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A Novel BPNN-Based Method to Overcome the GPS Outages for INS/GPS System

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ABSTRACT In order to improve the performance of the global positioning system (GPS) and inertial navigation system (INS) integrated system during GPS outages, a novel fusion algorithm based on back propagation neural network (BPNN) is proposed. A new model is built which relates the INS velocity, inertial measurement unit (IMU) outputs and the duration of GPS outages to the GPS position increment. Performance of the proposed method has been experimentally evaluated in a land vehicle navigation test. The test results show: (1) the proposed model can efficiently predict the increment of position and compensate the INS errors accumulation during GPS outage; (2) the advantage of new model on positioning accuracy becomes more obvious when the GPS observations are unavailable for a long time; (3) utilizing the current and past 2-step information as the input of BPNN model can effectively balance the computation burden and accuracy.

INDEX TERMS INS/GPS integrated system, BP neural network, global positioning system (GPS) outages.

I. INTRODUCTION

The GPS-equipped devices are becoming more and more widely used in our daily life. As we know, the GPS could provide long-term accurate position and velocity information. However, the accuracy and availability will be deteriorated when the vehicles working within urban scenarios such as urban canyons, tunnels or indoor environment because of the signal masking and multipath [1]. To solve the problem, GPS is usually combined with INS, which is a self-contained system having a short-term accurate solution. The integration of GPS and INS which combines the advantages, therefore, has superior performance in comparison with either GPS or INS stand-alone system.

In GPS/INS integrated navigation system, Kalman Filter (KF) is the most popular fusion method in recent years for its practicability and suitability [2]. KF contains two processes: the time update process is to estimate the errors state of vehicle according to the dynamic model, and the other process which corrects the INS errors accumulation using the GPS information is called measurement update process. However, if the GPS is unavailable for a long time, the accuracy of integrated system would decay due to the measurement update does not work during this period. Aiming to conquer the above problem and get an accurate navigation result continuously, a number of effective methods are proposed. One solution is zero velocity update (ZUPT) which utilizes the zero velocity condition during every stop to control the navigation error growth. The velocity error curve fitting is one common method for applying the ZUPT, considering the velocity error is an approximate quadratic curve [3]. The long-time and high-frequency stop is the biggest disadvantage of hindering the application of ZUPT [4]. The artificial intelligence (AI) related solutions are drawing more attention with the development of computer technologies in hardware and software. When GPS works well, the AI learns GPS/INS behavior patterns and builds the model mapping the vehicle's dynamics (attitude, velocity or position) with the corresponding errors [5]. The errors derived from AI model will be used to compensate the INS drift during the GPS signal outages. In recently years, a lot of research has been conducted on this aspect. Wavelet multi-resolution analysis (WRMA) and radial basis function (RBF) were combined to improve the positioning accuracy during GPS outages. The input of the RBF network is the INS position and time information, while the output is the INS position error [6].

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Fuzzy neural network was employed to generate the velocity correction using the GPS, odometer and IMU information as the input [7].

The same shortcoming of traditional AI models mentioned above is that the outputs consist of both INS and GPS information which are difficult to decouple. An accurate prediction result is hard to be obtained with these models. Therefore, besides the traditional AI solutions, a few modified models have been raised recently to set up relationship between the INS information and the GPS result directly. Based the multi-layered feed forward neural networks (MFNNs), the AI model that receives the azimuth and velocity from the INS along with the time information and exports the pseudo GPS azimuth and velocity had been built [8]. The support vector machine (SVM) model was proposed that mimics the increments of GPS position with the INS information including velocity, attitude and the IMU measurement. Utilizing the model, best result can be reached if the current and past 1-step INS information is collected as the input of the model [9].

Previously, all methods are under the hypothesis that the INS error characteristics are consistent during training phase and predicting phase. However, due to the variability and uncertainty of INS errors, the error characteristics during predicting phase are not consistent with that during training phase [10]. Taking the velocity error for example, its trend seems as a long-term and time-related quadratic curve. In this situation, the compensation deprived from the model which not considers the error changes may be inaccurate. To solve this problem, input delay neural network (IDNN) has been proposed to model both the INS position and velocity errors based on current and some past samples of INS position and velocity. The road test showed a significant improvement in positioning accuracy [11]. Then, the comparison of different predicting results has been done with some typical number of past information. The conclusion is that the best prediction could be obtained using past 10 steps information with the wavelet neural network (WNN) [12].

In the methods mentioned above, the common way of eliminating the long-term errors is to increase the number of past information. And more past information are involved, better performance is commonly achieved. With no doubt, the huge computation burden will also increase simultaneously. In order to overcome the problems of previous methods mentioned above, a novel back propagation neural network (BPNN) model has been proposed. The output of the model is the increment of position deprived from GPS. The input not only includes the INS velocity, angular rate and specific force, but also the time from the start point of training model to now. Apparently, the new model separates the INS and GPS errors into the input and output respectively. It is beneficial to improve the accuracy of the prediction result. In addition, the novel module, due to the inclusion of time information, has the ability of modeling the time-related changes of velocity error. Therefore, even if the characteristics of velocity errors in training and predicting stages are not consistent, the novel model can predict and eliminate the errors caused by this inconsistency.

The problem of large computation also disappears naturally, since we do not need to increase the past information in quantity.

