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A Study of RSCMAC Enhanced GPS Dynamic Positioning

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***Abstract*—**The purpose of this research is to develop and apply the RSCMAC to enhance the dynamic accuracy of Global Positioning System (GPS). GPS devices provide services of accurate positioning, speed detection and highly precise time standard for over 98% area on the earth. The overall operation of Global Positioning System includes 24 GPS satellites in space; signal transmission that includes 2 frequency carrier waves (Link 1 and Link 2) and 2 sets random telegraphic codes (C/A code and P code), on-earth monitoring stations or client GPS receivers. Only 4 satellites utilization, the client position and its elevation can be detected rapidly. The more receivable satellites, the more accurate position can be decoded. Currently, the standard positioning accuracy of the simplified GPS receiver is greatly increased, but due to affected by the error of satellite clock, the troposphere delay and the ionosphere delay, current measurement accuracy is in the level of 5~15m. In increasing the dynamic GPS positioning accuracy, most researchers mainly use inertial navigation system (INS) and installation of other sensors or maps for the assistance. This research utilizes the RSCMAC advantages of fast learning, learning convergence assurance, solving capability of time-related dynamic system problems with the static positioning calibration structure to improve and increase the GPS dynamic accuracy. The increasing of GPS dynamic positioning accuracy can be achieved by using RSCMAC system with GPS receivers collecting dynamic error data for the error prediction and follows by using the predicted error to correct the GPS dynamic positioning data. The ultimate purpose of this research is to improve the dynamic positioning error of cheap GPS receivers and the economic benefits will be enhanced while the accuracy is increased.

***Keywords*—**Dynamic Error, GPS, Prediction, RSCMAC.

I. Introduction

SO far, most researches on increasing GPS dynamic positioning accuracy apply inertial navigation system (INS) and installation of other sensors or maps for the assistance, some of these researches combined with neural network, such as traditional neural network, recursive neural network, multi-level neural network, wavelet neural network, etc., to do the DGPS error prediction [4]-[14]. Although there is a certain effect on these researches, many progresses can still be improved. Cerebellar Model Articulation Controller (CMAC) [1], [2] is a neural network being applied in linking control in early days, its advantages are learning convergence to LMSE, good generalization capability, rapid learning, etc. Recurrent S_CMAC_GBF (RSCMAC) [3] has more capabilities of input-output relationship, fixed addressing structure and time correlation, its learning convergence assurance is proved. This research utilizes the RSCMAC advantages of fast learning, learning convergence assurance, solving capability of time-related dynamic system problems with the static positioning calibration structure [15] to improve and increase the GPS dynamic accuracy. It will first introduce RSCMAC in the next section, GPS equipment installation and data collection is proposed in the 3rd section, the error prediction structure of GPS dynamic positioning is explained in the 4th section, the error improvement situation of the positioning system is demonstrated in the last section.

II. RSCMAC

RSCMAC is to imitate human cerebellum to deliver and store messages in the multi-link mode. RSCMAC uses supervised, repeated learning and will update its weight values. Fig. 1 shows the basic structure of RSCMAC, this research utilizes RSCMAC excellent nonlinear system learning capability to quantify input variables and map to its corresponding related memory, the output is the combination of these memories (weight values). The memory (weights) of RSCMAC is basically the product of several differentiable basis functions multiplies the height (v_i).

