Real Time Pseudo-Range Correction Predicting by a Hybrid GASVM Model in Order to Improve RTDGPS Accuracy

M. H. Refan* (C.A.), A. Dameshghi* and M. Kamarzarrin*

Abstract: Differential base station sometimes is not capable of sending correction information for minutes, due to radio interference or loss of signals. To overcome the degradation caused by the loss of Differential Global Positioning System (DGPS) Pseudo-Range Correction (PRC), predictions of PRC is possible. In this paper, the Support Vector Machine (SVM) and Genetic Algorithms (GAs) will be incorporated for predicting DGPS PRC information. This study uses GAs to select parameters of SVMs. Online training for real-time prediction of the PRC enhances the continuity of service on the differential correction signals and therefore improves the positioning accuracy in Real Time DGPS. Given a set of data received from low cost GPS module, the GASVM can predict the PRC precisely when the PRC signal is lost for a short period of time. This method which is introduced for the first time to predict of PRC is compared to other recently published methods. The time step of the prediction was six second. The experiments show that the total RMS prediction error of GASVM is less than 0.186m for one step and 0.76m for 10 step ahead cases.

Keywords: Genetic Algorithm, Pseudo-Range Correction, RTDGPS, Support Vector Machine**.**

1 Introduction

The Global Positioning System (GPS) allows properly equipped users to determine their position based on the measured pseudo-ranges to at least four satellites [1]. It provides two levels of broadcast service to the GPS user, the standard positioning service (SPS) and the precise positioning service (PPS). SPS is a positioning and timing service available world-wide to all GPS users. GPS signal contains the coarse acquisition code (C/A) and a navigation data message [2]. The GPS measurements are usually corrupted by several errors. These errors can be categorized into two basic types: bias errors (ionosphere and random errors (receiver noise and multipath) [3]. In order to recover the accuracy of GPS, differential techniques must be applied. In GPS, a typical technique for estimating the position of a moving rover object is DGPS, where two receivers are used, the base receiver is stationary and its exact position is known, while the other receiver is "roving" and its position needs to be estimated. Since the position of base station is accurately known, the position of the rover receiver may be computed using the corrections to the Pseudo-Range Measurements (PRM) [4]. Differential correction can be applied in real-time directly in the field or during post processing data in the office [5]. DGPS technology can achieve higher accuracy because of the high correlation between observations made to the same satellites at the same time by different receivers. DGPS potentially has a problem of slow updates. It sometimes cannot send correction information every minute at a time, due to radio interference or loss of signals. Absence of DGPS correction means that the accurate position of the unit cannot be identified [6]. To overcome such degradation caused by the loss of DGPS PRC, predictions of pseudo-range corrections is needed [5]. DGPS corrections prediction has an important role in accurate and real time positioning of GPS. When the status of differential signal is normal, the network remains in the training phase; once the signal fails, the network starts to provide predicted PRC data [3]. Since DGPS correction is a function of time, it can be modeled and predicted using a SVM. Recently, SVM has been developed for solving pattern recognition and nonlinear regression estimation problems [7]. The SVM model is able to increase forecasting accuracy by selecting suitable parameters. Therefore, constructing an adapted procedure to select suitable parameters is an essential task [8]. In this study, a SVM model with GAs is proposed to examine the feasibility of predicting system reliability. The genetic algorithms are used to determine

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the three parameters of the proposed model. The successful implementation of the SVM methodology requires the specification of several techniques parameters. This is usually accomplished through trial-and-error procedures [9]. In the proposed methodology GAs are used to select optimal parameters which are required for the development of SVM models. The data collected from the time domain simulation is then used as input to the SVM in which support vector regression is used as a predictor to determine DGPS correction. To reduce training time and improve accuracy of the SVM, the Kernel function type and Kernel parameter are considered [8]. In recent years, various artificial neural networks methods have been proposed to predict PRC. A technique of predicting the DGPS pseudo-range corrections based on Diagonal Recurrent Neural Networks (DRNN) modeling was presented by Sang et al (1997) [10]. In 2004, the Auto-Regressive Moving-Average (ARMA) neural network was applied to predict the PRC (Jwo et al 2004) [3]. More recently, Mohasseb et al (2007) tested different neural network structures with various training algorithms [11]. Although their research provided useful results, the difficulty of predicting PRC online has not yet been overcome. To verify the effectiveness of the proposed GASVM method, its performance is compared with ARMANN [3]. The rest of this paper is organized as follows. In Section 2 the preliminary background on RTDGPS structure is briefly reviewed. In Section 3, the GASVM techniques are discussed. Topology for PRC prediction is described in Section 4. Experimental results are evaluated in Section 5. The conclusion is given in Section 6.