II. MODEL DESCRIPTION

As mentioned in Section, there have been many AI models used in the GPS/INS integrated system. The common idea is to build the relation between the INS outputs (angular velocity, specific force, velocity, position, *et al.*) and some GSP information. When the GPS signal is available, the GPS information can be obtained and used to train the AI model along with the INS outputs. In case of GPS outage, the pseudo GPS information can be achieved from the well-trained AI model. One of such model is $O_{INS} - \delta P_{INS}$, which establishes the relation between the output of INS (O_{INS}) and the position error of INS (δP_{INS}). Because the δP_{INS} is the difference of the INS and GPS position, the established model always be influenced by the errors of GPS and INS simultaneously. To avoid the problem, a $O_{INS} - \Delta P_{GPS}$ model has been proposed. Because the model output (ΔP_{GPS}) is only the position increment of GPS, the $O_{INS} - \Delta P_{GPS}$ model shows a better performance than $O_{INS} - \delta P_{INS}$ in the comparison test [9]. The above methods are all under the hypothesis that the error characteristics of the INS output are consistent during training phase and predicting phase. However, due to the variability of INS errors, the characteristics during predicting phase are not consistent with that during training phase. The normal solution to mitigating the errors caused by the inconsistence is that increase the number of training samples. However, the large computation comes with the increasing past information involved. To reduce the computation burden, a novel $O_{INS}T - \Delta P_{GPS}$ model is proposed. The time information (T) is added in this model. Fig. 1 shows the configuration of the model. ω is angular velocity, f is specific force, V_{INS} and P_{INS} are respectively velocity and position of INS. Symbol k-1 and k denote the time $k - 1$ and k. When GPS works well, the outputs of INS and GPS are integrated by KF. In the meantime, the BPNN module is trained, whose inputs are the time $k - 1$, k and the samples of the specific force, angular rate, and velocity at these two moments, while the expected output is the GPS position increment $\Delta P_{GPS}(k-1, k)$. Suppose the training phase starts from the time 1, and GPS outages occur on the time k. The GPS position increment $\Delta P_{GPS}(k, k + 1)$ will be predicted and accumulated to achieve the pseudo GPS position on the time $k + 1$. Then, this pseudo GPS position is used as the input of KF to form the observation vector with INS position. The inputs of the BPNN model are carefully selected to satisfy the requirement of mimicking the position increment. Due to the high-accuracy, the errors of GPS position and velocity can be ignored. Therefore, the position increment

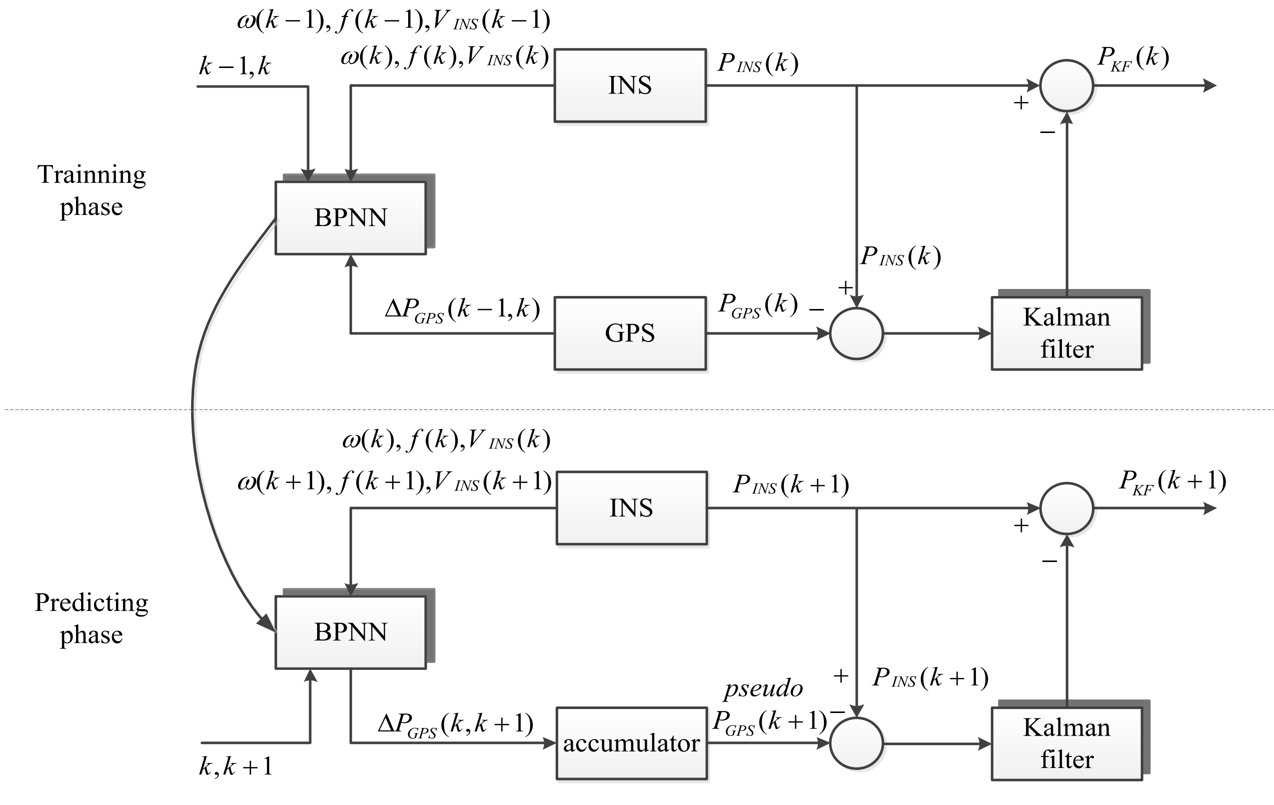

FIGURE 1. Configuration of the proposed fusion algorithm.

and velocity can be modeled as

$$\Delta P_{GPS}(k,k+1) = \int_{k}^{k+1} V_{INS}(k) + (V_{INS}(k+1) - V_{INS}(k))\,t - \underbrace{(\delta V_{INS}(k))}_{①} + \underbrace{(\delta V_{INS}(k+1) - \delta V_{INS}(k))t)dt}_{②} \tag{1}$$

where $V_{INS}(k)$ and $V_{INS}(k+1)$ are the INS velocity on time k and k + 1, $\delta V_{INS}(k)$ and $\delta V_{INS}(k+1)$ are the errors of the velocity $V_{INS}(k)$ and $V_{INS}(k+1)$ respectively. From equation (1), we can see that if these errors can all be modeled accurately, the position increment error contained in the $\Delta P_{GPS}(k, k+1)$ will be known. The above mentioned velocity errors are classified into two kinds, long-term error ① and short-term error ②. The former one approximates a quadratic curve on the time, and the latter is related to the motion states of vehicle. Accordingly, if we want to establish an accurate model for the velocity errors, both the time information and the motion state related quantity (angular velocity, specific force) should be considered to mimic the long-term and short-term part of velocity error simultaneously.

