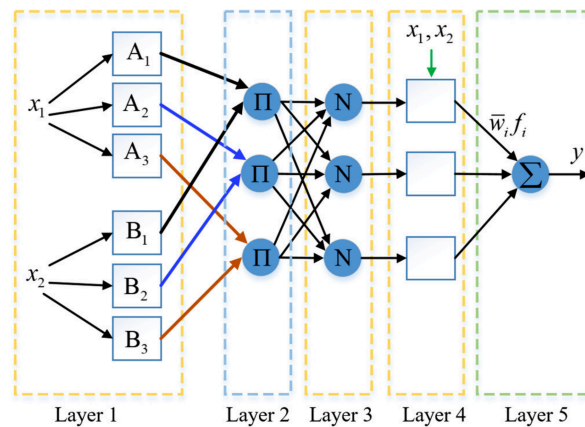


Figure 1. The structure of ANFIS.

Layer 1: Fuzzy Layer

In this model, the first layer contains two input variables, x_1 and x_2 . A_1 , A_2 , and A_3 are fuzzy sets related to x_1 . B_1 , B_2 , and B_3 are fuzzy sets related to x_2 . In the fuzzy layer, the fuzzy operation on the input data is performed. The fuzzy operation is implemented using membership functions. In this paper, the generalized bell-shaped membership function is taken as an example. Then, the output after fuzzification of the input data is

$$\begin{cases} O_{1,i} = \mu_{A_i}(x_1) & i = 1, 2, 3 \\ O_{1,j} = \mu_{B_j}(x_2) & j = 1, 2, 3 \end{cases} \quad (10)$$

Among these, i and j represent the indices of the fuzzy subsets related to the input, and the generalized bell-shaped membership function is:

$$\mu_{A_i}(x) = \frac{1}{1 + \left[\frac{(x-c_i)^2}{a_i^2} \right]^{b_i}} \quad (11)$$

$$\mu_{B_j}(x) = \frac{1}{1 + \left[\frac{(x-c_j)^2}{a_j^2} \right]^{b_j}} \quad (12)$$

where a_i , b_i and c_i are the parameters of the membership function corresponding to the fuzzy set A_i , while a_j , b_j and c_j are the parameters of the membership function corresponding to the fuzzy set B_j , which are also known as antecedent parameters.

Layer 2: Rule Layer

Based on the Takagi-Sugeno fuzzy model, three if-then rules are designed for the fuzzy subsets in Figure 1. The specific rules are as follows.

Rule 1: if x_1 is A_1 and x_2 is B_1 , then $f_1 = p_1x_1 + q_1x_2 + r_1$;

Rule 2: if x_1 is A_2 and x_2 is B_2 , then $f_2 = p_2x_1 + q_2x_2 + r_2$;

Rule 3: if x_1 is A_3 and x_2 is B_3 , then $f_3 = p_3x_1 + q_3x_2 + r_3$.

p_i , q_i and r_i (where $i = 1, 2, 3$) are the result parameters, also known as the consequent parameters. Then according to the rule, the output of each node in the rule layer is

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(x) \quad (13)$$

Layer 3: Normalization Layer (Fuzzy Inference Layer)

Each node in Layer 3 is marked with “N”. It calculates the ratio of the excitation intensity of each rule to the sum of the excitation intensities of all rules. The calculation formula is as follows:

$$O_{3,j} = \bar{w}_j = \frac{w_j}{\sum_{i=1}^3 w_i}, j = 1, 2, 3. \quad (14)$$

Layer 4: Defuzzification Layer

At each node of this layer, there are adaptive nodes with node functions, representing the output result of each rule. The output of each rule is

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i (p_i x_1 + q_i x_2 + r_i) \quad (15)$$

Layer 5: Output Layer

This layer sums up the outputs from Layer 4 to obtain the final output, which is

$$y = \sum_{i=1}^3 \bar{w}_i f_i \quad (16)$$

In the five-layer structure of ANFIS, the antecedent parameters in the first layer and the consequent parameters in the fourth layer are variable and are the parameters that need to be determined.

3.2. The Proposed Model

3.2.1. Output of the Proposed Model

Currently, many similar studies adopt the position error of the navigation system as the model output. These approaches may cause significant risks, especially when the cumulative errors over time are used as the model output. As shown in Figure 2 below, this is a schematic diagram of the position error of a vehicle over a short period.

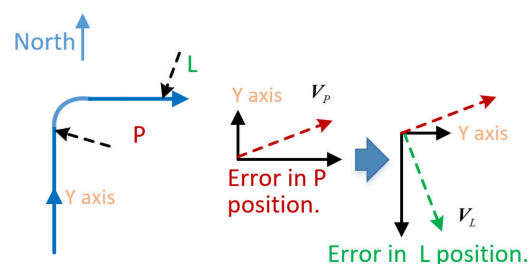


Figure 2. The diagram of position-error variation in a short time.

After the inertial sensors in the MINS system have been calibrated, the factors that affect the accuracy of position mainly include the dynamic bias of the gyroscope and accelerometer, noise caused by high-frequency vibration, and slow random drift. Usually, the dynamic bias of the gyroscope after calibration can be less than $0.1^\circ/\text{s}$. Assuming that the vehicle travels north at a speed of 60 km/h for 60 s and reaches point P, then turns right and drives to point L (it takes 60 s as well). If positioning is solely achieved using MINS during the first 60 s period, then the updated heading using the gyroscope may have a deviation of 6 degrees (assuming the dynamic uncalibrated bias of the gyroscope is $0.1^\circ/\text{s}$). At this time, assuming that the northward position error of V_P is approximately 5 m, and the eastward position error is approximately 104 m.

The error V_P generated by the above GNSS outage assumption is typically used for training. If GNSS is out of service at the second 60 s, then the biases of the inertial sensors can be considered to remain unchanged for a short period of time. In that case, the position

errors in the forward direction (Y-axis) and lateral direction (X-axis) at point L will be similar to those at point P, but in different directions, as shown by the green error vector V_L in Figure 2.