2 RTDGPS Structure

RTDGPS is, by definition, a relative positioning methodology supported by the continuous GPS satellites in view. RTDGPS correction data distribution has been providing GPS users a means to accomplish their tasks with high accuracy positioning in real-time. As shown in Fig. 1, it contains two GPS receivers. For real-time users of DGPS, the resources required are the establishment of a reference station and a radio link to transmit data to the users. The standard format of the broadcasted data developed by the Radio Technical Commission for Marine Services (RTCM) is in wide use and RTCM has defined data messages and an interface between the data link receiver and the DGPS receiver [12]. In general, the data stream is mainly of message type 1 or 9, which consists of a correction message such as PRC. In navigation application, the PRC is needed in real-time and it can be transmitted to the users via a communication link. As can be shown in Table 1, according to the coding information, every frame of RTCM telegraphs is made up of N+2 words (the first two words and the following N information words). The type of the telegraphs is defined by the first word, while the format of the remaining N words decides the information's type. Every word includes 30 bits; the last byte of the word is a verification code. In this standard, there are 63 kinds of information, pseudo-range measurement adopting type 1 and 3. Type 1 contains modified information of DGPS, while type 3 includes the coordinates of reference station [13]. In this study, the most important factor (PRC) to consider is message No. 1.

2.1 Pseudo-Range Corrections

The basic principle of DGPS is to utilize the knowledge that systematic errors such as due to the satellite clock, ephemeris and atmospheric propagation largely affect both the base receiver and rover receiver. Because the position of the base receiver is accurately known, the combined error of each satellite can be estimated. If the rover receives the estimated error, the correlated error can be subtracted and the accuracy of the position estimation will be improved. For any satellite, the measured GPS pseudo-ranges at the base station and rover station can be expressed as:

$$\rho_B = r_B + C(\delta t_B - \delta t^s) + I_{\rho B} + T_{\rho B} + \varepsilon_{\rho B} \quad (1)$$

$$\rho_R = r_R + C(\delta t_R - \delta t^s) + I_{\rho R} + T_{\rho R} + \varepsilon_{\rho R} \quad (2)$$

where r_B and r_R are the geometric range between the (unknown) user position and the (known) satellite position for rover and base station, respectively. δt is the receiver clock bias and δt^s is the bias in the satellite clock, both measured relative to GPS Time. $I_{\rho B}$ and $I_{\rho R}$ reflect the delays associated with the transmission of the signal through the ionosphere and the troposphere, respectively. ε_ρ is used to denote UN modeled effects, modeling errors and measurement error. Because the position of the base station is already known, the error in ρ_B,which is referred here as the PRC at the base station, is computed as:

$$e_B = r_B - \rho_B = -C((\delta t_B - \delta t^s) - I_{\rho B} - T_{\rho B} - \varepsilon_{\rho B} \quad (3)$$

The differentially-corrected pseudo-range measurement of the rover GPS is:

$$\breve{\rho}_R = \rho_R + e_B \approx r_R + C(\delta t_R - \delta t_B) + (I_{\rho R} - I_{\rho B}) + (T_{\rho R} - T_{\rho B)} + \varepsilon_{\rho R} + \varepsilon_{\rho B} \quad (4)$$

The satellite clock bias of the base receiver is similar to that of the rover receiver [4]. The user is generally far

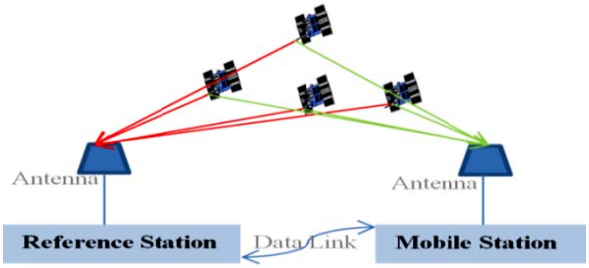

Fig. 1 Real time DGPS topology.

Table 1 RTCM Type 1 Differential GPS Correction.

	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25~30
																									PARITY
First word	PREAMBLE								MESSAGE TYPE						PEFERENCE STATION ID										PARITY
Second word	MODIFIED Z-COUNT														SEQ.NO.		LENGTH OF FRAME				STAT. HEALTH				PARITY
$2*N_s$ word	S	UD.		SATELLITE ID					PSEUDO-RANGE CORRECTION																PARITY
$2*N_s+1$ word	RANGE-RATE CORRECTION								ISSUE OF DATA (IOD)						REPEAT										PARITY

from the reference station; so, it should correct measurement based on a previous or "old" message. To reduce the problem caused by this time latency, the reference stations have generated and have sent the corrections with Range Rate Correction (RRC) [14]. This has compensated the PRC at the previous time t_{k-1}, for the time $t_k - t_{k-1}$, lineally as shown in Eq. (5) and Fig. 2.

$$PRC(t_k) \approx PRC(t_{k-1}) + PRC(t_{k-1}).\Delta t \quad (5)$$

where $\Delta t = t_k - t_{k-1}$.

However, the receiver cannot estimate RRC correctly because of the measurement noise and atmospheric bias. To approximate the exact value of PRC in the time delay or loss of RTCM signal GASVM algorithms are used to predict PRC. Given the rate of message No. 1, RTCM signal is very important and sends it as soon as possible. Thus, PRC prediction increases the accuracy of the RTDGPS.