A. GPS/INS LOOSELY COUPLED MODEL

A 15-state KF has been constructed for GPS/INS integration. The process model and observation model are:

$$\begin{cases} \dot{\boldsymbol{X}} = \boldsymbol{\Phi X} + \boldsymbol{\Gamma W} \\ \boldsymbol{Z} = \boldsymbol{HX} + \boldsymbol{V} \end{cases} \tag{2}$$

where $\boldsymbol{X}$ and $\dot{\boldsymbol{X}}$ are the state vector and its differential, $\boldsymbol{\Phi}$ is system matrix. $\boldsymbol{\Gamma}$ is system noise matrix, and $\boldsymbol{W}$ is the process noise vector. $\boldsymbol{Z}$ is observation vector, and $\boldsymbol{H}$ is observation matrix. $\boldsymbol{V}$ is the observation noise vector. The observation vector $\boldsymbol{Z}$ can be obtained with the difference between INS position and GPS position. Once the GPS outages happen, the vector $\boldsymbol{Z}$ will be composed with the INS position and the pseudo GPS position derived from AI model instead of the true GPS position.

The states vector $\boldsymbol{X}$ is expressed as

$$\boldsymbol{X} = [\phi_E \quad \phi_N \quad \phi_U \quad \delta V_E \quad \delta V_N \quad \delta V_U \quad \delta L \quad \delta\lambda \quad \delta h \quad \nabla_x \quad \nabla_y \quad \nabla_z \quad \varepsilon_x \quad \varepsilon_y \quad \varepsilon_z] \tag{3}$$

where ϕ_E, ϕ_N, and ϕ_U are the misalignment angles of the calculated platform in local geographical frame, δV_E, δV_N, and δV_U are velocity errors of three axes of local geographical frame, δL, $\delta\lambda$ and δh denote position errors, ∇_x, ∇_y, and ∇_z represent accelerometers biases of the body frame, ε_x, ε_y, and ε_z are gyros biases in three axes of the body frame, the system matrix $\boldsymbol{\Phi}$ is constructed according to INS error equations:

$$\dot{\boldsymbol{\varphi}} = \boldsymbol{\varphi} \times \boldsymbol{\omega}_{ig}^{g} + \boldsymbol{\delta\omega}_{ig}^{g} - \boldsymbol{\delta\omega}_{ib}^{g} \tag{4}$$

$$\boldsymbol{\delta\dot{V}}^{g} = \boldsymbol{f}^{g} \times \boldsymbol{\varphi} + \boldsymbol{V}^{g} \times (2\boldsymbol{\delta\omega}_{ie}^{g} + \boldsymbol{\delta\omega}_{eg}^{g}) - (2\boldsymbol{\omega}_{ie}^{g} + \boldsymbol{\omega}_{eg}^{g}) \times \boldsymbol{\delta V}^{g} + \boldsymbol{\delta f}^{g} + \boldsymbol{\delta g}^{g} \tag{5}$$

$$\delta\dot{L} = \frac{1}{R+h}\delta V_N^{g} - \frac{V_N}{(R+h)^2}\delta h \tag{6}$$

$$\delta\dot{\lambda} = \frac{\sec L}{R+h}\delta V_E^g + \frac{V_E^g \sec L \tan L}{R+h}\delta L - \frac{V_E^g \sec L}{(R+h)^2}\delta h \quad (7)$$

$$\delta\dot{h} = \delta V_U^g \quad (8)$$

where $\boldsymbol{\omega}_{ie}^g$ and $\delta\boldsymbol{\omega}_{ie}^g$ are the earth angular rate vector and it error, $\boldsymbol{\omega}_{ig}^g$ and $\delta\boldsymbol{\omega}_{ig}^g$ are the angular rate vector of frame g to the inertial frame and its error.

The discrete-time form of (2) is expressed as

$$\begin{cases} \boldsymbol{X}_k = \boldsymbol{\Phi}_{k,k-1}\boldsymbol{X}_{k-1} + \boldsymbol{\Gamma}_k \boldsymbol{W}_k \\ \boldsymbol{Z}_k = \boldsymbol{H}_k \boldsymbol{X}_k + \boldsymbol{V}_k \end{cases} \quad (9)$$

where $\boldsymbol{\Phi}_{k,k-1}$ is one step transition matrix of system state from epoch k-1 to k. Suppose that the mean of the process noise vector and observation noise vector are both equal to zero. The covariance of $\boldsymbol{W}_k$ and $\boldsymbol{V}_k$ can be denoted as $\boldsymbol{Q}_k$ and $\boldsymbol{R}_k$, besides, the $\boldsymbol{Q}_k$ and $\boldsymbol{R}_k$ are nonnegative and positive definite matrix respectively. Then the prediction and update processes of KF are described as follows [13]:

$$\hat{\boldsymbol{X}}_{k/k-1} = \boldsymbol{\Phi}_{k,k-1}\hat{\boldsymbol{X}}_{k-1} \quad (10)$$

$$\hat{\boldsymbol{X}}_k = \hat{\boldsymbol{X}}_{k/k-1} + \boldsymbol{K}_k(\boldsymbol{Z}_k - \boldsymbol{H}_k\hat{\boldsymbol{X}}_{k/k-1}) \quad (11)$$

$$\boldsymbol{K}_k = \boldsymbol{P}_{k/k-1}\boldsymbol{H}_k^T(\boldsymbol{H}_k\boldsymbol{P}_{k/k-1}\boldsymbol{H}_k^T + \boldsymbol{R}_k)^{-1} \quad (12)$$

