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RTDGPS Implementation by Online Prediction of GPS Position Components Error Using GA-ANN Model

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ABSTRACT

If both Reference Station (RS) and navigational device in Differential Global Positioning System (DGPS) receive signals from the same satellite, RS Position Components Error (RPCE) can be used to compensate for navigational device error. This research used hybrid method for RPCE prediction which was collected by a low-cost GPS receiver. It is a combination of Genetic Algorithm (GA) computing and Artificial Neural Network (ANN). GA was used for weight optimization and RS and Mobile Station (MS) were implemented by the software. The experimental results demonstrated which GA-ANN had great approximation ability and suitability in prediction; GA-ANNs prediction' RMS errors were less than 0.12 m. The simulation results with real data showed that position components' RMS errors in MS were less than 0.51 m after RPCE prediction.

1. Introduction

Global Positioning System (GPS) is a location system based on constellation of at least 24 satellites orbiting the earth at altitudes of approximately 11,000 miles [1]. GPS allows properly equipped users to determine their position referenced on the measured pseudo-ranges to at least four satellites. GPS positioning accuracy is limited by measurement errors [2]. These errors can combine and become significant and include satellite/receiver clocks, satellite orbits, and multipath, and Selective Availability (SA) and GPS receivers' internal circuitry [3]. In order to recover accuracy of GPS, differential techniques must be applied. Differential Global Positioning System (DGPS) is a potential means for improving navigation accuracy in a local area. A single DGPS monitor station in a known location can compute range error corrections for all the GPS satellites in view. These error corrections are then broadcast to users in the vicinity. By applying corrections to the received signals, a user within a 100km range can typically improve accuracy. The ability of DGPS in providing real-time sub meter or even decimeter level accuracy has revolutionized agricultural industry [4]. If both Reference Station (RS) and navigational device in DGPS receive signals from the same satellite, RS Position Components Error (RPCE) can be used to compensate for navigational device error. The RPCE is calculated as follows:

$$\vec{E} = \vec{P} - \vec{U} \qquad (1)$$

where $\vec{P}=(x_n,y_n,z_n)$ is estimated vector of RS at time n and $\vec{U}=(x_b,y_b,z_b)$ is known vector of RS [5]. The process includes receiving and processing spatial coordinates, calculating RPCE and sending it, which takes about 2 sec. Thus, RS requires RPCE prediction to compensate for MS error. For prediction, the predictors take a series of differences such as $\vec{E}(n)$, $\vec{E}(n-1)$,…,$\vec{E}(N-P)$ and use these values to predict $\hat{\vec{E}}(n+N)$ [6]. Artificial Neural Networks (ANNs) apply principles from neurology to find patterns in complex data and have successfully been used to prediction. In this paper, evolutionary design of an ANN model was discussed for RPCE predicting and Genetic Algorithm (GA) was used for weight optimization of ANN. ANNs have been shown to have the potential of well performance for classification problems in many different environments, including business, science and engineering. A majority of the studies have relied on a gradient algorithm, typically variation of Back Propagation (BP), to obtain weights of the model. Although limitations of gradient search techniques applied to complex nonlinear optimization problems, such as the ANN, are well known, many researchers still prefer to use these methods for network optimization [7]. This ANN is trained using GA by adjusting its weights and biases in each layer. The rest of this paper is organized as follows; Section 2 provides brief introduction to implementing the DGPS structure. In Section 3, GA-ANN methods are proposed. Experiments and simulation results are reported in Section 4 and finally conclusion are made in Section

2. SYSTEM DESCRIPTION

A. Accuracy theory

The original and GPS receiver data of the reference station are known; also, GPS receiver data of the MS are known; but, original data of the MS are unknown. The received signal of GPSS_m at MS can be expressed as:

$$S_m = (S_m)_{error} + (S_m)_{original} \quad (2)$$

$$(S_m)_{original} = S_m - (S_m)_{error} \quad (3)$$

where$(S_m)_{original}$ represents original position of MS and $(S_m)_{error}$ represents error signal occurring in GPS reading at MS. The received signal of GPS S_r at RS can be expressed as:

$$S_r = (S_r)_{error} + (S_r)_{original} \quad (4)$$

where (S_r) original represents RS original position and (S_r) error represents error signal occurring in GPS reading at RS. Since the two readings of GPS in both mobile and reference stations are achieved at the same time; the error signal occurring in both GPS readings in mobile and reference stations are the same or: (S_r) error = (S_m) error = (S_{error}) [8].