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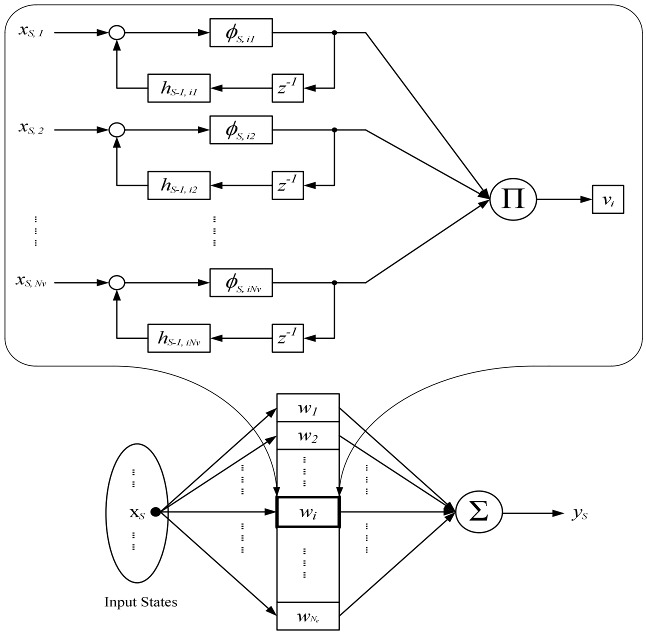


Fig. 1 RSCMAC structure

To make it have the capability of time sequence, its output is feedback to itself so it will be easier to learn the dynamic system. The basis function input item of RSCMAC is not only the state vector variable $\mathbf{x_s}$ but also includes the function output value of the previous time sequence, which means to feedback the output of the previous time sequence to itself. The ith weight value can be expressed as:

$$w_i(\mathbf{x_s}) \equiv v_i b_{s,i}(\mathbf{x_s} + \Phi_{s-1,i} \cdot \mathbf{h}_{s-1,i}) \tag{1}$$

where $b_{s,i}(\mathbf{x_s} + \Phi_{s-1,i} \cdot \mathbf{h}_{s-1,i}) \equiv \prod_{j=1}^{N_v} \phi_{s,ij}(x_{s,j} + \phi_{s-1,ij} \cdot h_{s-1,ij})$, v_i is the height, $\mathbf{\Phi}_{s-1,i}$ is the previous time sequence function output value, $\mathbf{h}_{s-1,i}$ is the feedback ratio vector and $b_{s,i}$ is the product of Gaussian function, every function uses the previous function time sequence output value as its input value. Gaussian function is defined as:

$$\phi_{ij}(x_{s,j}) = \exp\left[-\frac{\left(x_{s,j} + \phi_{s-1,ij} \times h_{ij} - m_{ij}\right)^2}{\sigma_{ij}^2}\right] \tag{2}$$

where m_{ij} is mean and σ_{ij}^2 is variance.

The output value is expressed as:

$$y(\mathbf{x_s}) = \sum_i^{N_e} \left[a_{s,i} \cdot w_i\right] = \sum_i^{N_e} \left[a_{s,i} \cdot v_i \cdot \prod_{j=1}^{N_v} \phi_{s,ij}(x_{s,j} + \phi_{s-1,ij} \cdot h_{s-1,ij})\right]$$

(3)

The learning rule of RSCMAC output is to lower down the minimum error function. Error function is defined as:

$$E \equiv \frac{1}{2}(\hat{y}_s - y_s)^2 \tag{4}$$

and the learning rule of v_i is expressed in (5).

$$\Delta v_i = -\frac{\alpha_v}{N_e}\frac{\partial E}{\partial v_i} = \frac{\alpha_v}{N_e}\left(\hat{y}_s - \mathbf{a_s^T w(x_s)}\right) \cdot a_{s,i} \cdot \prod_{j=1}^{N_v} \phi_{s,ij}(x_{s,j} + \phi_{s-1,ij} \times h_{s-1,ij}) \tag{5}$$

where $\frac{\alpha_v}{N_e}$ is the learning rate.

Likewise, the learning rules of mean value (m_{ij}), variance (σ_{ij}^2) and feedback ratio (h_{ij}) can be derived in the same way.