$$\boldsymbol{P}_{k/k-1} = \boldsymbol{\Phi}_{k,k-1}\boldsymbol{P}_{k-1}\boldsymbol{\Phi}_{k,k-1}^T + \boldsymbol{\Gamma}_{k-1}\boldsymbol{Q}_{k-1}\boldsymbol{\Gamma}_{k-1}^T \quad (13)$$

$$\boldsymbol{P}_k = (\boldsymbol{I} - \boldsymbol{K}_k\boldsymbol{H}_k)\boldsymbol{P}_{k/k-1} \quad (14)$$

where $\hat{\boldsymbol{X}}_{k/k-1}$ is the predicted state estimate, $\boldsymbol{P}_{k/k-1}$ is the corresponding variance matrix, $\boldsymbol{K}_k$ is KF gain matrix, $\hat{\boldsymbol{X}}_k$ is the updated state estimate, $\boldsymbol{P}_k$ is the variance matrix of $\hat{\boldsymbol{X}}_k$.

B. BACK PROPAGATION NEURAL NETWORK

The BPNN is a multi-layer feedforward neural network trained by error back propagation algorithm.

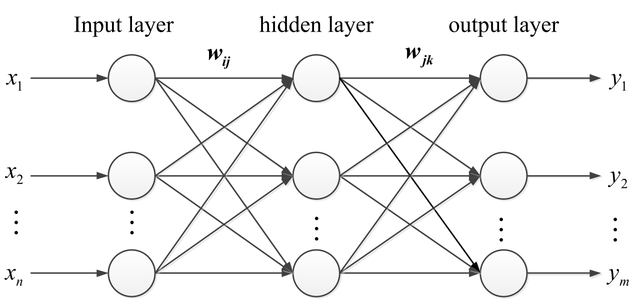

FIGURE 2. Configuration of the BPNN.

It adopts the gradient descent method to approach the goal of minimizing the total error of the output. Fig. 2 shows the configuration of BPNN. In this network, there is an input layer, an output layer, and one or more hidden layers between them.

Suppose that the BP network is composed of n inputs and m outputs, besides s neurons in the hidden layer, the output of the hidden layer and out layer are b_j and y_k, the threshold value of the hidden layer and out layer are θ_j and θ_k, the

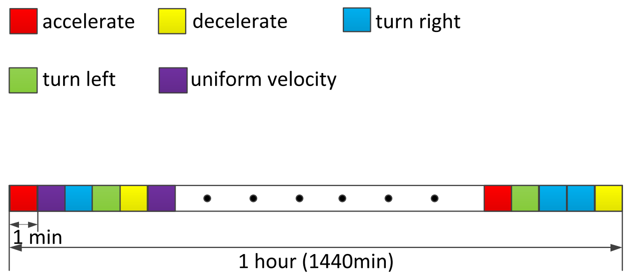

FIGURE 3. Motion states in the simulation experiment.

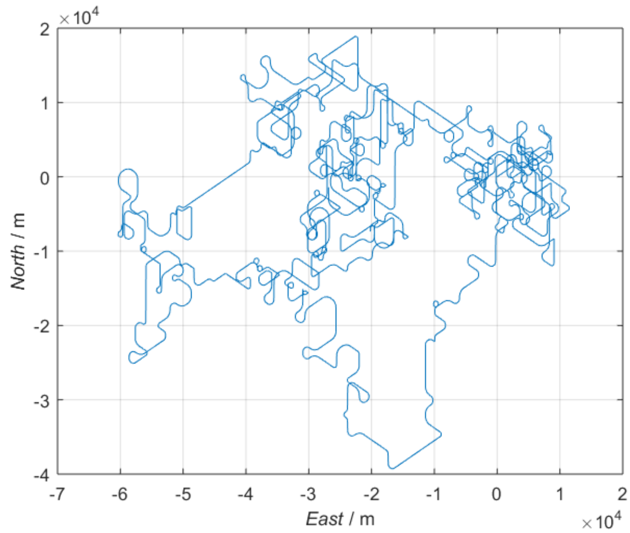

FIGURE 4. Vehicle trajectory in the simulation experiment.

TABLE 1. The parameters of the inertial measurement unit.

System No.	Gyro bias (°/h)	Accelerometer bias (μg)
S1	0.01	50
S2	1	100
S3	30	1000

transfer function of the hidden layer and output layer are f_1 and f_2, the weight from input layer to hidden layer is ω_{ij}, the weight from hidden layer to output layer is ω_{jk}. During the training phase, the desired output is available, and denoted as t_k. The output of j th neuron of the hidden layer is:

$$b_j = f_1(\sum_{i=1}^{n} w_{ij}x_i - \theta_j \ )(i=1,2,\ldots,n; j=1,2,\ldots,s) \quad (15)$$

Then, the result of output layer can be derived

$$y_k = f_2(\sum_{j=1}^{s} w_{jk}b_j - \theta_k) \ \ (j=1,2,\ldots,s; k=1,2,\ldots,m) \quad (16)$$