B. System structure

The DGPS implemented in this investigation included three parts: Satellite Part (SP), RS and MS. Fig. 1 shows the implemented proposed positioning system.

(1) SP*:* All the receivers use some algorithm based on Geometric Dilution of Precision (GDOP) to select the best set of satellites for tracking among the group of satellites in view [9]. If a selected subset of satellites for MS and RS is different, sources of error in these two stations will be affected. So, RS error does not compensate for MS error. The satellites seen by the GPS receiver are limited to four satellites in two stations; it increases error of GPS position components up to 25 m but MS error is reduced by applying RS error.

(2) RS: Structure of RS is shown in Fig. 2. It contains a GPS receiver (U-blox LEA-6H), computer system that uses MATLAB software to perform the calculations and prediction and radio transmitter that transmits the difference data to the MS via ZigBee ZS10 module. Predictive model is equipped with two inputs; one output and one target. As shown in Fig. 2, GPS receiver is placed at the known reference position to collect data. The Differential Data (DD) can be found as the position difference between real coordinates of the RS and the coordinates that are recorded by GPS receiver. This data could be expressed as:

$$DD = (Dx = x_p - x_r, Dy = y_p - y_r, Dz = z_p - z_r) \quad (5)$$

For $Dx(t)$, after the 1st and 2nd delay, $Dx(t-1)$ and $Dx(t-2)$ can be obtained. Both delay data are input to the proposed GA-ANN, and $Dx(t)$ is the set as the target; then, the output is predicted $Dx(t)$.The $Dy(t)$ and$Dz(t)$ are also similar. In case of using the same satellites, by applying these corrections to other receiver positions, many of inherent errors of the received measurements range are eliminated [10].

(3) MS: In Fig. 3, the structure shows usage of RPCE predicted by GA-ANN for adjusting the real data. The proposed method was at the same time to compensate for the output real value of the receiver.

The MS receives two signals: the first one is received by GPS receiver and the second one is received from the radio transmitter which contains prediction DD and time of GPS receiver. The GPS readings at MS in the form of X_m, Y_m and Z_m can be corrected accurately as follows:

$$X_{mc} = X_m - Dxp \quad (6)$$

$$Y_{mc} = Y_m - Dyp \quad (7)$$

$$Z_{mc} = Z_m - Dzp \quad (8)$$

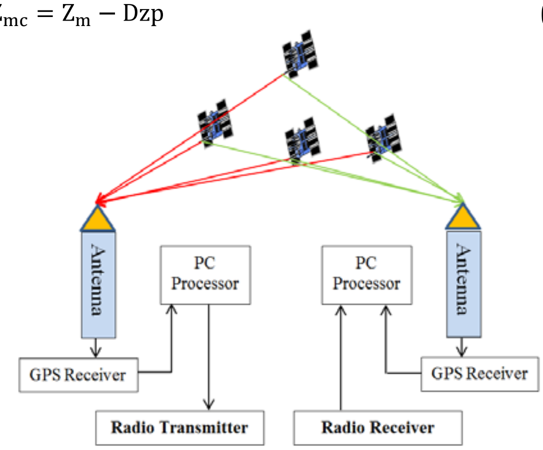


Figure 1: Positioning system

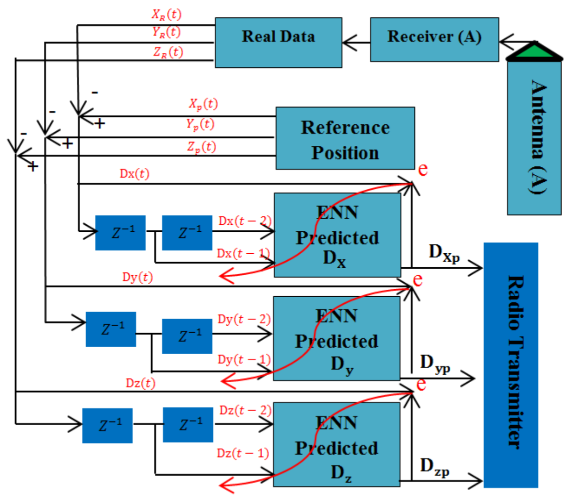


Figure 2: Structure of RS

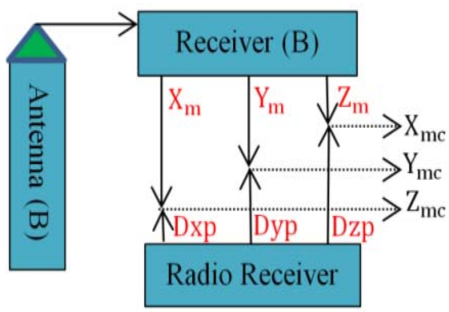


Figure 3: Structure of MS for compensating for GPS receiver output data

3. Prediction Method

ANN and GA are two of the most promising natural computation techniques. In recent years, ANN has become a very powerful and practical method for modeling very complex non-linear systems [11, 12] and GA can be found in various research fields for parameter optimization [13, 14]. The GA and ANN have been widely used for prediction. Combination of GA computing and ANN is called GA-ANN. Although ANNs are important data mining techniques, research for the optimal ANN is still a challenging task. In order to avoid the local minima encountered in most of the optimization methods, scientists tend to use random search methods such as GA to find an optimal network. The optimum network topology is usually decided by an expert or a trial and error approach. Generalization capability in these networks directly depends on training, architecture, number of layers and number of neurons in each layer. If the number of neurons in the network is increased, the network attracts to overfit the training set; thus, the interpolation capability will be decreased. On the other hand, if the number of neurons is less than the necessary number, the network cannot learn all the data. Therefore, for every application, there is a particular number of neurons, which maintains the best interpolation generalization balance. The designer needs some methods for finding an appropriate choice for keeping this balance. Topology parameters of ANN such as range of initial weights, learning rates, momentum, number of hidden layers and number of neurons in hidden layers can strongly affect the solution searching ability of a BP algorithm. Their optimization by GA can enhance probability of finding a globally optimum solution [15, 16].

Artificial Neural Network

ANNs are widely accepted as a technology offering an alternative way to simulate complex and ill-defined problems. ANNs has great capacity in predictive modeling; i.e. all the characters describing the unknown situation can be presented to the trained ANNs, and then prediction of systems is guaranteed. They have been used in diverse applications in control, robotics, pattern recognition, forecasting, power systems, manufacturing, optimization, signal processing, etc. and are particularly useful in system modeling. ANN is a computational structure, consisting of a number of highly interconnected processing units, called neurons. The neurons sum weighted inputs and then apply a linear or non-linear function to the resulting sum to determine the output. The neurons are arranged in layers and are combined through excessive connectivity.

BPN [11, 18] is a typical ANN that has been widely used in many research fields. BPNs have hierarchical feed forward network architecture and the outputs of each layer are sent directly to each neuron in the above layer. While BPNs can have many layers, all regression and classification tasks can be accomplished by a three-layer BPN [18]. BPNs are trained by repeatedly presenting a series of input/output pattern sets to the network. The NN gradually 'learns' the governing relationship in the data set by adjusting the weights between its neurons to minimize the error between actual and predicted output patterns of the training set. A separate set of data called the testing set is usually used to monitor network's performance. When the mean squared error (MSE) of the testing set reaches a minimum, network training is considered complete and the weights are fixed. In essence, an NN is a function that maps input vectors to output ones. NNs are adjusted, or trained, so that a particular input leads to a specific target output. The ANN weights are adjusted based on the comparison of the output and target until the network output matches the target. Typically, many such input/target pairs are needed to train a network. The graphic representation of this learning is given in Fig. 4.