III. GPS Equipment and Data Collection

The research uses 2 types GPS receivers, one is Trimble 5700, this receiver has advanced Trimble Maxwell dedicated measurement type GPS chip, its advantage is a 24-channel GPS receiver that uses on low noise, low multipath error, low time correlation and high dynamic reaction, the equipment appearance is shown in Fig. 2 (a). This Trimble 5700 receiver accuracy is ±0.25m RMS in horizontal and ±0.5m RMS in vertical, its price is between 400,000~500,000 NT dollars. The other receiver used in this research is Trimble Lassen IQ receiver, as shown in Fig. 2 (b); this is a commercial module type of GPS manufactured by Trimble Company. Its advantage is can be fully embedded in different area products, it has 12 channel GPS receiver, the working voltage is 3.3V, and its size is small, price is low, and has sensitive receiving and low power consumption. The accuracy is ±6m (50%), ±9m (90%) in horizontal and ±11m (50%), ±18m (90%) in vertical, the price is about 3,000 NT dollars. Our goal is to predict and correct the dynamic error of Trimble Lassen IQ receivers to make it has the same accuracy as of Trimble 5700 receiver.

(a) Trimble 5700 (b) Trimble Lassen IQ

Fig. 2 Trimble GPS receiver

In the data collection, Taoyuan high-speed rail station area is selected as the test area (wide place, less vehicles, easier to test different vehicle speeds and their status). After GPS receivers are standard installed, data collection is carried out. The obtained data format is GGA (time, latitude, longitude, number of satellite, etc.) Data retrieving is every 10 seconds per datum. Fig. 3 shows the X, Y, Z coordinates errors between Trimble 5700 and Trimble Lassen IQ in Taoyuan high-speed rail station area; the observed errors are in the range of ±10m.

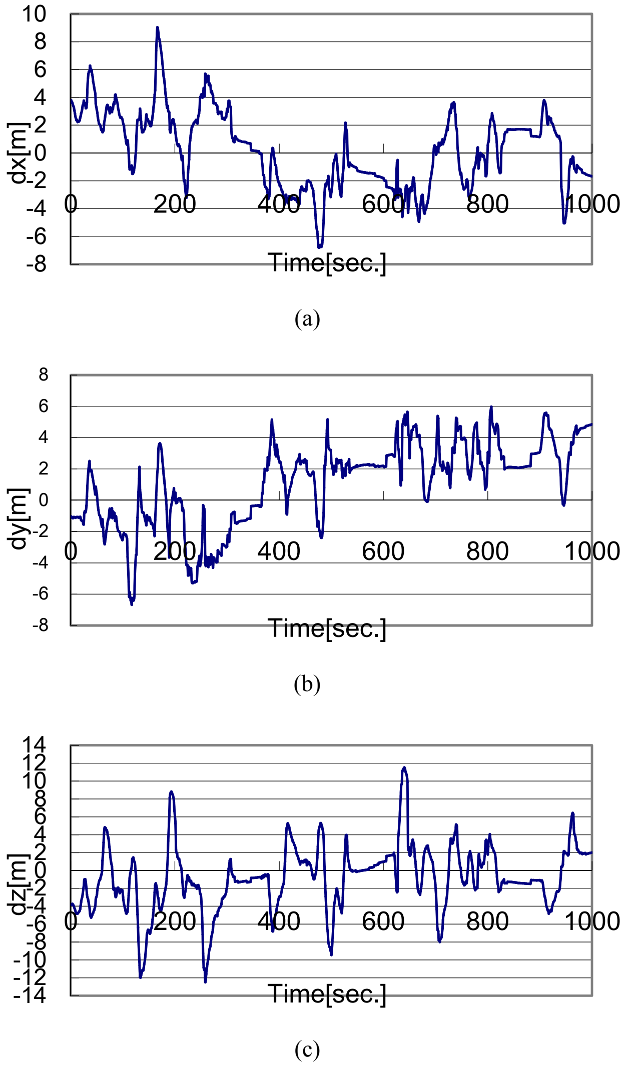


Fig.3 The errors between Trimble 5700 and Trimble Lassen IQ

IV. RSCMAC Based GPS Dynamic Error Training Structure and Procedure

In Fig. 3, it is shown the error between 2 receivers is around 10 meters, how to reduce the error of Trimble Lassen IQ receiver to close to the error of Trimble 5700 is the purpose of this research. The prediction structure and experimental procedure of GPS dynamic error are proposed in the followings, and the feasibility and effect are also proved.