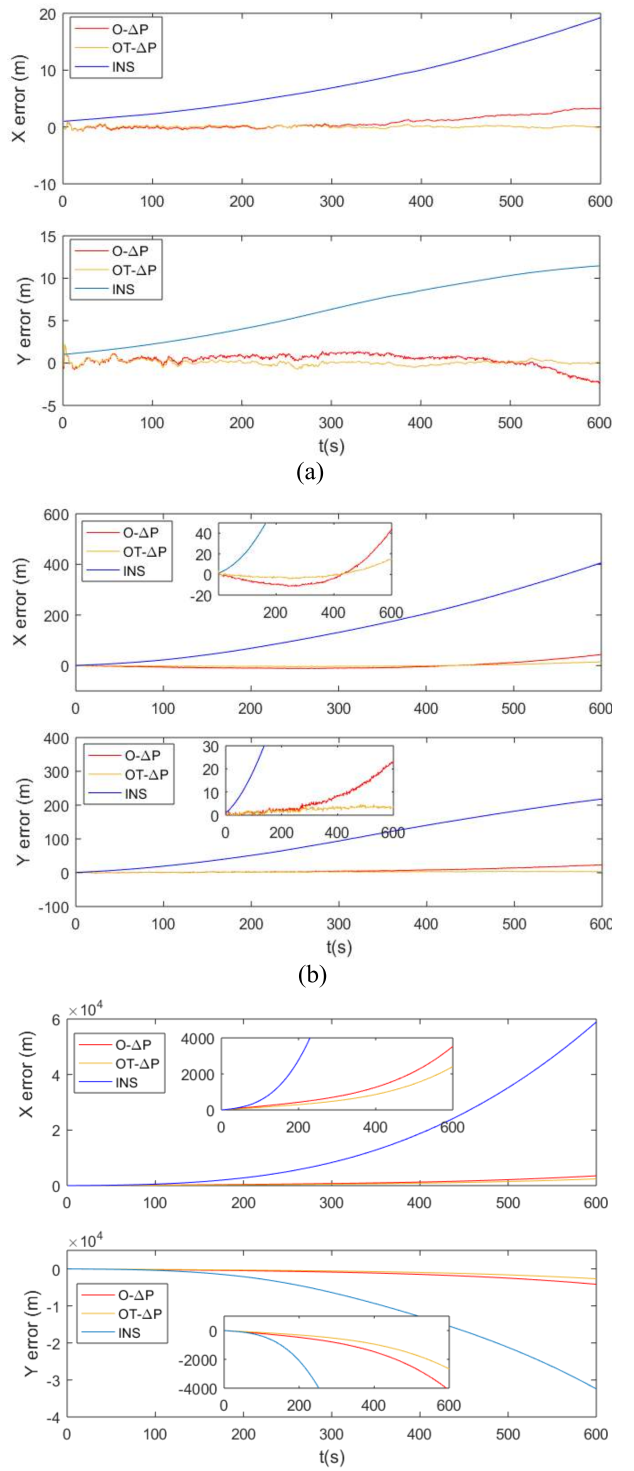

FIGURE 5. Average position error during the GPS outages with different accuracy integration systems. (a) S1 system; (b) S2 system; (c) S3 system.

Defining the error function by the network actual output, that is:

$$e = \sum_{k=1}^{m} (t_k - y_k)^2 \tag{17}$$

TABLE 2. The parameters of the inertial measurement unit.

Gyro bias (°/h)		Accelerometer bias (μg)	
Constant	Random (white noise)	Constant	Random (white noise)
< 0.01	< 0.01	±50	< 50

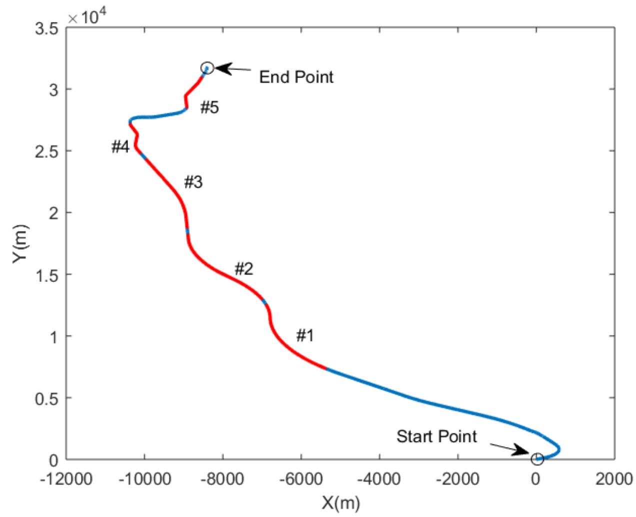

FIGURE 6. Vehicle trajectory in the road experiment.

The network training is a process of continual readjustment between the weights and the threshold, in order to make the network error reduce to a pre-set minimum or stop at the pre-set training steps [14].

A three-layer BP neural network can approach any non-linear functions with any accuracy. However, since the BP algorithm is based on the gradient information of error function, some problems also appear, such as poor rate of convergence, and getting stuck in local minimum easily. To overcome the disadvantages, some effective measures have been taken as follows.

1) ADDITIONAL MOMENTUM

An additional momentum that contains the gradient descent information of past 2 iterations is adopted. If the errors keep decreasing during past 2 iterations, the momentum could accelerate the convergence. In contrast, the momentum will change the variation direction of weight value.

$$\boldsymbol{w}(n_0+1) = \boldsymbol{w}(n_0) + \eta \boldsymbol{d}(n_0) + \alpha \Delta \boldsymbol{w}(n_0) \tag{18}$$

$$\boldsymbol{d}(n_0) = -\frac{\partial e}{\partial \boldsymbol{w}(n_0)} \tag{19}$$

$$\Delta \boldsymbol{w}(n_0) = \boldsymbol{w}(n_0) - \boldsymbol{w}(n_0 - 1) = \eta(n_0 - 1)\boldsymbol{d}(n_0 - 1) \tag{20}$$

where $\boldsymbol{w}(*)$ is the weight values of the $*$th iteration ($* = n_0 - 1, n_0, n_0 + 1$), η is the learning rate, $\boldsymbol{d}(*)$ is the additional momentum of the $*$th iteration ($* = n_0 - 1, n_0$), α is the momentum factor which is set between 0.1 and 0.8.