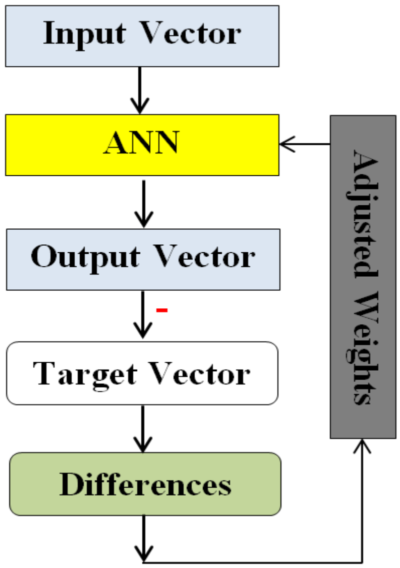


Figure 3: A learning Cycle in the ANN model

A. Genetic algorithm

GAs are the search algorithms designed to mimic principles of biological evolution in natural genetic system. GAs are also known as stochastic sampling methods and can be used to solve difficult problems in terms of objective functions that possess 'bad' properties such as multi-modal, discontinuity, non-differentiable, etc. These algorithms maintain and manipulate a population of solutions and implement their search for better solutions based on 'survival of the fittest' strategy. GAs solve linear and non-linear problems by exploring all regions of the state space and exploiting promising areas through mutation, crossover and selection operations applied to individuals in the population. Use of a GA requires determining six fundamental issues [19], i.e. chromosome representation, selection function, genetic operators making up the reproduction function, creation of the initial population, termination criteria and evaluation function.

GAs are presented as follows:

1. (Initialization): Randomly establish an initial population of chromosomes.
2. (Evaluating fitness): Evaluate fitness of each chromosome. In this work, a negative NMSE was used as the fitness function as follows

$$\text{Fitness function} = -\frac{1}{\sigma^2 N}\sum_{i=1}^{N}(d_i - y_i)^2 \tag{9}$$

where $\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(d_i - \overline{d_i})^2$, N is total number of data in the testing set, d_i is actual value and y_i is predicted value.

3. (Selection): Select a mating pair, #1 parent and #2 parents, for reproduction.

4. (Crossover and mutation): Create new offspring by performing crossover and mutation operations.

5. (Next generation): Generate a population for the next generation.

6. (Stop conditions): If the number of generations equals a threshold, then the best chromosomes are presented as a solution; otherwise, go back to Step 2.

Fig. 5 shows basic steps of GA [21].

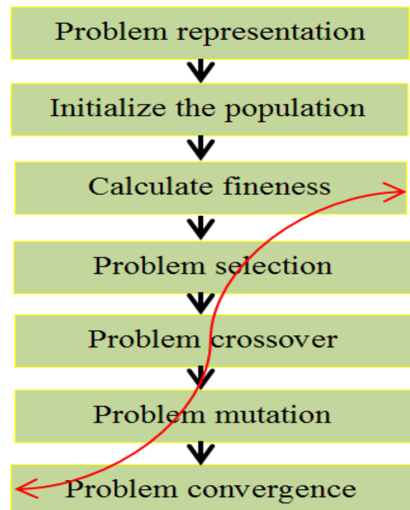


Figure 4: Basic steps of GA

B. Topology for optimization

NNs use inductive learning and in general require examples while GAs use deductive learning and require objective evaluation function. A synergism between the two techniques has been recognized which can be applied to enhance each technique performance in what may be referred to as evolutionary NNs. An area that has attracted the highest interest is use of GAs as an alternative learning technique instead of gradient descent methods, such as error back propagation. Supervised learning algorithms suffer from the possibility of getting trapped on suboptimal solutions [20-22]. GAs enable the learning process to escape from entrapment in local minima in instances where back propagation algorithm converges prematurely. Furthermore, because GA does not function in the task domain, they may be used for weight learning in recurrent networks where suitable training algorithms are still a problem. Studies have attempted to take advantage of both techniques. Algorithms which combine GAs and error back propagation have been shown to exhibit better convergence properties than the pure back propagation. The GA is used to rapidly locate region of optimal performance and then gradient descent back propagation can be applied in this region. GAs have been also studied as generalized structure/parameter learning in neural systems. This type of learning combines as complimentary tools both inductive learning through synaptic weight adjustment and deductive learning through modification of network topology to obtain automatic adaptation of system knowledge of the domain environment. Such hybrid systems are capable of finding both weights and architecture of an NN, including number of layers, processing elements per layer and connectivity between processing elements. In summary, GAs have been used in the area of NNs for three main tasks: -Training weights of the connections, designing structure of the network and finding an optimal learning rule. A sequence of input signals is fed to both plant and NN and their output signals are compared. The absolute difference is computed and sum of all errors for the whole sequence is used as a measure of fitness for the considered particular network, as shown in Fig. 6. Genetic operators can be applied to create a new population.