If the projection of V_P in the navigation coordinate system is used for model training, then similar prediction errors will be obtained at point L, which neglects the variation in driving direction and causes huge prediction errors. Therefore, it is a better choice to select the position errors of the forward direction and the lateral direction as the output of the model (i.e., the position error of the body-coordinate system). Considering generality, the model output is the position error of the body coordinate system $\delta P_i^b(ls)$, where i represents the components of the error vector on the three axes ($i = x, y, z$).

3.2.2. Details of the Proposed ANFIS Structure

In Section 3.1, Figure 1 shows the ANFIS structure of a Takagi-Sugeno fuzzy system with two inputs. Based on this structure and the above analysis, the inputs are changed to four, namely the x -component and y -component of the accelerometer measurement vector f^b , the data of the gyroscope z -axis ω_z^b , and the duration of the GNSS outage ls . Taking the x -axis as an example, the structure of the ANFIS error prediction model for the x -axis of the carrier coordinate system is shown in Figure 3 below.

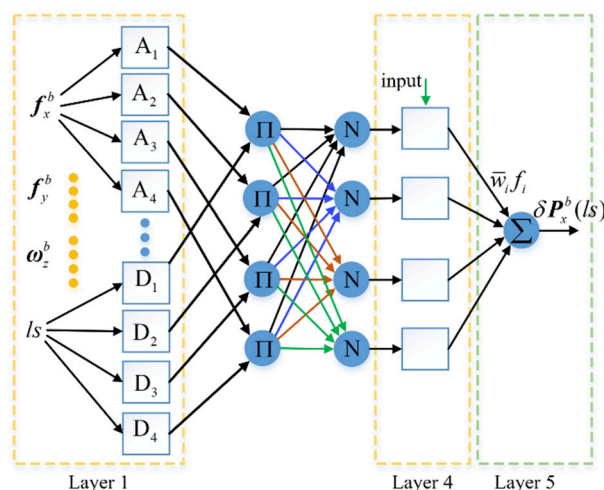


Figure 3. The proposed ANFIS model of X-axis error.

The “•” in Figure 3 indicate that similar structures have been omitted. Four input items are combined to form the vector X^{ANFIS} as shown in Formula (17) below.

$$X^{ANFIS} = \begin{bmatrix} f_x^b & f_y^b & \omega_z^b & ls \end{bmatrix}^T = \begin{bmatrix} \hat{x}_1 & \hat{x}_2 & \hat{x}_3 & \hat{x}_4 \end{bmatrix}^T \quad (17)$$

Then, four rules corresponding to this ANFIS structure were designed, as follows.

Rule 1: if x_1 is A_1 , x_2 is B_1 , x_3 is C_1 and x_4 is D_1 , then

$$f_1 = p_{1,1} \hat{x}_1 + p_{1,2} \hat{x}_2 + p_{1,3} \hat{x}_3 + p_{1,4} \hat{x}_4 + r_1 \quad (18)$$

Rule 2: if x_1 is A_2 , x_2 is B_2 , x_3 is C_2 and x_4 is D_2 , then

$$f_2 = p_{2,1} \hat{x}_1 + p_{2,2} \hat{x}_2 + p_{2,3} \hat{x}_3 + p_{2,4} \hat{x}_4 + r_2 \quad (19)$$

Rule 3: if x_1 is A_3 , x_2 is B_3 , x_3 is C_3 and x_4 is D_3 , then

$$f_3 = p_{3,1} \hat{x}_1 + p_{3,2} \hat{x}_2 + p_{3,3} \hat{x}_3 + p_{3,4} \hat{x}_4 + r_3 \quad (20)$$

Rule 4: if x_1 is A_4 , x_2 is B_4 , x_3 is C_4 and x_4 is D_4 , then

$$f_4 = p_{4,1}\hat{x}_1 + p_{4,2}\hat{x}_2 + p_{4,3}\hat{x}_3 + p_{4,4}\hat{x}_4 + r_4 \quad (21)$$

Based on the four rules, four subsets are designed for each input item (such as f_x^b), and each subset corresponds to a membership function. The membership function here adopts the generalized bell-shaped membership function. Then, the output of the first layer is

$$\mu_{i,j}(\hat{x}_i) = \frac{1}{1 + \left[\frac{(\hat{x}_i - c_{i,j})^2}{a_{i,j}^2} \right]^{b_{i,j}}} \quad (22)$$

In Formula (22), i represents the index of the input item, and j represents the index of the membership function corresponding to each input item. Then, for each output of the ANFIS prediction model, there are 16 membership functions, 48 antecedent parameters, and 20 consequent parameters. After the mapping of the first layer of ANFIS, the outputs of the second and third layers are

$$O_{2,j} = w_j = \prod_{i=1}^4 \mu_{i,j}(\hat{x}_i) \quad (23)$$

$$O_{3,j} = \bar{w}_j = \frac{w_j}{\sum_{i=1}^4 w_i} \quad (24)$$

The outputs of the fourth and fifth layers of the model are

$$O_{4,j} = f_j = (p_{j,1}\hat{x}_1 + p_{j,2}\hat{x}_2 + p_{j,3}\hat{x}_3 + p_{j,4}\hat{x}_4 + r_j) \quad (25)$$

$$O_5 = \delta P_x^b = \sum_{j=1}^4 \bar{w}_j f_j \quad (26)$$

The above is the error prediction model for the b -coordinate system's x -axis based on ANFIS, which is a multi-input single-output model. While the prediction model for δP_y^b has the same structure as the δP_x^b , only the antecedent parameters and consequent parameters are different.

3.3. Acquisition of Training Data and Prediction Flow

This paper studies the local short-term error prediction model, which is an online-created error prediction model. In the MINS/GNSS integrated navigation system, when the GNSS outage time is short (such as 2 s, 5 s), the absolute positioning error of the integrated navigation system will not increase too much. This is because during the vehicle's maneuvering process, through the Kalman filtering estimation process, most of the uncalibrated bias errors of the accelerometer and gyroscope have been estimated.

As an online creation and training method for error prediction, the online acquisition of training data is particularly important. Since the training data is obtained online, the data volume of the training dataset is limited, and it should be relatively close to the denial moment of the GNSS. As shown in the following Figure 4, this is a schematic diagram of obtaining training data during the integrated navigation process.