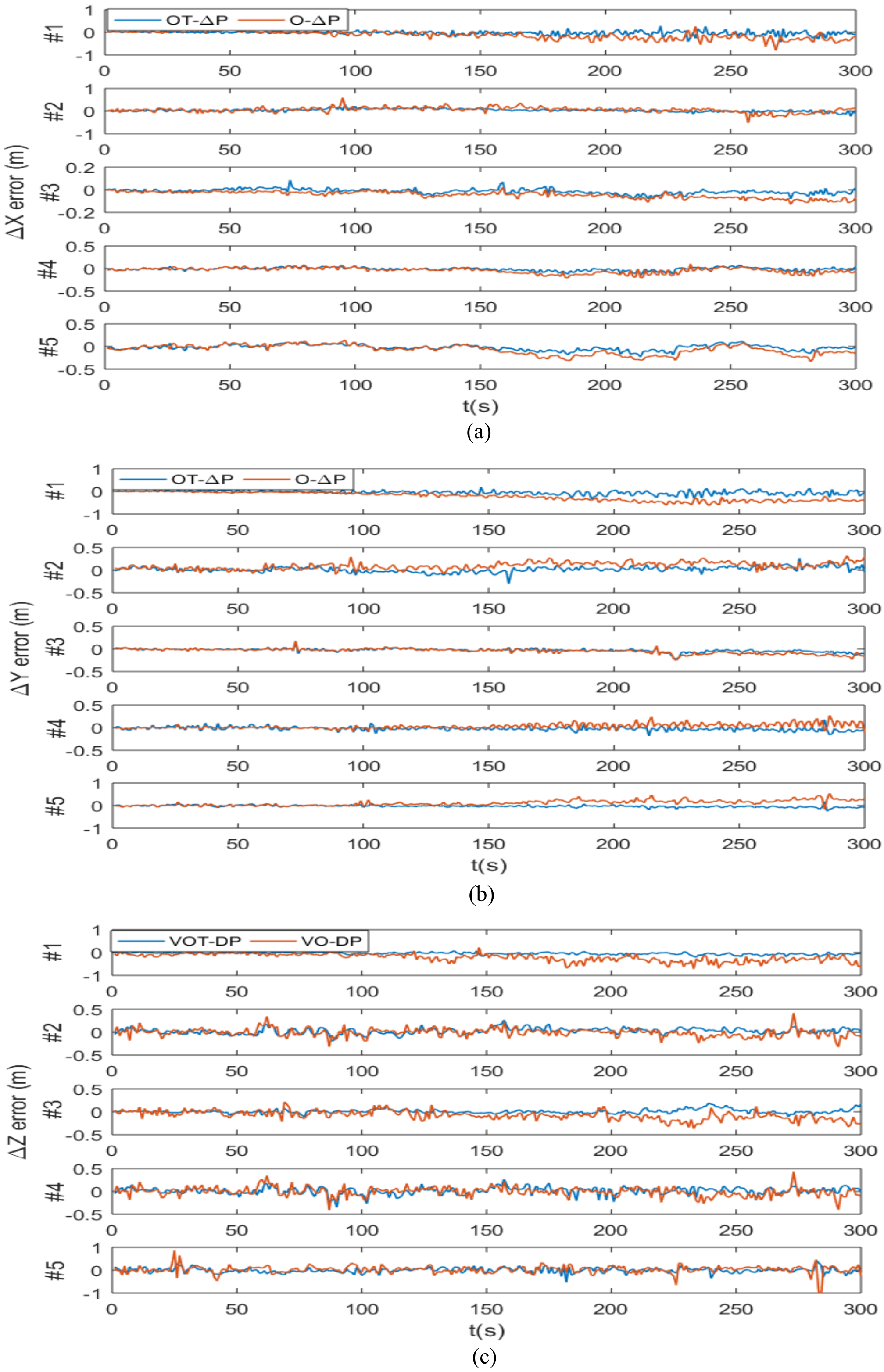

FIGURE 7. Comparison of the predicting errors during 3 sections of GPS outages. (a) East direction. (b) North direction. (c) Down direction.

2) HIDDEN UNIT COMPETITION

Aiming to avoid getting stuck the local minimum, the hidden unit competition algorithm has been employed. The process is as follows: Firstly, calculate the δ error of every hidden unit. Then correct normally the weight value of the unit which has the maximum error, while the weights of last units are corrected in the opposite direction. The change of weight value can be denoted by the mathematical formula [16]:

$$w_{ji}(n_0+1) = w_{ji}(n_0) + \eta\delta_j x_j(n_0) \tag{21}$$

$$\delta_j = \begin{cases} \max(\delta), & \delta_j = \max(\delta), \\ -\frac{1}{4}\max(\delta), & others. \end{cases} \tag{22}$$

III. SIMULATION EXPERIMENT

In order to verify the effectiveness of this method, we designed a simulation experiment lasting 24 hours. The experiment is divided into equal 1440 sections, and every section lasts for 1 minute. During the different section, the vehicle stays random motion states such as uniform speed, acceleration, deceleration, left turn and right turn. The simulated motion states showed in the Fig. 3 and the trajectory in the Fig. 4 are even more complex than those in reality.

Then, three vehicles equipped with different accuracy grade INS/GPS integration systems (S1, S2, S3) are simulated. The parameters of the systems are listed in the Table 1. These vehicles move according to the Fig. 3 and Fig. 4.

In addition, 48 artificial 600s GPS outages are introduced in the experiment. The position errors during these outages are averaged and showed in the Fig. 5. Three pictures (5(a), 5(b), 5(c)) are included, and illustrate the position errors of three different systems (S1, S2, S3) respectively. The x-axis represents the GPS outages time, and the y-axis the average position error in horizontal direction.

From Fig. 5, we can see that the $O-\Delta P$ method and the $OT-\Delta P$ proposed by us both gain obvious improvement compared the pure INS. With the increment of the outages time, the latter method achieves the more accurate position than the former one, especially in the low-accuracy system. When the 600s GPS outages happen, we can see a few meters or hundreds meters improvement on position accuracy in the Fig. 5. The position result of the low-accuracy is still unacceptable when the GPS outages last for a long time, even the improvement has been made. We hold the reason is that the systematic error in the low-accuracy system is so random and changes quickly with time. And it is too difficult to establish the model accurately. However, the problem does not exist for the high-accuracy system whose systematic error is stable. Considering this situation, we recommend to use the $OT-\Delta P$ method on the high-accuracy INS/GPS system to overcome the GPS outages. And the method is seemed always effective during the whole outages which last for hundreds of seconds. While for the low-accuracy system, only when the short-term outages occur does the novel method is recommended. So we will put more attention on the high-accuracy system in the following study.