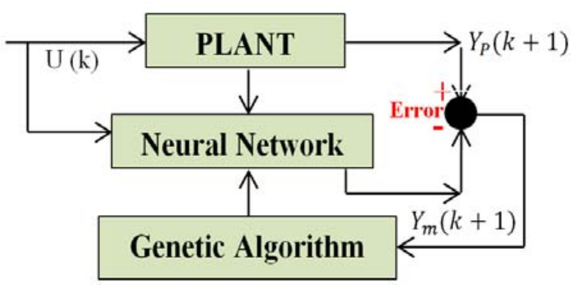


Figure 5: Schemes for GA-AAN

In this work, initial population with 50 chromosomes was randomly created. Using the algorithm of BP and 1000 iterations, NN was trained. After training the population chromosomes by the corresponding NN, the error rate was calculated. Mating was done using the roulette method. Mating rate had probability of 0.7, mutation rate of 0.01 and number of generations of 30.

4. Experimental and Simulation Results

A. Data collection

In order to demonstrate effectiveness of the GA-ANN method, real GPS signals were collected. A GPS receiver, U-bloxLEA-6H, was used for data collection. Significant features of the GPS receiver used in data collection process included 50-channels, capable of keeping track of up to 16 satellites and measuring with maximum accuracy in SPS mode (6m). Fig. 7 shows interface board for GPS receiver; it had RS232 and USB connection. It was connected to a notebook computer via USB connection. The data sets were collected at the GPS Research Lab, Shahid Rajaee Teacher Training University (SRTTU).

Coordinate of the position was ($x_P = 3226206$ $y_P = 4054570 z_P = 3709308$). The data were accessed per second. Simulation was conducted using an 2.5 GHz CORE™ i5 CPU. The computer code was constructed using Matlab 2010 software. The data were collected in two data files; one file for training and another for testing purposes.

B. Accuracy of prediction models

In order to evaluate accuracy of the prediction, RMS and NRMSE were used as below:

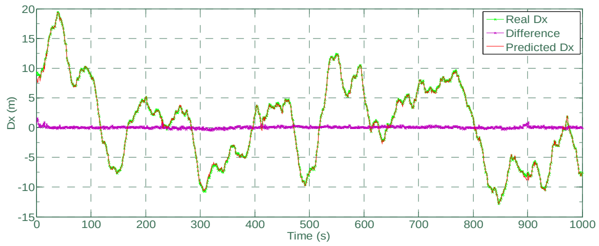
$$\mathrm{RMS} = \sqrt{\frac{1}{M}\sum_{i=1}^{M}(d_i - y_i)^2} \tag{10}$$

$$\mathrm{RMSE}=\sqrt{\sum_{i=1}^{M}(T_i - P_i)^2/M} \tag{11}$$

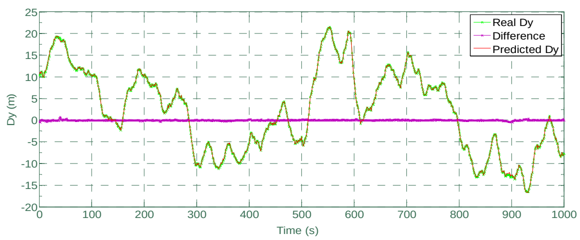
$$\mathrm{NRMSE}=\frac{\mathrm{RMSE}}{\sum_{i=1}^{M} T_i/_M} \times 100 \tag{12}$$

where M is test numbers, d_i denotes the desired response of output, y_i presents the output at test i, T_I denotes real values and P_i is predicted. Figs. 8 (a), 8 (b) and 8 (c) show Dx(t), Dy(t)and Dz(t) predictions, respectively, for 1000 test data using GA-ANN in RS. In this figure, the red point is very close to the green point which means excellent prediction performance for GA-ANN. In this figure, pink line shows prediction errors (difference between the predicted and real values). The GA-ANNs have great approximation ability and suitability in RPCE prediction. Table 1 shows prediction errors' statistically significant characteristics for 1000 test data using GA-ANN. It is found total RMS error is less than 0.12 m.