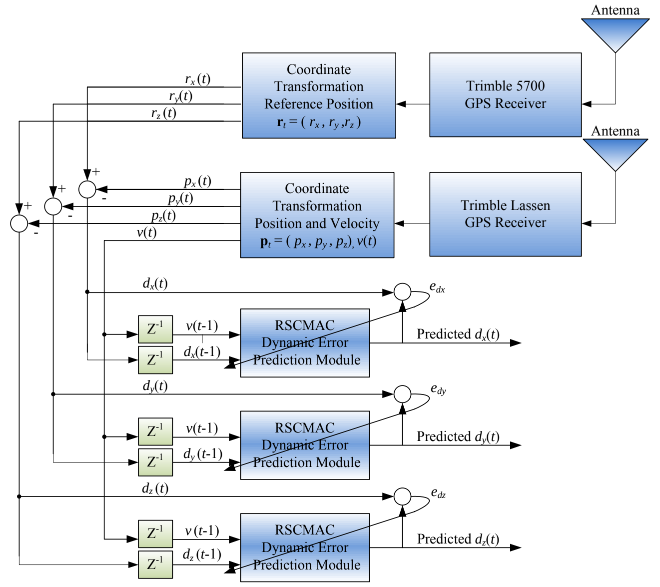


Fig. 4 RSCMAC based GPS dynamic error prediction training structure

Fig. 4 shows the RSCMAC based GPS dynamic error training structure, the structure includes antenna, GPS receiver, reference point coordinate transformation, retarder, etc. This research uses the previous second positioning error $d_x(t)$ and velocity $v(t)$ of the 2 receivers as the input data of RSCMAC to predict the next second positioning error. In the training stage, 2 different prices and accuracy GPS receivers (Trimble 5700 and Trimble Lassen IQ) are used to collect data, the higher accuracy Trimble 5700 data are used as the reference (target values) and the lower-priced Trimble Lassen IQ data are used as the actual values. These 2 receivers are simultaneously placed on a moving vehicle to collect data, and then to predict the error of X, Y and Z coordinates separately.

The followings are the descriptions of GPS error training structure and the procedure.

Step1. Satellite Signal Receiving

Simultaneously place GPS receivers (Trimble 5700 and Trimble Lassen IQ) on a moving vehicle to collect data, the vehicle simulates different driving conditions (such as acceleration, deceleration, constant speed, high speed, turning, stop, etc.), satellite information is recorded by computer through antenna. Data retrieving is set to every second per datum.

Step 2. Coordinate Transformation

The GPS received original data are the geodetic coordinate, the geodetic coordinate has to be transformed into the geocentric coordinate $\mathbf{r}_t = (r_x, r_y, r_z)$ to understand and predict the every second positioning change of the receiver in triaxial space. The most severe amplitude 1000 data are retrieved for the prediction research (as shown in Fig. 8).

