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A Novel Prediction Algorithm of DR Position Error Based on Bayesian Regularization Back-propagation Neural Network

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Abstract

It is difficult to accurately reckon vehicle position for vehicle navigation system (VNS) during GPS outages, a novel prediction algorithm of dead reckon (DR) position error is put forward, which based on Bayesian regularization back-propagation (BRBP) neural network. DR, GPS position data are first de-noised and compared at different stationary wavelet transformation (SWT) decomposition level, and DR position error data are acquired after the SWT coefficients differences are reconstructed. A neural network to mimic position error property is trained with back-propagation algorithm, and the algorithm is improved for improving its generalization by Bayesian regularization theory. During GPS outages, the established prediction algorithm predicts DR position errors, and provides precise position for VNS through DR position error data updating DR position data. The simulation results show the positioning precision of the BRBP algorithm is best among the presented prediction algorithms such as simple DR and adaptive linear network, and a precise mathematical model of navigation sensors isn't established.

Keywords: *dead reckon (DR), position error, back-propagation, Bayesian regularization, stationary wavelet transformation (SWT)*

1. Introduction

GPS is capable of providing precise positioning information for unlimited numbers of users anywhere on the planet. Vehicle navigation system (VNS) gets positioning information through GPS generally, but this service isn't always continuous in large building, mountain, canyon, forest and valley areas dues to signal blockage. Dead reckon (DR) system is a low cost inertial navigation system (INS), which can supply continuous positioning and velocity information, and DR is yet adopted to provide positioning service for VNS [1, 2, 3, 4, 5, 6]. However, DR can't operate appropriately as a stand-alone navigation system for vehicle because its long-term positioning accuracy may be deteriorated with the presence of residual bias errors in both odometer and gyroscope. Therefore, GPS/DR integration is an adequate solution for VNS that has superior performance in comparison with either a GPS or a DR stand-alone navigation system [3, 4, 5].

The GPS/DR integration is typically carried out through Kalman filter (KF), which has been proven to be one of the best integration solutions. However, it is difficult to establish a precise mathematical model and describe the long-term behavior of navigation sensors errors for the vehicle GPS/DR integrated navigation system because these navigation sensors may include white noise, correlated random noise, bias instability and angle random walk [4, 5]. Then, an adaptive linearneural (ADLINE) network prediction algorithm of DR position error is put forward in the reference [3], but the prediction algorithm has little effect in complex running trajectory as ADLINE network is only capable of linear fitting and classification [5]. Therefore, this paper put forward a new algorithm to accurately estimate vehicle position depending only on DR outputs in case of GPS signal blockage. The algorithm makes use of stationary wavelet transformation (SWT) [7, 8, 9] to de-noise and compare DR and GPS outputs at different resolution levels before processing them by Bayesian regularization back-propagation (BRBP)

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neural network [4, 10] to mimic the vehicle dynamic property and accurately reckon its position during GPS outages.

2. SWT De-Noising Algorithm

SWT uses redundant discrete wavelet basis, and the translation is invariance. The wavelet coefficients and scale coefficients of SWT are as long as the original signal, can weaken the oscillation effect on the discrete binary wavelet transformation, and its decomposition formula is as follows [4, 7, 8, 9]:

$$c_{j,k} = \sum_n h_0^{\uparrow 2^j}(n-2k)c_{j-1,n} \tag{1}$$

$$d_{j,k} = \sum_n h_1^{\uparrow 2^j}(n-2k)c_{j-1,n} \tag{2}$$

Where, $c_{j,k}$ is scaling coefficient; $d_{j,k}$ is wavelet coefficient; $h_0^{\uparrow 2^j}$, $h_1^{\uparrow 2^j}$ represented inserting $2^j - 1$ zeros between h_0, h_1 respectively; $h_0 =< \varphi_{1,0}, \varphi_{0,k} >$; $h_1 =< \psi_{1,0}, \psi_{0,k} >$; ψ is wavelet function; φ is scaling function; $n = 0,1,\ldots,N-1$ (n is signal length).

The corresponding reconstruction formula is [7, 8, 9]:

$$c_{j-1,k} = \frac{1}{2}\sum_k (g_0(n-2k) + g_0(n-2k-1))c_{j,k} + \frac{1}{2}\sum_k (g_1(n-2k) + g_1(n-2k-1))d_{j,k} \tag{3}$$

Where, $g_0(k)$, $g_1(k)$ are dual basis of $h_0(k)$, $h_1(k)$ respectively.