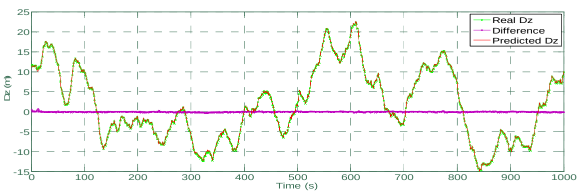
Figure 6: U-blox LEA-6H receiver



(a)



(b)



(c)

Figure 8: 2s ahead RPCE prediction and prediction error using GA-ANN at RS

TABLE1
COMPARING PREDICTION ERRORS' STATISTICALLY SIGNIFICANT CHARACTERISTICS

Parameters	MAX	MIN	VAR	AVE	RMS
Dx	0.6946	0	0.0280	0.0175	0.0112
Dy	0.6079	0	0.0013	0.0103	0.1018
Dz	0.7514	0	0.0159	0.0131	0.1155

Table 2 shows accuracy and CPU time of error prediction using GA-ANN on an 2.5 GHz CORE™ i5 CPU, as shown in Table 2. NRMSE for GA-ANN is 8.98.

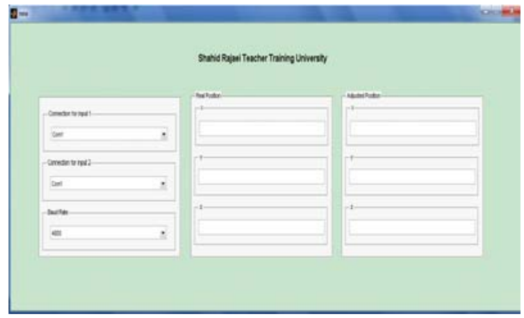
TABLE 2
ACCURACY AND CPU TIME OF ERROR PREDICTION USING GA-ANN

Method	Accuracy (m)	NRMSE	CPU time (ms)
Value	0.12	8.98	2.73

C. Structure for RTDGPS experiments

First of all, the satellites' data were simultaneously collected by passing through the antenna in RS and MS in about 17 min (1000 Data). For RS and MS, the software was designed by MATLAB GUI. Software images of RS and MS are shown in Figs. 9 (a) and (b), respectively.

(a)



(b)

Figure 9: Software image of RS and MS

This software was connected to GPS receiver by RS232 to USB port. It had two com ports as input and output. RS software operating these steps did the following items:

Receiving POSECEF message from input com, including time and X, Y and Z coordinators.

Parsing the message.

Calculating RPCE (Dx, Dy, Dz).

Predicting RPCE.

Making the message: @@RPCE Time, Dx, Dy, DZ &&.

Sending the message to output com.

Output com was connected to a radio transceiver (transmitter/receiver) that was used RS232 connection. This radio was able to receive or transfer DGPS corrections. It was a ZigBee radio transceiver (Type ZS10). ZS10 module received the data from software and sent them to other ZS10 module, which was connected to MS software.

In MS, software received the data from two ports of GPS USB and ZS10 module RS232 to USB port. MS software has two input com. MS software operating these steps did the followings:

Receiving POSECEF message from input com, including time and X, Y and Z coordinators.

Parsing the POSECEF message.

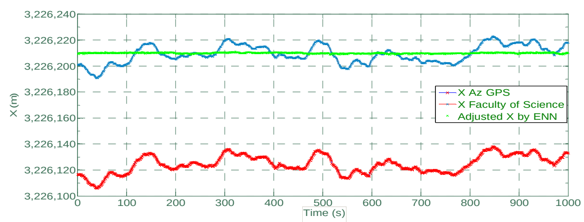
Parsing the received message from RS (inputcom 2).

Calculating the adjusted position.

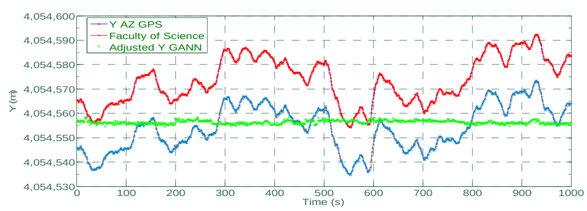
Accuracy of RTDGPS

Fig. 10 shows 1000 real data of before training in

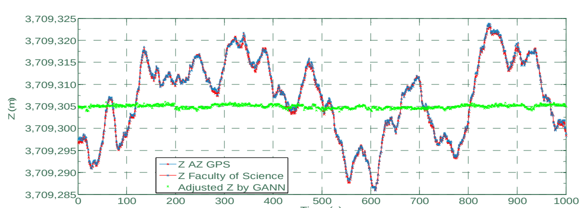
RS and 1000 real data in MS from receiver U-blox LEA 6H while satellites in two stations were identical and number of satellites were 4. The distance between two stations was 84 m. RS was at the building of GPS Research Lab in SRTTU and MS at SRTTU, Faculty of Sciences. As can be seen in Figure 10, the observed changes in X, Y and Z in two stations were similar; as a result, errors relative to the reference location (Dx, Dy, Dz) in two stations were very close to each other. So, the reference station error factors (Dx, Dy, Dz) can correct location of MS. After initial calculation of the RS, RPCE factors were online predicted and sent in real time via ZS10 to MS. Note that, the RS data were being collected and sufficient training data were available for the first prediction. Corresponding to the structure in Fig. 3, RPCE predicted by GA-ANN was used to adjust the real data of MS.