Step 3. Construct Training Data

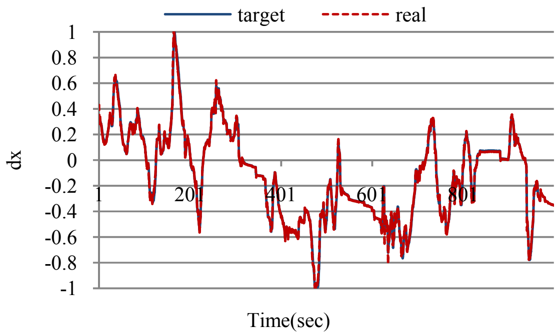
The positioning data $\mathbf{r}_t$ of Trimble 5700 are treated as the reference position, the difference between this position and the position of Trimble Lassen IQ receiver at time t is defined as $\mathbf{d}_t = \mathbf{r}_t - \mathbf{p}_t$, then the triaxial positioning errors are $d_x(t)$, $d_y(t)$ and $d_z(t)$. $d_x(t)$, for example, would be $d_x(t\text{-}1)$ after one delay, this is called previous second positioning error data, so the triaxial error information can be obtained. The data of speed $v(t)$ and the previous second positioning error $d_x\,(t\text{-}1)$ are the input of the training pattern, target value is the error $d_x(t)$ at current time t, there are total 1000 training patterns.

Step 4. Training Dynamic Error Prediction by RSCMAC

Initialize the parameters and learning rate of RSCMAC, $N_e = 20$, initial variance=0.1, $\alpha_v = 0.1$, $\alpha_\sigma = 0.1$, $\alpha_h = 0.1$. After 1000 cycles training, an output approximated to the actual value $d_x(t)$ can be obtained and is called Predicted $d_x(t)$. In the same way, the prediction values of $d_y(t)$ and $d_z(t)$ can be obtained by the other 2 sets of RSCMAC.

Simulation Result

As shown in Fig. 5, target is the error between Trimble Lassen IQ and Trimble 5700, real is the prediction value after RSCMAC learning. It is clear that even with large amplitude, the target value is still able to be traced.



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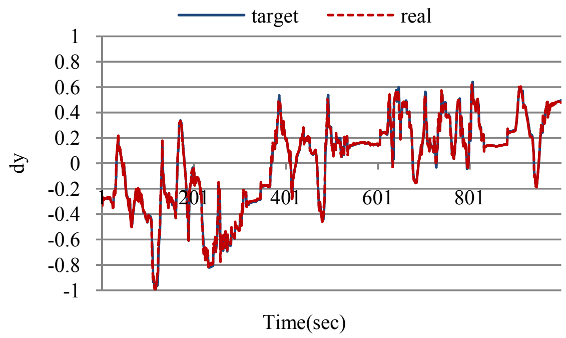

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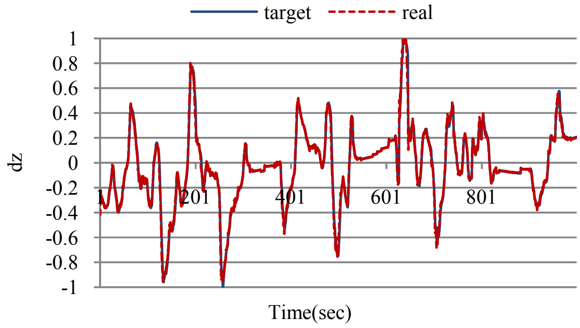

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Fig. 5 RSCMAC dynamic error prediction training result

V. RSCMAC Based GPS Dynamic Error Test Structure and Procedure

Fig. 6 shows the RSCMAC based GPS dynamic error test structure, in training stage, Trimble 5700 is used as the reference, but during test (actual stand-alone operation), there is no reference value, therefore, it is not able to find out the value of the positioning error $d_x\,(t\text{-}1)$.