Mallet and other researchers found that, the wavelet coefficients of the signal and noise are increased and decreased respectively as the scale of the wavelet transform increases, and wavelet coefficients of noise are removed basically or have small amplitude after doing a number of wavelet transformation [4, 11]. According to the above analysis and the characteristics of the soft-threshold de-noising method, the hard-threshold de-noising method and their improved method, and a SWT de-noising algorithms is put forward for the GPS, DR signals, which based on the modulus square soft-threshold de-noising algorithm. The novel algorithm as follow [4, 7, 11]:

1) Decompose the GPS, DR signals with formula (1), (2) and SWT function, the SWT coefficient $d_{j,k}$ is obtained.

2) Calculate root mean square error (RMSE) of every resolution scale SWT coefficient with empirical formula (4).

$$\sigma_j = median\,(|d_{j,k}|)/0.6745 \tag{4}$$

3) Calculate threshold of every resolution scale SWT coefficient with empirical formula (5).

$$\lambda_j = \sigma_1\sqrt{2\log_2 N}/\ln(j+1) \tag{5}$$

Estimate and correct every point new SWT coefficient with modulus square soft-threshold de-noising method, and its de-noising formula as follow

$$\hat{d}_{j,k} = \begin{cases} sign(d_{j,k})\sqrt{d_{j,k}^2 - \lambda_j^2} \quad , & |d_{j,k}| \geq \lambda_j \\ 0 \quad , \quad |d_{j,k}| < \lambda_j \end{cases} \tag{6}$$

4) Reconstruct the de-noised SWT coefficient with formula (3), and realize de-noising for the GPS, DR signals.

3. Principle of BRBP Neural Network

As regularization technology may improve generalization capability of back-propagation (BP) neural network, a novel neural network algorithm is made by adding an additional term on the base of BP neural network's objective function. The novel network's objective function can be described in the following formula [4, 10]:

$$F = \alpha E_W + \beta E_D \tag{7}$$

Where, E_W is the sum of squares of the network weights; E_D is the sum of squares of errors between the neural network response and its target; and α, β are objective function parameters. The relative size of the objective function parameters dictates the emphasis for training. If $\alpha << \beta$, training will drive the network error smaller, and over-fitting will occur. If $\alpha >> \beta$, training will emphasize weight size reduction at the expense of network errors, thus will produce a smoother network response.

The main problem with implementing regularization is setting the correct values for the objective function parameters. David MacKay put forward a method to optimize the parameters with Bayes statistical rule. Through theoretical formula derivation, the optimal objective function parameters are obtained and computed in the following formula:

$$\alpha^{MP} = \frac{\gamma}{2E_W(W^{MP})} \tag{8}$$

$$\beta^{MP} = \frac{N-\gamma}{2E_D(W^{MP})} \tag{9}$$

Where, W is the matrix of weights; N is the size of training sample data sets; and γ is called the effective number of parameters in the network.

The effective number of neural network parameters is computed in the following formula:

$$\gamma = n - 2\alpha^{MP} tr((H^{MP})^{-1}) \tag{10}$$

Where, H is the Hessian matrix of the objective function; n is the total number of parameters in the network.

The effective number γ is a measure of how many parameters in the neural network are effectively used in reducing the error function, and can range from zero to n. The effective number computation show that, as long as rough values are only set for the structure and parameters of BP neural network, the optimal structure and parameters are ultimately obtained with repeated training and optimization [10]. Then the difficult to design BP neural network is solved, and the improved BP neural network is called "BRBP neural network".

4. Principle of BRBP Neural Network

Research founds that, the DR position errors relative to GPS are actually related to all time series of the DR position in the east and north before that moment. Therefore, the input layer of BP neural network is designed three components, includes the east and north position of DR, the corresponding time; the output layer of BP neural network is the DR position errors in the east and north.

GPS, DR signals are decomposed by SWT (the wavelet function is $db3$), are de-noised with the modulus square soft-threshold de-noising algorithm, the SWT coefficients deffences are acquired by comparing with the SWT coefficient of GPS, DR signals at every resolution scale, and the DR position errors relative to GPS are obtained with reconstructing the SWT coefficients deffences. The BP neural network training samples are composed with the DR position data, the DR position errors and the corresponding time. To simple BP neural network structure, improve generalization performance and increase the network training speed, this paper adopts Bayesian regularization rules to train the network, and the BRBP prediction algorithm of DR position error is yet obtained.