IV. ROAD EXPERIMENT

The performance of the proposed $O_{INS}T-\Delta P_{GPS}$ model was examined with a field test in Nanjing, Jiangsu Province, China. The test was conducted on a vehicle platform equipped a PHINS inertial system, a FlexPark6 GPS receiver as well as an IMU. The PHINS is a high performance inertial navigation system equipped a fiber optic gyroscope (FOG), and was developed by French IXBLUE. It provides 200Hz reference position information combined with the FlexPark6 in our test. The IMU contains three FOGs and three quartz accelerometers. The parameters of these sensors are showed in the Table 2. The road experiment lasted for 2160s, and the moving distance was about 40 kilometers during this period.

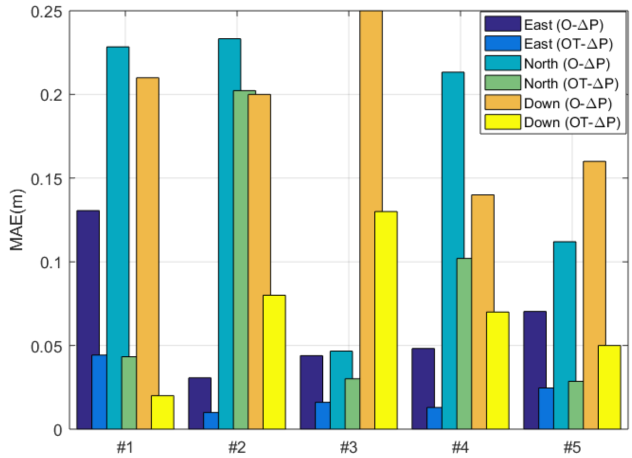

FIGURE 8. MAE of predicting result.

TABLE 3. The mae of the predicting result with different steps past information.

Inputs of BPNN	MAE in east(m)	MAE in north(m)	Mean MAE(m)
past 2-step	0.0971	0.1686	0.1329
past 3-step	0.1040	0.0848	0.0944
past 4-step	0.0536	0.1095	0.0816
past 5-step	0.0142	0.1491	0.0816

Over the whole trajectory of test, no natural GPS outages occurred, and thus the accurate position information which obtained from INS/GPS system can be consistent. The trajectory in rectangular coordinate was plotted in the Fig. 6 where GPS outages are marked by red lines. Five artificial 300s GPS outages (#1, #2, #3, #4 and #5) intentionally introduced in order to test the stability of $O_{INS}T-\Delta P_{GPS}$ model. In addition, GPS outages occurred when the vehicle was in different dynamics conditions, so that the robustness of the module can also be examined.

A. COMPARISON OF PREDICTION RESULTS BETWEEN DIFFERENT MODELS

In this test, proposed model termed as $O_{INS}T-\Delta P_{GPS}$, is applied to predict the position increment of GPS. In order to verify the performance of $O_{INS}T-\Delta P_{GPS}$, $O_{INS}-\Delta P_{GPS}$ is employed as comparison which was the most accurate model in previous [9].

If the proposed algorithm achieves the same accuracy as others with fewer neurons in the input layer (lower time complexity), the higher efficiency can be proved. However, it is