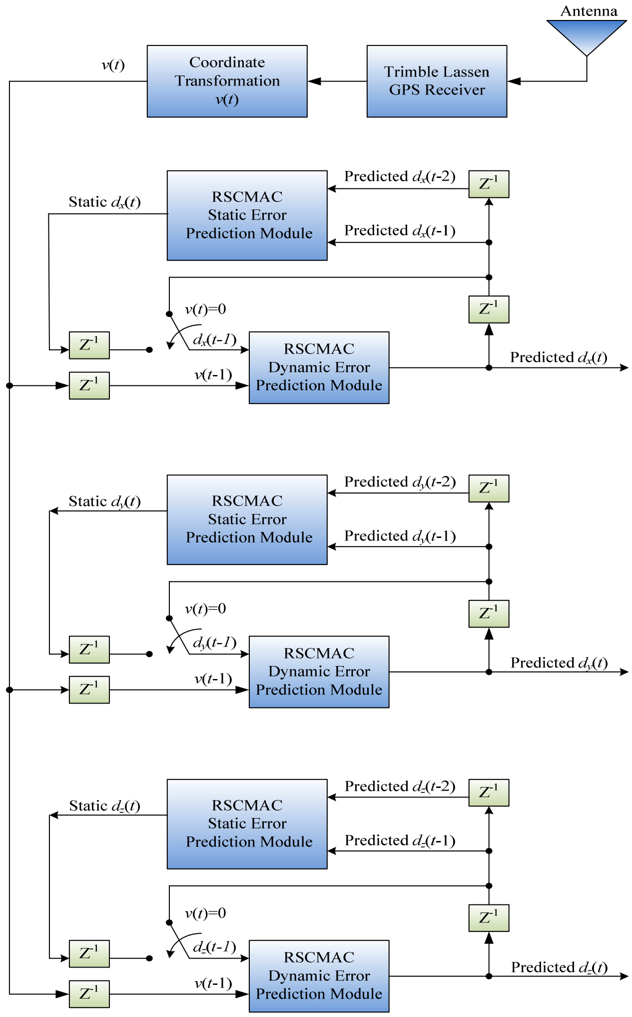
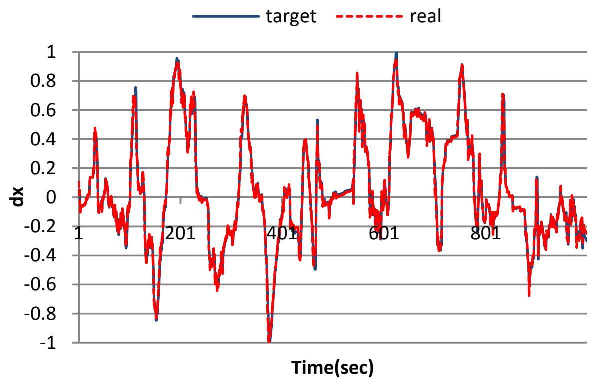


Fig. 6 GPS dynamic error prediction test structure of RSCMA

In Fig. 6, it is assumed that the output Predicted $d_x(t)$ of RSCMAC Dynamic Error Prediction Module is very closed to the input of the actual positioning error d_x (t-1) (which means the prediction accuracy), then at $v(t)\neq 0$, Predicted $d_x(t)$ is used as the input of the next second prediction module; at $v(t)=0$ (static), the output $d_x(t)$ of RSCMAC Static Error Prediction Module is used as the input of the next second prediction module. In such a structure, it only exits GPS (Trimble Lassen IQ) with to-be-corrected error. Each axis coordinate has 2 sets RSCMAC, one for dynamic error prediction, the other for providing static positioning error; the latter must be off line to learn static error before incorporated into the system.

Simulation Result of Dynamic Error Test

It has to finish RSCMAC Static Error Prediction Module offline training before test, the satellite signal receiving and coordinate transformation are the same as the training structure, the most big difference is to use the positioning error of a static vehicle or a moving vehicle as the prediction module input. Test pattern is the 1000 untrained and different route data. Test result is shown in Fig. 7, target is the error between Trimble Lassen IQ and Trimble 5700, real is the output (predicted value) of RSCMAC dynamic error module.