(a)



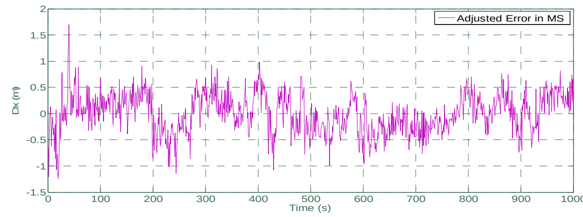
(b)



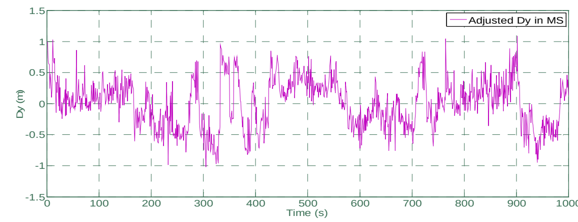
(c)

Figure 10: Real data of RS, real and adjusted data by GA-ANN of MS

The errors relative to the reference position of MS after improvement are shown in Fig. 11. The experiment proved that GA-ANN can greatly increase accuracy of the GPS receiver. The maximum error for real data was 20m while this parameter was 2m for the adjusted data by accurate prediction. Table 3 shows the improved error's statistically significant characteristics for 1000 real values. As shown in Table 3, total RMS error of the LEA 6H real data were reduced to less than 0.5m using GA-ANN method.



(a)



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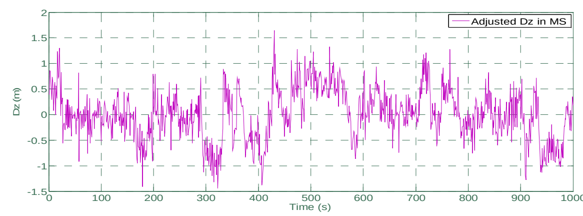

(c)

Figure 11: The error to the reference position after improvement in MS

TABLE 3
IMPROVEMENT ERROR'S STATISTICALLY SIGNIFICANT CHARACTERISTICS OF MS

	X Component		Y Component		Z Component	
	Real	Adjusted	Real	Adjusted	Real	Adjusted
MAX	18.3	1.82	21.56	1.15	22.4	1.63
MIN	0.00	0.00	0.00	0.00	0.00	0.00
RMS	4.98	0.49	9.59	0.51	8.96	0.49
AVE	3.25	0.09	2.45	0.03	1.66	0.08
VAR	48.8	0.15	86.0	0.34	77.7	0.17

5. CONCLUSION

This research proposed a method to improve DGPS accuracy using RPCE prediction. In the procedure, GA-ANN utilized two time step error data to predict the following time step error and the predicted error was calculated and adjusted the real data of the GPS receiver. It was found that the compensated data performed with more excellent accuracy than the real data to the recognized reference position. The proposed GA-ANNs were implemented on low cost GPS receiver data. The results were highly effective predictions for accurate positioning. So, RPCE RMS errors of MS were less than 0.51 m after GA-ANNs prediction.

REFERENCES

[1] K. Kawamura, and T. Tanaka, "Study on the Improvement of Measurement Accuracy in GPS," 2006 *SICE-ICASE International Joint Conf.,* pp. 1372-1375.

[2] A. Indriyatmoko, T. Kang, Y.J. Lee, G.I. Jee, Y.B. Cho and J. Kim, "Artificial Neural Networks for Predicting DGPS Carrier Phase and Pseudo-Range Correction," *Journal of GPS Solutions*, vol. 12, no. 4, pp. 237-247, 2008.

[3] M. R. Mosavi and H. Nabavi, "Improving DGPS Accuracy using Neural Network Modelling," *Australian Journal of Basic and Applied Sciences*, vol. 5, no. 5, pp. 848-856, 2011.