Figure 1 shows that, this paper adopts the trained prediction algorithm of DR position error to predict the DR position errors during GPS outages, and the precise position is provided for the vehicle with the predicted DR position error data updating the DR position data.

Another thing need to be point out is that, in order to simplify the network structure and improve the speed of network training, this paper establishes two same structure prediction model (algorithm) to predict the DR position errors in the east and north respectively, and realizes an accurate, real-time navigation and positioning for the vehicle GPS/DR integrated navigation system.

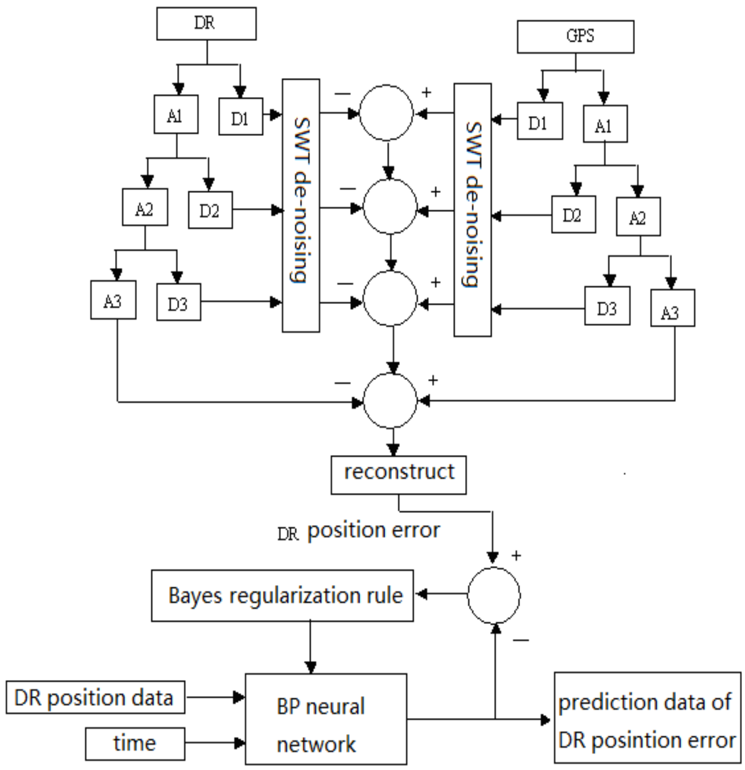


Figure 1. BRBP prediction algorithm of DR position error

5. Simulationl Experiment and Its Results Analysis

According to the actual vehicle running situation on the ground, assume that the vehicle runs straight forward along a 45^0 course angle with a constant speed of $10\sqrt{2}$ m/s from the coordinate origin, the total running time is 1280s, the sampling cycle is T=1s. In order to examine the validity of prediction algorithm of DR position error, respectively, add the east, the north output position signal of GPS receiver and the output signal of gyroscope, odometer with Gaussian white noise $N(0,(9m)^2)$, $N(0,(9m)^2)$, $N(0,(0.0015rad)^2)$ and $N(0,(0.5m)^2)$, and the GPS receiver fails to receive GPS signal after running 1024 s in the mountains and canyons, urban buildings and the likes.