Figure 3, it can be known that the output value of the third layer is related to the model input. Suppose there are n training data vectors $\mathbf{X}_k^{ANFIS}$ ($k = 1, 2, \dots, n$), after passing through the first three layers, n vectors with s_n dimension (where s_n is the number of rules) can be obtained. Then, the output value of each node in the fourth layer is

$$f_{k,i} = (p_{i,1}\widehat{x}_{k,1} + p_{i,2}\widehat{x}_{k,2} + p_{i,3}\widehat{x}_{k,3} + p_{i,4}\widehat{x}_{k,4} + r_i) \quad (29)$$

In Equation (29), $i = 1, 2, \dots, s_n$. For a set of consequent parameters $p_{i,j}$ and r_i ($j = 1, 2, 3, 4$), the output value y_k can be obtained.

$$y_k = \sum_{i=1}^{s_n} \bar{w}_i f_{k,i} \quad (30)$$

Rewriting the above equation, we can obtain

$$\mathbf{X}^* \mathbf{P}^* = \mathbf{Y} \Leftrightarrow \begin{bmatrix} \bar{w}_{1,1}\mathbf{x}_1^* & \cdots & \bar{w}_{1,s_n}\mathbf{x}_1^* \\ \vdots & \cdots & \vdots \\ \bar{w}_{n,1}\mathbf{x}_n^* & \cdots & \bar{w}_{n,s_n}\mathbf{x}_n^* \end{bmatrix} \cdot \begin{bmatrix} \mathbf{p}_1^* \\ \vdots \\ \mathbf{p}_{s_n}^* \end{bmatrix} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} \quad (31)$$

where $\mathbf{x}^*$ and $\mathbf{p}^*$ are

$$\mathbf{x}_i^* = \begin{bmatrix} \widehat{x}_{i,1} & \widehat{x}_{i,2} & \widehat{x}_{i,3} & \widehat{x}_{i,4} & 1 \end{bmatrix}, i = 1, 2, \dots, n \quad (32)$$

$$\mathbf{p}_j^* = \begin{bmatrix} p_{j,1} & \cdots & p_{j,4} & r_j \end{bmatrix}^T, j = 1, 2, \dots, s_n \quad (33)$$

Thus, the least squares estimate (LS) of the consequent parameters can be obtained.

$$\hat{\mathbf{P}}^* = [(\mathbf{X}^*)^T \mathbf{X}^*]^{-1} (\mathbf{X}^*)^T \mathbf{Y} \quad (34)$$

The least squares estimation of the consequent parameters speeds up the optimization process of the parameters compared to a parameter search algorithm that calculates the gradients of all parameters. From the estimation Formula (34), it can also be seen that the least squares estimation value of the consequent parameters depends on the estimation of the antecedent parameters. Next, the antecedent parameter estimation method based on a genetic algorithm is introduced.

4.2. Antecedent Parameters Estimation

The genetic algorithm (GA) is an intelligent algorithm that simulates and borrows the mechanisms of natural selection and genetic evolution in living organisms. It is an important branch of evolutionary algorithm research. The genetic algorithm converts the solution to a nonlinear problem into a set of codes, and transforms the solution process into evolutionary operations such as selection, genetic operations, and mutation of the codes, thereby finding the solution that meets the requirements.

The main process of genetic algorithms includes population initialization, the calculation of individual fitness values, selection operations, crossover, and mutation. This process repeats continuously until parameters that meet the requirements are found. All operations are performed on the encoded parameter variables. When estimating the antecedent parameters of the ANFIS model, the antecedent parameters are arranged in sequence according

to the input variables to form a one-dimensional column vector $\mathbf{X}^{ga}$, which is called an “individual” in the population. The specific elements of $\mathbf{X}^{ga}$ are

$$\mathbf{X}^{ga} = [\mathbf{X}_1^p \quad \cdots \quad \mathbf{X}_4^p]^T \quad (35)$$

$$\mathbf{X}_i^p = [c_{1,i}, a_{1,i}, b_{1,i} \quad \cdots \quad c_{s_m,i}, a_{s_m,i}, b_{s_m,i}] \quad (36)$$

In Equations (35) and (36), $\mathbf{X}_i^p$ represents the row vector composed of all the parameters of the membership function corresponding to the i -th input item, and s_m represents the number of membership functions corresponding to the input. To facilitate the description of the algorithm, the input and output of the ANFIS model will be simply denoted as

$$y = \bar{F}(\mathbf{X}^{ANFIS}, \mathbf{X}^{ga}) \quad (37)$$

Here, $\mathbf{X}^{ga}$ represents the vector composed of the proposed model’s antecedent parameters. In the following, we will elaborate on the specific process of the genetic algorithm to obtain the antecedent parameters of the proposed ANFIS model in this section.

1. Population Initialization

First, based on the type of input parameters, determine the possible range of values for the parameters. Then, determine the “radius” or width of each element in $\mathbf{X}^{ga}$, and denote the vector composed of the widths of each element as $\mathbf{X}_w^{ga}$. The third step is to determine the approximate central parameter $\mathbf{X}_c^{ga}$, and then generate N^g “individuals” according to Formula (38).

$$\mathbf{X}_{i,j}^{ga} = \mathbf{X}_{c,j}^{ga} + \bar{r}_{i,j} \cdot \mathbf{X}_{w,j}^{ga} \quad (38)$$

In Formula (38), i ($i = 1, 2, \dots, N^g$) represents the individual index, and j represents the index of the vector component. $\bar{r}_{i,j}$ is a random number, and it satisfies $\bar{r}_{i,j} \in [-1, 1]$. This ensures that each “individual” varies within the range of $\mathbf{X}_c^{ga} \pm \mathbf{X}_w^{ga}$, and these N^g “individuals” constitute the initial population. In practice, the population was set to 100.

2. Calculate the individual fitness

Calculate the sum of squared errors (i.e., MSE) between the predicted and target outputs for each parameter vector as shown in the following formula.

$$MSE_i = \sum_{j=1}^n (\bar{F}(\mathbf{X}_i^{ANFIS}, \mathbf{X}_i^{ga}) - y_j)^2 \quad (39)$$

Then, calculate the fitness value fts for each individual according to the following formula.

$$fts_i = 1 - \frac{MSE_i}{\sum_{j=1}^n MSE_j}, \quad i = 1, 2, \dots, N^g \quad (40)$$

3. Selection process

During this process, the individuals that need to undergo genetic and crossover operations are determined. First, the individuals are sorted according to their fitness values from smallest to largest. Then, the individuals are determined as follows based on the following diagram. 10% of the individuals are used for genetic operations, and 30% of the individuals are used for crossover operations.