[4] M. R. Mosavi, "An Adaptive Correction Technique for DGPS using Recurrent Wavelet Neural Network," 2007 *IEEE Spectrum*, pp. 3029-3033.

[5] M. H. Refan, K. Mohammadi and M.R. Mosavi, "Improvement on low cost positioning sensor accuracy," 2003 *IEEE conf. on sensors, Kuala Lumpur, Malaysia*, pp. 9–14.

[6] M. R. Mosavi, "Comparing DGPS Corrections Prediction using Neural Network, Fuzzy Neural Network, and Kalman Filter," *Journal of GPS Solutions*, vol. 10, no. 2 ,pp.97-107, 2006.

[7] R. Duvigneau and M. Visonneau, "Hybrid Genetic Algorithms and Arti_cial Neural Networks for Complex Design Optimization in CFD," *International journal for numerical methods in fluids*, vol. 44, no. 11, 2004.

[8] P. K. Enge, R. M Kalafus and M. F. Ruane, "Differential Operation of the Global Positioning System," *IEEE Communications Magazine*, vol. 26, no. 7, pp. 48-60, July 1988.

[9] DJ. Jwo, CC. Lai, "Neural network-based GPS GDOP approximation and classification," *Journal of GPS Solutions*, vol. 11, no. 1, pp. 51–60. 2007.

[10] Ch. T. Chiang, J. Sh. Hsu, and Ch. Y. Hsieh, "Improvement in DGPS Accuracy Using Recurrent S_CMAC_GBF," *World Academy of Science, Engineering and Technology*, Vol. 55, pp. 422-427, July 2009.

[11] B.H.M. Sadeghi, "ABP-neural network predictor model for plastic injection molding process," *J. Mater. Process. Technol*. Vol. 103, no. 3, pp.411–416, 2000.

[12] C.R. Chen, H.S. Ramaswamy, "Modeling and optimization of variable retort temperature (VRT) thermal processing using coupled neural networks and genetic algorithms," *J. Food Eng*. Vol. 53, no. 3, pp. 209–220, 2002.

[13] T.T. Chow, G.Q. Zhang, Z. Lin, C.L. Song, "Global optimization of absorption chiller system by genetic algorithm and neural network," *Energy Build*. Vol. 34, no. 1, pp. 103–109, 2002.

[14] D.F. Cook, C.T. Ragsdale, R.L. Major, "Combining a neural network with a genetic algorithm for process parameter optimization," *Eng. Appl. Artif. Intell*. Vol. 13, no. 4. pp. 391–396, 2000.

[15] L. Rigal and L. Truffet, "A new genetic algorithm specifically Referenced on mutation and selection," *Advances in Applied Probability,* Vol 39, 141-161, 2007.

[16] K. Okyay, E Alpaydin. E. Xu, L. (Eds.) Springer, "Artificial Neural Networks and Neural Information," Vol. 2714 ISBN 3540404082, 2003.

[17] M. NirmalaDevi, N. Mohankumar and M. Karthick, "Design of Genetically Evolved Artificial Neural Network Using Enhanced Genetic Algorithm," *International Journal of Recent Trends in Engineering*, Vol. 1, no. 2, May 2009.

[18] S.L.B. Woll, D.J. Cooper, "Pattern-based closed-loop quality control for the injection molding process," Polym. Eng. Sci. vol. 37, no. 5, pp. 801–812 1997.

[19] R. H. Christopher, A. J. Jeffery, G. K. Michael. The Intranet Architecture: A Genetic Algorithm for Function Optimization: A MATLAB Implementation. Available: www.ie.ncsu.edu/mirage

[20] S. Alla, A. Aulia, S. Kumar and R. Garg, "Using Hybrid GA-ANN to Predict Biological Activity of HIV Protease Inhibitors," 2008 *IEEE CIMCB*.

[21] Ms. Dharmistha, D. Vishwakarma, "Genetic Algorithm based Weights Optimization of Artificial Neural Network," *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering* Vol. 1, no. 3, August 2012.

[22] Sh. Changyu, W.Lixia, L. Qian, "Optimization of injection molding process parameters using combination of artificial neural network and genetic algorithm method," *Journal of Materials Processing Technology* 183, pp. 412–418, 2007.

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