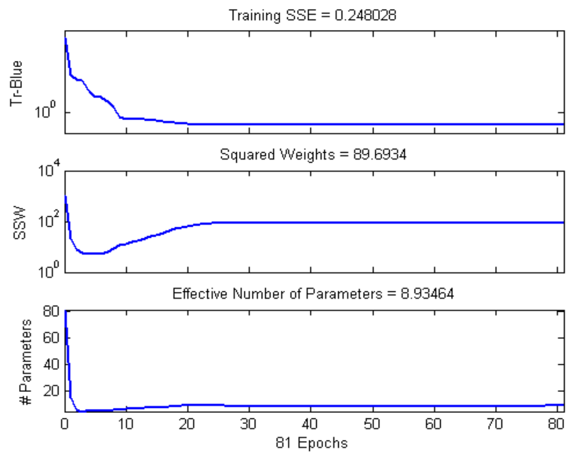
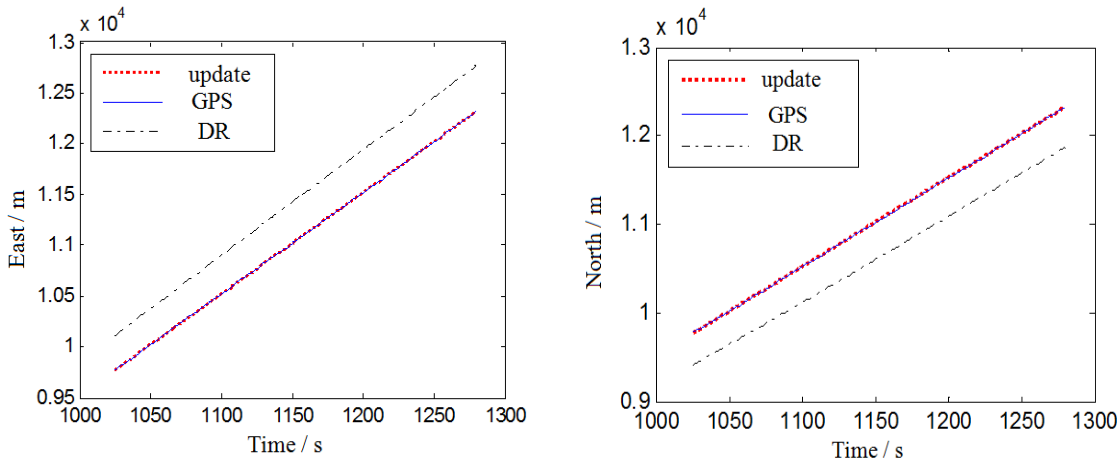


Figure 2. Train curves of prediction algorithm of DR position error before GPS outages (East)

Figure 2 is the training curve of BRBP neural network prediction algorithm of DR eastern position error until GPS outages. The network is designed to have only one hidden layer, the transfer function of the hidden layer is a double tangent *S* type function, and the initial unit of the network is set to be 20. In order to improve the training speed and stability of the network, this paper normalizes the training sample sets in advance. The Figure shows that the sum of squared error (SSE) keeps at 0.248028 almost unchanged after 81 times training, which means that the network training is basically completed and the training should be stopped, much less than training times of the standard BP neural network (usually several thousands of times), and be able to meet the requirements of real-time vehicle navigation and positioning. Effective parameters of the network are reduced from 80 to 9, which means that the network hidden layer unit decreased from the initial 20 to about 3. The sum of squared network weights (SSW) is also reduced from nearly 1000 to about 90.The reduction of the network structure and size can improve its generalization capability.



(a) East position error (b) North position error

Figure 3. Position results of vehicle running in a straight route during GPS Outages

As the Figure 3 (a) shows, simple DR east position error is 403.1 meter. The un-repaired DR east position error is 26.2 meter even if the vehicle GPS/DR integrated navigation system does DR "zero-point update" immediately before GPS Outages, and the accuracy still cannot meet the requirements of the system navigation and positioning. The updated (repaired)

DR east position error reaches to 2.1 meter, this means that the simple DR position error is corrected, and the updated DR east position can follow the change of the GPS east position.

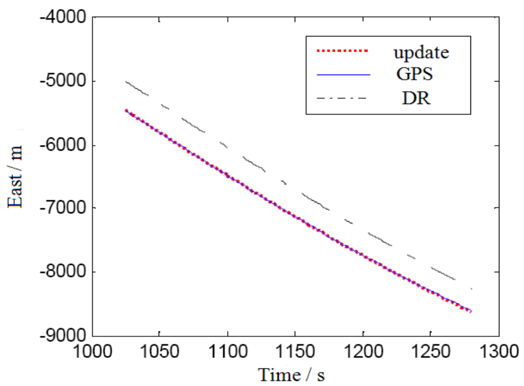
As the training curve of BRBP neural network prediction algorithm of DR north position error is similar to the east, this paper only gives comparison Figure of vehicle north position during GPS Outages, as shown in Figure 3 (b).

As the Figure 3 (b) shows, simple DR north position error is 415.4 meter, the un-repaired DR north position error is 37.7 meter even if the system does DR “zero-point update” immediately before GPS Outages. The updated DR north position error reaches to 3.8 meter, this yet means that the simple DR position error is corrected, and the updated DR north position can follow the change of the GPS north position.