4. Genetic process

In order to make the population evolve towards the optimal solution, 10% of the individuals' "genes" are passed on to the first 60% of the individuals, so that they have excellent "genes". Here, "genes" refer to the component elements of the parameter vector. During the genetic process, randomly select the object to be inherited (any one of the 10% individuals) and pass its "genes" to an individual among the 60% individuals. The "gene" inheritance formula is as follows

$$\tilde{\mathbf{X}}_i^{ga}(\text{ind}_1) = \tilde{\mathbf{X}}_j^{ga}(\text{ind}_1), i = 1, 2, \dots, 60 \quad (41)$$

In this formula, j represents an individual within the 10% group, and it is a randomly generated index. ind_1 represents the index corresponding to the "genes" to be inherited. Here, approximately 60% of the "genes" are randomly inherited.

5. Crossover Process

The crossover process is mainly carried out on the selected 30% of the individuals, and the "genes" of these individuals are crossed with each other. The crossover formula is as follows.

$$va = \tilde{\mathbf{X}}_i^{ga}(\text{ind}_2), \tilde{\mathbf{X}}_i^{ga}(\text{ind}_2) = \tilde{\mathbf{X}}_j^{ga}(\text{ind}_2), \tilde{\mathbf{X}}_j^{ga}(\text{ind}_2) = va \quad (42)$$

In Formula (42), i represents any individual among the 30% population, j represents a certain individual (randomly generated) among them, and $i \neq j$. ind_2 is the index corresponding to the randomly generated crossover "gene".

6. Mutation Process

The mutation operations are performed on 10% of the individuals with higher fitness. During the mutation process, parameters $\mathbf{X}_c^{ga}$ and $\mathbf{X}_w^{ga}$ are used to ensure that the newly generated "genes" do not exceed the parameter range. The mutation formula is as follows:

$$va = \mathbf{X}_c^{ga}(\text{ind}_3) + \bar{r} \cdot \mathbf{X}_w^{ga}(\text{ind}_3) \quad (43)$$

$$\tilde{\mathbf{X}}_i^{ga}(\text{ind}_3) = va \quad (44)$$

In Formulas (43) and (44), $\bar{r}$ is a diagonal matrix, and the values of its diagonal elements vary within the range of ± 1 . ind_3 is the index corresponding to the randomly generated variant "gene", and i is the index used to iterate through each individual in 10% of the population.

The above process constitutes the main process of the genetic algorithm in this paper. During the parameter search process, an iteration termination judgment also needs to be carried out. Suppose the minimum mean square error of the previous generation population is M_{old} , and the minimum mean square error of the current population is M_{new} . They need to be compared with each other to determine whether to stop the iteration. The specific implementation steps are as follows.

Step 1: Calculate the maximum component of $|\mathbf{X}_{old}^{ga} - \mathbf{X}_{new}^{ga}|$ and denote it as e_{xm} . If $e_{xm} < 0.01$, terminate the iterative process of the genetic algorithm; otherwise, proceed to Step 2.

Step 2: If $M_{old} \leq M_{new}$, it is not a downward direction. Then, execute $\mathbf{X}_w^{ga} = 0.3\mathbf{X}_w^{ga}$. Next, perform the genetic, crossover, and mutation operations of the genetic algorithm. Finally, calculate the fitness value and proceed to Step 1. If $M_{old} > M_{new}$, it is a downward direction. Then, proceed to Step 3.

Step 3: $M_{old} = M_{new}$, $\mathbf{X}_{old}^{ga} = \mathbf{X}_{new}^{ga}$. Execute the genetic, crossover, and mutation operations of the genetic algorithm, then calculate the fitness value, and proceed to Step 1.

5. Experiments

In order to test the performance of the proposed model in this paper, navigation experiments were conducted. During the experiments, data from the MEMS inertial measurement unit (IMU) during the vehicle's movement, positioning information from the GNSS receiver, and position information from the reference system were collected. As shown in Figure 6, this is a photo of the vehicle's trunk.

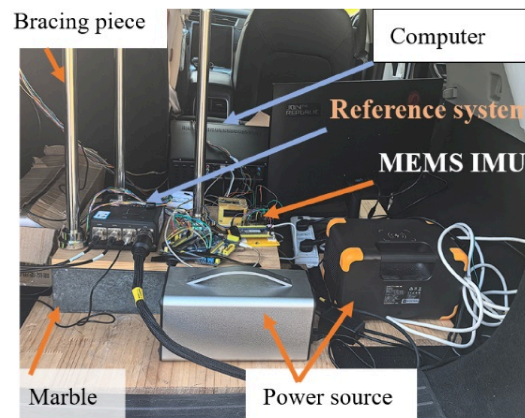


Figure 6. Experiment tools and instruments.

In this experiment, the MEMS IMU and the reference system were fixed on a wooden board, and the wooden board was adhered to a marble platform (25 kg). To prevent the MEMS IMU from jumping up and down due to vibrations, three bracing pieces were used to fix the marble platform, as shown in figure. Additionally, the MEMS IMU and the reference system were almost above the rear axle line. The reference system used in this experiment is the integrated navigation system CGI-610, which is produced by Shanghai Huace Navigation Technology Co., Ltd., Shanghai, China. It is a dual-antenna navigation system and supports Real-Time Kinematic (RTK) information. In the CGI-610 (as shown in Figure 7), the front antenna is used for orientation, and the rear antenna is used for positioning.