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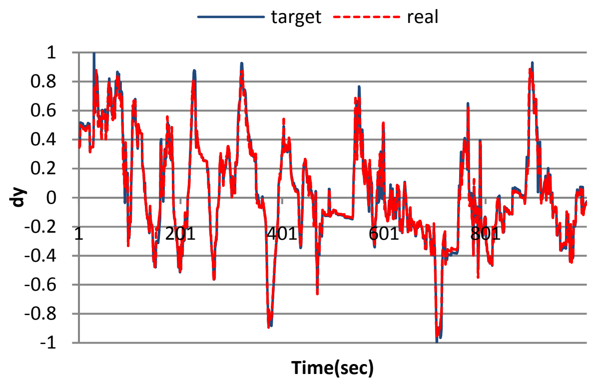

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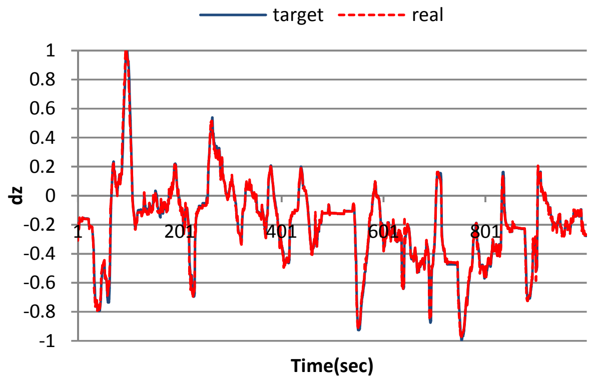

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Fig. 7 RSCMAC dynamic prediction error test result

VI. Error Improvement of Satellite Positioning System

The GPS dynamic error prediction based on RSCMAC has achieved an excellent result; the following task is to design a structure with a predicted error improving positioning accuracy. Fig. 8 shows the data improved structure after combining and correcting RSCMAC predicted error with the original data. Real Data are the actual data before GPS receiver (Trimble Lassen IQ) improvement. Predicted Data are the error values of Trimble Lassen IQ and Trimble 5700 errors after RSCMAC prediction. At time t, simultaneously compensate the predicted error and the receiver output actual data, those are the data after improvement.

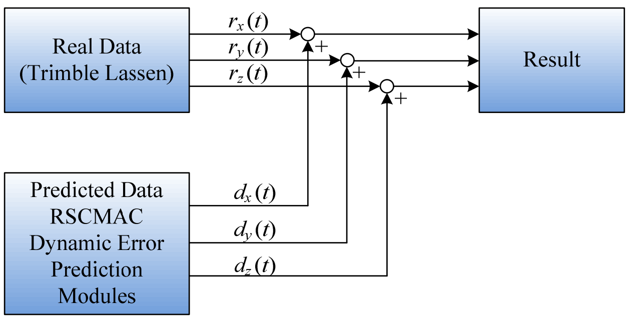
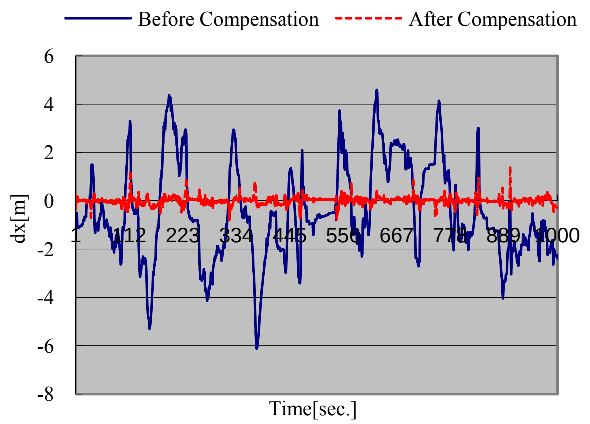


Fig. 8 GPS error improvement structure

Trimble Lassen IQ test error compensation is shown in Fig. 9, blue line is the error before compensation, red line is the error of Trimble Lassen IQ after improvement. This test didn’t use an expensive receiver (Trimble 5700). It is obvious Fig. 9, the cheap GPS receiver error after improvement is decreased. Originally, a big error exists between Trimble Lassen IQ and Trimble 5700, but the axis data after its structure being improved by RSCMAC dynamic error prediction is controlled in the vicinity of ±1.5m.