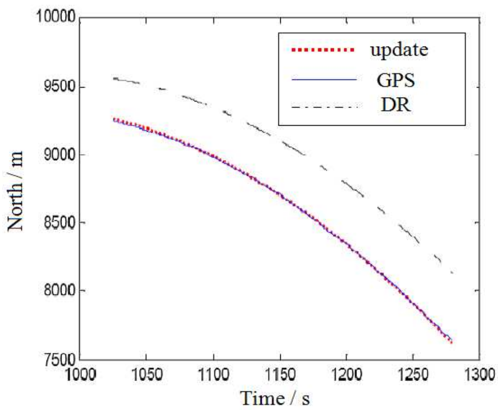
Obviously, the above simulation shows that the BRBP neural network prediction algorithm is fully capable of accurately predict DR position error when the vehicle runs in a straight route, and the updated DR position can follow the change of the GPS position. However, in fact the vehicle may change course during its running, then how well dose it work? So make the gyroscope’s angular acceleration at 0.00245437 *rad/s*, and the rest conditions remain unchanged and carry on the experiment again. The training curve of BRBP neural network prediction algorithm of DR position error is similar to Figure 2, this paper only gives the position comparison charts in the east and north during GPS outages, as shown in Figure 4.

During vehicle runs in an arc route, the BRBP neural network prediction algorithm of DR position error can predict DR position error accurately with analyzing Figure 4, and the updated DR position can follow the change of the GPS position yet.

As the running trajectory of vehicle is very complex with the changing of heading and speed both, so make the vehicle’s running speed at 10 *m/s*, 20 *m/s* respectively, the rest conditions remain unchanged and carry on the experiment again. Compare the un-repaired and updated DR position with Figure 2, 3, 4, the experiment results are similar, and are omitted in this paper. Meanwhile, in order to fully examine the feasibility of the BRBP neural network prediction algorithm of DR position error, this paper also compares these with the ADLINE network prediction algorithm of DR position error, the results are shown in table 1.



(a) East position error



(b) North position error

Figure 4. Position results of vehicle running in an arc route during GPS Outages

Table 1. Comparison of DR position precision during GPS outages

Methods	straight route (m)			arc route (m)		
	10 m/s	10√2m/s	10 m/s	10m/s	10√2m/s	10m/s
zero-point update (east)	18.4	28.4	18.4	19.6	14.0	16.0
zero-point update (north)	29.5	39.8	20.4	23.0	23.5	37.9
ADLINE (east)	0.4	0.2	0.2	5.5	31.3	17.4
ADLINE (north)	1.3	1.2	1.1	21.7	8.3	21.0
BRBP (east)	0.7	0.6	3.6	2.0	5.7	6.0
BRBP (north)	1.9	1.9	3.2	2.4	6.6	6.8

The experimental results can be found from the table 1:

1) Position error of simple DR is about 200 to 400 meters, and its position precision still cannot meet the requirements of vehicle navigation and positioning even if the vehicle is done “zero-point update” immediately before GPS outages.

2) Although the ADLINE network prediction algorithm of DR position error can predict DR position error accurately and its updated position can follow the changes of the GPS position in a straight running route, but the algorithm cannot in the arc route and other complicated situations, and cannot meet the requirements of the vehicle navigation and positioning.

3) The BRBP neural network prediction algorithm of DR position error reckoned DR position can keep pace with the changes of the GPS, its position precision can meet the requirements of the vehicle navigation and positioning in the straight line route, arc route, and other simple or complicated routes.

Other things to be point out:

1) For the required position data during the 256s period which GPS receiver failed to receive signals, the simulation experiment take the same simulation method during the 1024s period to do GPS data simulation to instead.

2) The initial design of the BRBP neural network prediction algorithm has only one hidden layer and 20 hidden units, the training times can be completed within 200 times, much less than the training times of standard BP neural network prediction algorithm, the training times of the latter usually demands several thousands to tens of thousands of times, and the former can meet the requirements of real-time navigation and positioning.

6. Conclusion

The BRBP neural network prediction algorithm of DR position error is a preliminary exploration of how the vehicle GPS/DR integrated navigation system works during GPS outages. The prediction algorithm first de-noises for the GPS, DR signals with SWT modulus square soft-threshold de-noising algorithm, and is established with BRBP neural network when GPS signal is available. The established prediction algorithm accurately predicts DR position error, and reckons the real-time vehicle position during GPS outages. The simulation results show that the navigation and positioning precision of the prediction algorithm is best among the presented algorithms such as simple DR and ADLINE. The prediction algorithm only needs to set the number of hidden layer, transfer function and approximate initial numbers of hidden layer units, do not need to establish a precise mathematical model of navigation sensors during it is established. The prediction model meets the mathematical-free model requirements of the prediction algorithm of DR position error, and is available for the vehicle integrated navigation system.

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