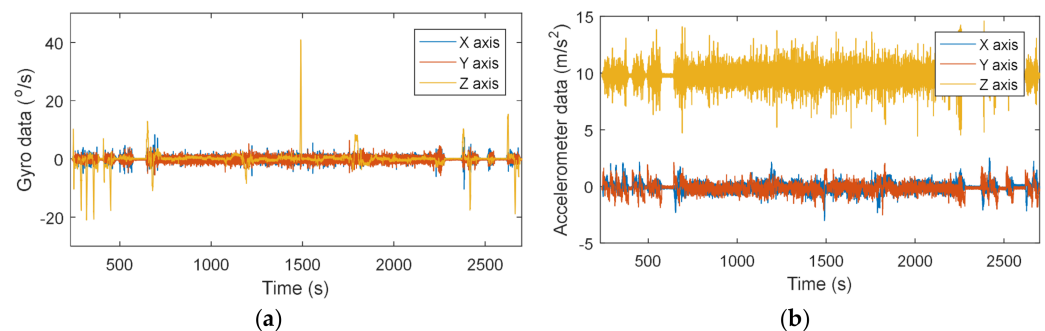
Figure 7. The picture of installation of the antennas.

When the GNSS information is interrupted for 10 s, the horizontal positioning accuracy can reach 0.2 m, which comes from the URL <https://www.huace.cn/technicalParameter/181> (accessed on 13 July 2026). Therefore, in this experiment, the positioning information provided by CGI-610 serves as the reference position. The model of the MEMS IMU is the ADIS16470, and its data characteristics after the vehicle starts are shown in Table 1.

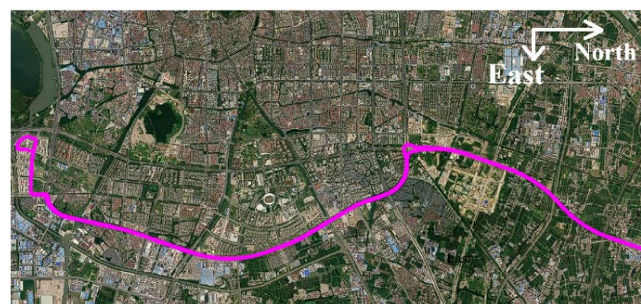
Table 1. The characteristics of ADIS16470 when the vehicle launched.

		X	Y	Z
Gyroscope	ARW ($^{\circ}/\sqrt{h}$)	0.25	0.79	0.19
	STD ($^{\circ}/s$)	0.043	0.133	0.033
Accelerometer	VRW ($\mu g/\sqrt{Hz}$)	663	490	806
	STD (m/s^2)	0.065	0.048	0.079

The curves shown in Figure 8 represents the data curves of the triaxial accelerometer and triaxial gyroscope of the ADIS16470. This data was collected by a data acquisition board based on the STM32F103 chip, with a sampling frequency set at approximately 100 Hz and without any filtering. In the embedded system, sensor data is obtained through the SPI communication protocol. After the data is collected, it is sent to the computer in Figure 6 via the serial port and stored on the computer. The baud rate of the serial port is set to 230400, and each transmission takes approximately 1 ms.

**Figure 8.** The data curves of ADIS16470 during driving. (a) Data curves of triaxial gyroscope; (b) Data curves of triaxial accelerometer.

Meanwhile, the computer also obtains reference data and GNSS receiver positioning information through two other serial ports. For ease of display, the original image of the vehicle's driving trajectory was rotated (clockwise by 90 degrees). The final positioning trajectory is shown in Figure 9. During the experiment, to fully stimulate the error parameters in the reference system (CGI-610), circular driving was performed for the first 10 min, and then normal driving began. The entire driving process included sections of low-speed driving, fast driving, and turning, providing reliable data for verifying the effectiveness of the proposed method.

**Figure 9.** The trajectory of the test car.

In urban environments, situations where GNSS positioning fails often occur beneath elevated structures, between tall buildings, and within tunnels. At such times, the accuracy of MINS/GNSS fusion positioning will decrease, which will affect route planning, map navigation, and road rescue. In these GNSS denial scenarios, the duration of time inside

tunnels is relatively long. Therefore, during the testing, we manually selected the sections with GNSS denial and set the duration of GNSS denial to 60 s. In this study, nine sections were selected to test the effectiveness of the proposed method. These nine sections are shown in Figure 10.

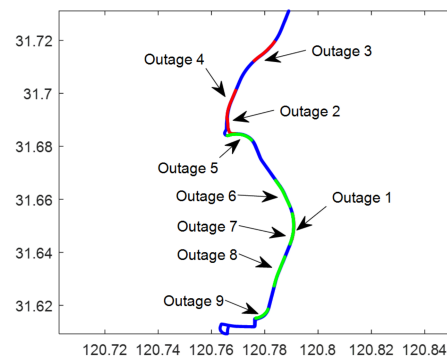


Figure 10. The schematic diagram when GNSS information is unavailable (GNSS outage).

All the methods were performed on a computer. The CPU of this computer is I7-10700, which can speed up the calculation process. When applying the proposed method, the traditional fusion method based on the Kalman filter without a predictive algorithm (denoted as KF in the figures below), the ANFIS method from reference [6] (denoted as ANFIS-M1 in the figure below), and the Radial Basis Function-based prediction method [16] (denoted as RBF in the figures below) were all executed simultaneously. The position information was obtained for integration was from a single GNSS receiver, rather than RTK information. The predicted trajectories of these four methods for the first outage section are shown in Figure 11.

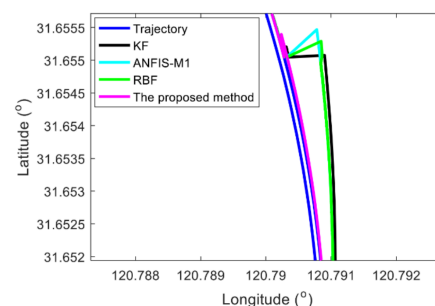


Figure 11. The trajectories around the GNSS outage 1.

Existing studies often present the positioning errors in the eastward and northward directions as the key results. In Figure 12 of this paper, the eastward and northward positioning errors of outage road section 1 are also given. Figure 12a shows that the method proposed in this paper has the smallest eastward error in this road section, outperforming the other three methods. However, the northward error is indeed very large, and it is worse than the result without prediction.