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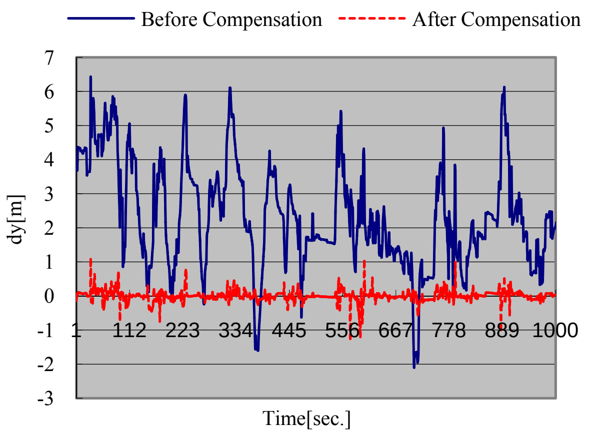

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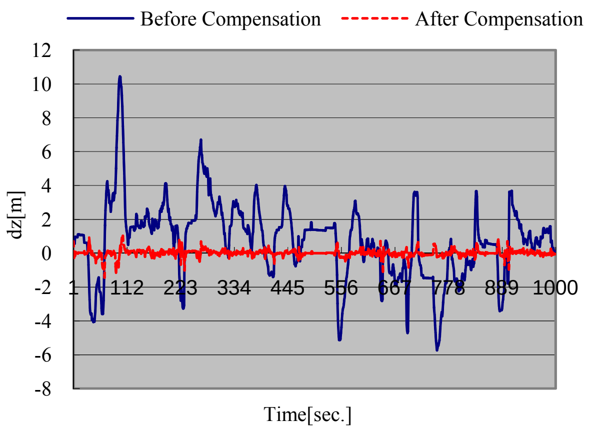

(c)

Fig. 9 Trimble Lassen IQ test error compensation

The error between Trimble Lassen IQ receiver original data after the experiment and Trimble 5700 are shown in Table I. The experiment proves by applying RSCMAC dynamic error prediction system, the accuracy of GPS receivers can be increased. By comparing the corrected data with Trimble 5700, it is found that the original error of about 10 m can be improved to within ±1.5m through accurate prediction; this also proves this research method can increase the accuracy of dynamic GPS receivers.

TABLE I
TRIMBLE LASSEN IQ DYNAMIC ERROR TEST IMPROVEMENT DATA TABLE

Dynamic Testing	d_x(m)		d_y(m)		d_z(m)	
	Before	After	Before	After	Before	After
MAX	4.5914	1.3771	6.4240	1.07917	10.4474	1.0232
MIN	-6.1104	-0.7875	-2.1040	-1.25711	-5.7429	-1.4453
RMS	2.0346	0.1813	2.7992	0.17500	2.4143	0.2166
Average	1.7064	0.1163	2.4215	0.10458	1.8748	0.1362
Variance	3.9185	0.0329	2.3337	0.03065	5.2527	0.0469
Standard Deviation	1.9795	0.1814	1.5277	0.17508	2.2919	0.2167

VII. CONCLUSIONS

This research completed a RSCMAC based GPS dynamic error prediction and calibration structure, the excellent dynamic error prediction is achieved and GPS dynamic positioning accuracy is improved. The actual simulation result proved the dynamic error of the cheap commercial GPS receiver (Trimble Lassen IQ) is corrected to the same level as the error of the expensive professional GPS receiver (Trimble 5700). Base on RSCMAC, in the training structure to use the input information of Trimble 5700 as the reference values and output as the target values to carry out supervised learning. The big difference at test is no reference value, it is designed to use the prediction module output or the static error prediction module output as the input of the prediction module, the final result is satisfied, it reduced the positioning error between cheap GPS receivers and expensive GPS receivers to within ±1.5m. This research achieved excellent performance on both GPS positioning and economics.

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