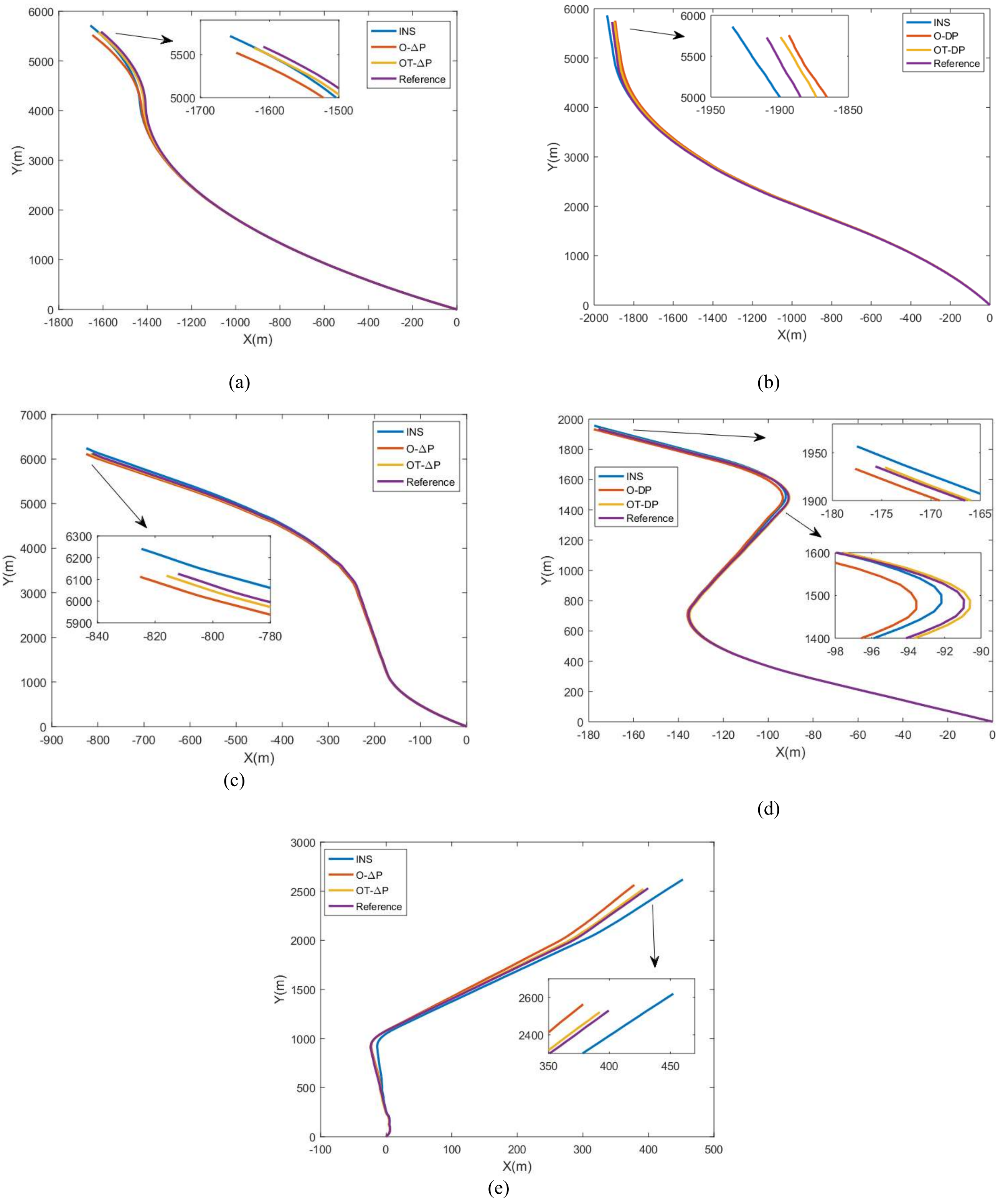

FIGURE 9. Positioning results with different algorithms.

not easy to get the same accurate results using different algorithms, because the accuracy is relative with many parameters and factors. In other way, if the proposed algorithm achieves the higher accuracy than the others with the same or almost same number of neurons in the input layer, the superiority on the computational efficiency can also be proved.

The position increments predicted by the two models are collected. Compared with the pure GPS result during the three

300s GPS outage, the eastern and northern prediction errors can be gained and illustrated in the Fig. 4. The prediction errors of two models are represented respectively by the blue and red curves.

In the Fig.7, two models shows the almost equivalent accuracy in case of short GPS outages, however, $O_{INS}T - \Delta P_{GPS}$ provides a significant improvement over $O_{INS} - \Delta P_{GPS}$ in case of long GPS outages(>100 s). For further analysis, the performance of $O_{INS}T - \Delta P_{GPS}$ and $O_{INS} - \Delta P_{GPS}$ both get worse as the GPS outages time increases, however, the latter's accuracy deteriorates faster than the former's. The reason for the phenomenon is exactly the long-term and time-related errors which not be eliminated in $O_{INS} - \Delta P_{GPS}$ module.

In order to describe the advantages of $O_{INS}T - \Delta P_{GPS}$ more intuitively, the mean value of absolute errors (MAE) have been calculated and shown in histogram. From Fig. 8, it can be clearly seen that the MAE of $O_{INS}T - \Delta P_{GPS}$ is always smaller than $O_{INS} - \Delta P_{GPS}$'s during 5 GPS outages sections. To sum up the above arguments, we can draw a major conclusion: the proposed $O_{INS}T - \Delta P_{GPS}$ can lead to a better performance in terms of providing accurate position information during GPS outages, especially when the GPS signals disappear for a long time. Under the condition that the time complexity of our algorithm is almost equal to the other one, but the improvement on accuracy is far greater than 10%. This result proves the advantage on the computation efficiency of our algorithm indirectly.

B. THE SELECTIN OF THE NUMBER OF STEPS IN THE PAST INFORMATION

In previous studies, the way of eliminating the long-term errors is to increase the number of information in the past. But now the time dimension was added in the $O_{INS}T - \Delta P_{GPS}$, the long-term INS velocity error trend can be modeled and eliminated. Consequently, it does not need to consider too much past information. The problem that needs to be solved now is to determine how many steps past information we should select to mimic the short-term errors. In this section, past 2-5 steps INS velocity and IMU information are used to predict GPS position increment. The MAEs of the prediction results are listed in Table 3.

As the Table 2 shows, the mean values of MAEs in both directions decline as the number steps of past information increases. In other words, the more steps are involved, the better performance is achieved in overall. However, the tendency slows down and even stops as more than 3 steps past information is added to the input of BPNN module. Taking into account both accuracy and computation efficiency, the past 3-step information is selected to predict position increment of vehicle in the following experiment.

C. COMPARISON OF POSITION RESULTS BETWEEN DIFFERENT ALGORITHMS

Fig. 9 shows the positioning results after compensation. The reference trajectory is provided by the PIHINS, while the INS trajectory is calculated with the IMU data. During these 5 sections of GPS outages, the best performance is always achieved when the time dimension was added to the input of NN module. The advantage of $O_{INS}T - \Delta P_{GPS}$ becomes more and more evident along with the increase of time. Obviously, considering the time information is helpful to model and eliminate the positioning error introduced by INS error changes over time.

V. CONCLUSIONS

In order to supply high-performance position information to the vehicles during GPS outages, an improved BPNN module is presented. When the GPS signal is available, the GPS position increment and some INS information are collected and trained by BPNN module. During GPS outages, the well trained model will provide the pseudo GPS position for the vehicles.

Considering the shortcoming of the conventional network modules, the time information are added into the input of the new module to slow down the accuracy degradation caused by the changes of INS error characteristic over time. Field test including 5 sections of 300s GPS outages has been conducted to evaluate the performance of the proposed method. It can be seen that, the novel $O_{INS}T - \Delta P_{GPS}$ model has more advantage on predicting the position increment over the traditional $O_{INS} - \Delta P_{GPS}$ model, especially, under the circumstance where the GPS outages last for a long time. Meanwhile, we explore the number of past information that should be selected to balance the computation burden and the accuracy. The past 3-steps information is determined as the optimal inputs of the proposed $O_{INS}T - \Delta P_{GPS}$ module.

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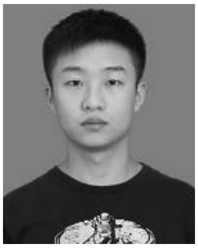

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