In the trajectory, although the positioning trajectory proposed in this method is close to the real trajectory, the positioning is ahead of time. This indicates that the positioning errors in the eastward and northward directions cannot easily show the effectiveness of the method. Considering the different directions of vehicle travel (as shown by the arrow in Figure 13), the eastward and northward positioning errors can be replaced by the horizontal positioning error δP_{2-D} (or called two-dimensional error, denoted as 2-D error below). The

horizontal positioning error is the modulus of the vector of the eastward and northward positioning errors $([\delta P_E, \delta P_N]^T)$, and it can be calculated according to Formula (45).

$$\delta P_{2-D} = \sqrt{\delta P_E^2 + \delta P_N^2} \quad (45)$$

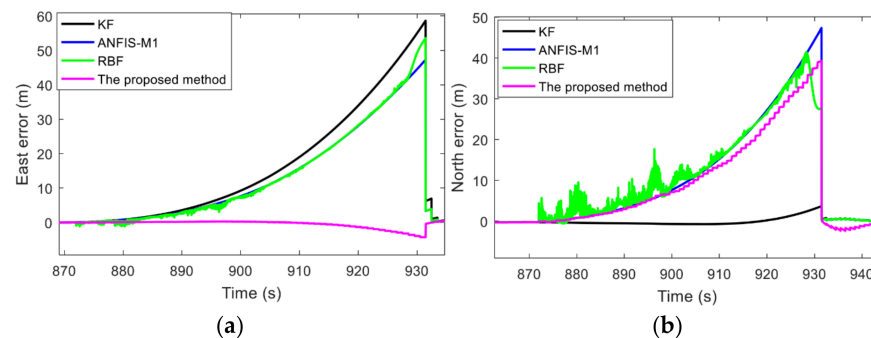


Figure 12. The position error at the outage 1. (a) The east errors at the outage 1. (b) The north errors at the outage 1.



Figure 13. Different orientations during drying.

After calculation according to Formula (45), the positioning errors of the different methods on road section I are shown in Figure 14. From the figure, it can be seen that the horizontal positioning error of the method proposed in this paper is smaller than those of the other three methods. The maximum error is approximately 17 m, 25 m, and 20 m lower than those of the KF, ANFS-M1, and RBF methods, respectively. This indicates that the method proposed in this paper is effective on this road section.

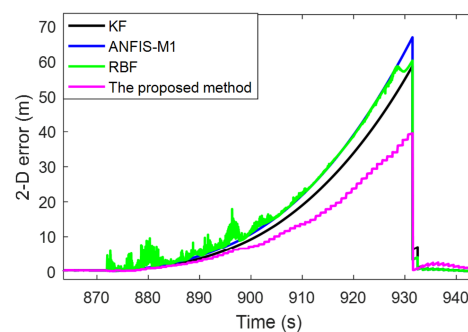


Figure 14. 2-D position errors of outage 1.

As shown in Figure 15, it presents the trajectories and predicted results of outage road sections 3, 4, and 5. The results of Figure 14 may be less significant compared with Figure 15. This is due to the small error of the KF method (about 60 m) in outage 1. We should pay more attention to the max error of positioning. The driving trajectories in Figure 15a,b are in the southwest direction, while the trajectory of outage road section 6 in Figure 15c is in the southeast direction. For outage road sections 3 and 6, the proposed method, ANFIS-M1, and RBF method all predicted partial errors, but the fluctuation of the RBF method is slightly larger. In outage road section 4, the positioning error of the method in this paper is smaller than the other three methods and is more stable. Similar trajectories are shown in Figure 16.

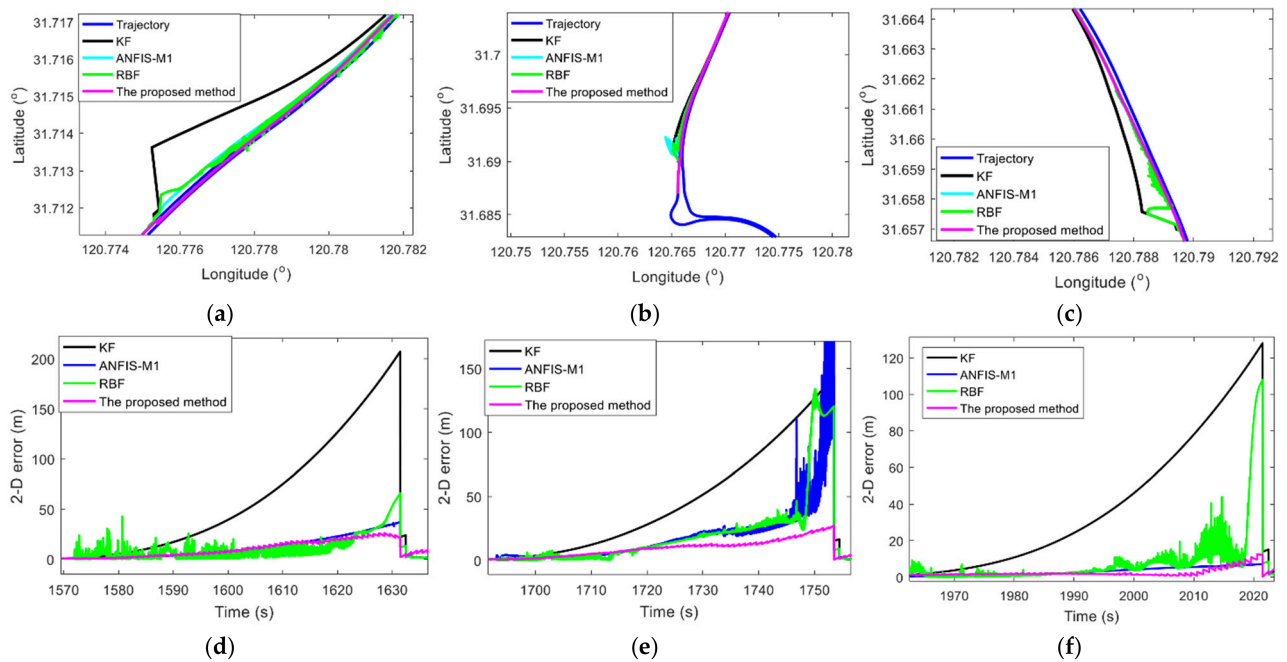


Figure 15. The results of outage 3, 4, and 6. (a) Trajectory of outage 3; (b) Trajectory of outage 4; (c) Trajectory of outage 6; (d) 2-D position error of outage 3; (e) 2-D position error of outage 4; (f) 2-D position error of outage 6.

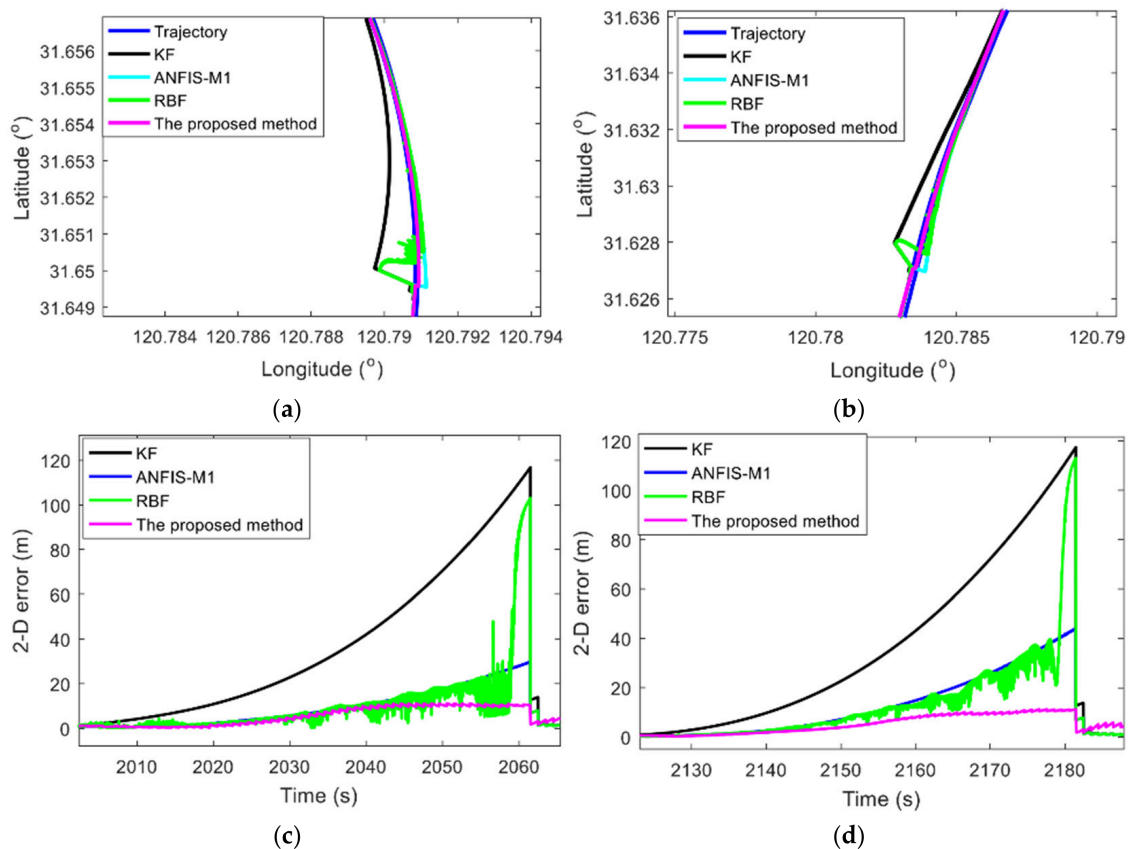


Figure 16. The results of outage 7 and 8. (a) Trajectory of outage 7; (b) Trajectory of outage 8; (c) 2-D position error of outage 7; (d) 2-D position error of outage 8.

As can be seen from Figure 16, the driving direction on outage road section 7 is southward, while the driving direction on outage road section 8 is southwestward. In these two outage sections, all three prediction methods can predict part positioning errors and

make compensation. However, the method in this paper and ANFIS-M1 are superior to the RBF method in terms of stability. Moreover, as the outage time increases, the prediction results of the proposed method on these two sections are better than those of the RBF method. In addition, apart from the approximately straight driving trajectory, this paper also tested the trajectory of turns, and the results are shown in Figure 17.

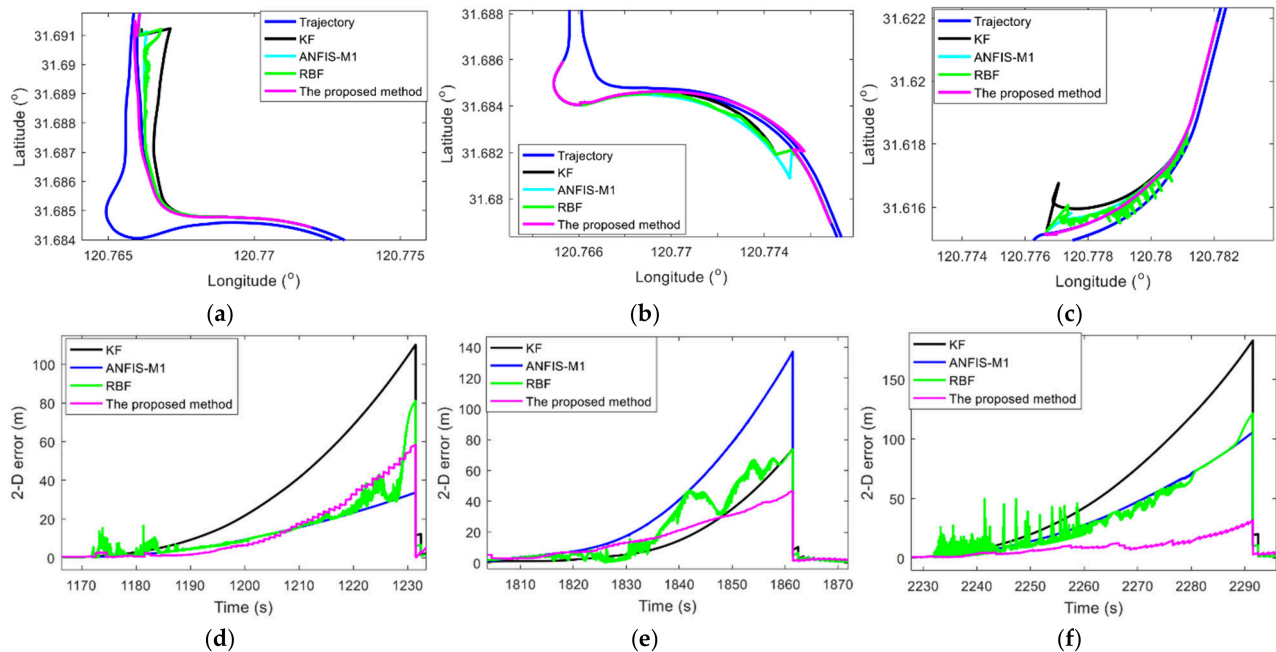


Figure 17. The results of outage 2, 5 and 9. (a) Trajectory of outage 2; (b) Trajectory of outage 5; (c) Trajectory of outage 9; (d) 2-D position error of outage 2; (e) 2-D position error of outage 5; (f) 2-D position error of outage 9.

In Figure 17, outage road section 2 is for westward travel and then a turn to the north. Outage road section 5 is for southward travel, first a turn to the east, then another turn to the south. The trajectory of this section is a trajectory that first turns left and then turns right. Outage road section 9 is for straight southward travel, then a right turn, heading towards the southwest. From the positioning results of outage road sections 2 and 5, it can be observed that the method proposed in this paper can predict positioning errors and improve positioning accuracy. However, in road section 5 with continuous turns, the fluctuation of the RBF method was compared, and the ANFIS-M1 method failed in prediction. From outage road section 9, it can be known that the positioning error of the proposed method in this paper is significantly better than those of the ANFIS-M1 and RBF methods.

From the positioning error curves of the outage sections, the changing trends of the positioning errors of the proposed method in this paper and the comparison methods can be seen. To provide quantitative results, the maximum values of the horizontal positioning errors of the 9 outage sections and the RMSE were statistically analyzed. The results are shown in Table 2. In this table, the unit of RMSE and the max error is m (meters).

In Table 2, “Trj” represents the outage sections. “Trj-1” represents outage section 1, and other representations have similar meanings. RMSE reflects the stability of the prediction. From Table 2, it can be seen that the proposed method in this paper has a maximum horizontal positioning error smaller than those of the ANFIS-M1, RBF methods, and the combination without prediction on most sections.

Table 2. The RMSE and max error of 2-D position error.

	KF		ANFIS-M1		RBF		The Proposed Method	
	RMSE	Max	RMSE	Max	RMSE	Max	RMSE	Max
Trj-1	15.72	55.01	18.02	62.86	17.41	58.65	10.77	37.67
Trj-2	30.33	104.13	9.61	32.24	12.07	70.01	15.33	54.23
Trj-3	56.41	195.52	9.90	34.94	9.86	52.74	7.98	26.13
Trj-4	39.56	136.52	17.15	197.11	25.04	134.26	6.15	25.30
Trj-5	18.29	67.98	36.52	128.46	22.53	67.85	12.38	43.58
Trj-6	34.65	120.76	2.03	6.91	9.27	85.90	1.82	11.04
Trj-7	36.94	116.78	9.08	29.86	17.41	103.02	3.75	11.19
Trj-8	32.08	110.83	11.96	41.78	12.28	88.60	3.85	11.21
Trj-9	50.77	173.43	29.44	100.62	29.13	111.21	6.43	28.39

The results in Table 2 demonstrate the effectiveness of the proposed method in prediction. As an online training model, the time consumption during parameter acquisition is also an important factor. By retesting four segments, with each segment undergoing the method three times, we obtained the training time results. The 12 tests showed that the time consumed ranged between 10 and 19 s. The inconsistent time consumption of the proposed method may be due to:

- (1) The program code has not been optimized;
- (2) The genetic algorithm employs random functions in the population generation, selection, and crossover processes, leading to inconsistent time consumption.

This suggests that in future research, we can optimize the algorithm's parameters to achieve both the desired performance and controllable time consumption.

6. Conclusions

For the problem of divergence in positioning errors of the combined system integrating a low-cost MEMS IMU and GNSS positioning information in outage environments, this paper proposes a new position prediction model based on ANFIS and a method for obtaining its parameters. The proposed model takes the position error of the carrier coordinate system as the target output and uses the output values of the accelerometer x and y axes, the output value of the gyroscope z axis, and the GNSS outage time as the input of the model. An input-output model of ANFIS is established. In the parameter acquisition of the model, a consequent parameter estimation method based on the least squares method is given, and an antecedent parameter estimation method based on a genetic algorithm is proposed. Through iterative estimation, the model parameters that meet the requirements are obtained.

In order to verify the effectiveness and potential of the proposed method, MEMS IMU data from the vehicle driving process, positioning information from the GNSS receiver, and reference information were collected. During the method test, straight driving sections and turning sections were manually selected as GNSS outage sections (a total of 9 sections), and the outage time for each section was 60 s. At the same time, prediction methods based on the RBF and ANFIS-M1 models were implemented for comparison.

The test results of the nine outage sections show that the method proposed in this paper can effectively predict partial positioning errors on most sections, thereby improving positioning accuracy. On 6 of the outage sections, compared to the positioning errors without prediction, the method in this paper reduced the maximum horizontal positioning error by 80%, significantly enhancing the positioning accuracy of the MINS/GNSS. For the

other three outage sections, the maximum horizontal positioning errors were reduced by 31%, 47%, and 35% respectively. Compared with the other two prediction methods, the proposed method also demonstrated its advantages.

The proposed method in this paper is effective on most of the test sections and also indicates its potential in the direction of predicting positioning errors. However, there are still some deficiencies in the model and parameter acquisition. For example, the time consumption of training varies significantly. In addition, the test datasets are not sufficient. In future research, studies on model optimization and iterative parameter updates will be carried out, and more datasets will be collected for verification.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this paper:

ANFIS	Adaptive Neuro-Fuzzy Inference System
GNSS	Global Navigation Satellite System
IMU	Inertial Measurement Unit
MEMS	Micro Electromechanical Systems
MINS	Micro Inertial System
RBF	Radial Basis Function
RTK	Real-Time Kinematic
RMSE	Root Mean Square Error

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