3 Hybrid GASVM Model

Recently, SVMs have been developed for solving pattern recognition and nonlinear regression estimation problems. The SVM model is able to increase forecasting accuracy by selecting suitable parameter. Therefore, constructing an adapted procedure to select suitable parameters is an essential task [15]. In this study, a SVM model with GAs is proposed to examine the feasibility of predicting system reliability. To design a SVM, one must choose a kernel function, set the kernel parameters and determine a soft margin constant C. The parameters that should be optimized include the penalty parameter C and the kernel function parameters [16]. Combining GA with SVM, this hybrid approach to optimize the parameters, to improve the strength of each individual technique and compensate for each other's weaknesses. Therefore, this research applies GA to optimize C, ε, σ parameters in the SVM model.

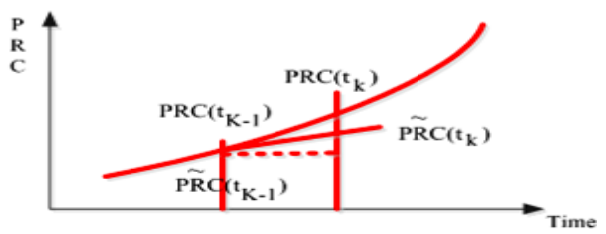

Fig. 2 Compensation PRC for time latency.

3.1 SVM

SVMs have been used for a variety of purposes. They can be used in two ways: for classification and for regression. Support Vector Regression (SVR) has been proven especially useful in prediction of time-series.

SVM was originally introduced by Vapnik and co-workers for classification tasks and was subsequently extended to regression problems [16]. The idea behind SVMs is the following: input points are mapped to a high dimensional feature space, where a separating hyper-plane can be found. The algorithm is chosen in such a way as to maximize the distance from the closest patterns, a quantity which is called the margin. SVMs are learning systems designed to automatically trade-off accuracy and complexity by minimizing an upper bound on the generalization error provided by the Vapnik-Chervonenkis (VC) theory. The aim of support vector classification is to device a computationally efficient way of learning how to separate hyper planes well in a high dimensional feature space [17]. SVMs are less prone to over fitting because the classifier is characterized by the number of support vectors rather than the dimensionality of the data. The number of support vectors found can be used to compute an upper bound on the expected error rate of the SVM classifier. Good generalization can be achieved by having SVM with small number of support vectors irrespective of the dimension of the dataset [16-18].

3.1.1 SVR

The basic principle of SVR is to map data in the input space to a high dimensional feature space by using a nonlinear mapping. Then, a linear mapping is made in the high dimensional space. A set of data $(x_i, y_i), i = 1, 2, \ldots, m$ where $x_i \in R^n$ and $y_i \in R^n$, are supposed to be the corresponding output. SVM regression theory is to find a nonlinear map from input space to output space and map the data to a higher dimensional feature space through the map, then the following estimate function is used to make linear regression [19]:

$$f(\bar{x}) = w.\varphi(\bar{x}) + b \quad (6)$$

where $\varphi(\bar{x})$ denotes the high-dimensional feature space, w denotes the weight vector and b denotes the bias term. The problem of the function approximation is equivalent with minimizing the following problem [20]:

$$R_{reg}[f] = R_{reg}[f] + \lambda\|w^2\| = \sum_{i=1}^{!} L^{\varepsilon}\left(y_i, f(\bar{x_i}, w)\right) + \lambda\|w^2\| \quad (7)$$

$R_{reg}[f]$ is objective function and l is the number of the sample, $L^{\varepsilon}(y_i, f(\bar{x}_i, w))$ is called loss function. Where l denotes the sample size, λ is regularization constant, L^{ε} is the ε -insensitive loss function which is given by:

$$L(y_i, f(\bar{x}_i, w)) = \begin{cases} 0 & \text{for } |f(x) - y| < \varepsilon \\ |f(x) - y| < \varepsilon & otherwise \end{cases} \quad (8)$$

The target function Eq. (8) can be minimized by solving quadratic programming problem, which is uniquely solvable. Empirical risk function is:

$$R^{\varepsilon}{}_{emp}[f] = \frac{1}{l}\sum_{i=1}^{l}|y - f(x)|_{\varepsilon} \quad (9)$$

It can be normalized as follows:

$$\varphi(w, \xi) = \frac{1}{2}|w|^2 + C\sum(\xi_i^- + \xi_i^+) \quad (10)$$

$$\text{subject to} \begin{cases} y_i - \langle w, \varphi(\bar{x}_i)\rangle - b \le \varepsilon + \xi_i^- \\ \langle w, \varphi(\bar{x}_i)\rangle + b - y_i \le \varepsilon + \xi_i^+ \\ \xi_i^-,\ \xi_i^+ \ge 0 \end{cases}$$

where, C is a pre-specified value and ξ_i^-, ξ_i^+ are slack variables representing upper and lower constraints on the outputs of the system. The first part of this cost function is a weight decay which is used to regulate weight size and penalizes large weights. Due to this regulation, the weight converges to smaller values. Large weights deteriorate the generalization ability of SVM because, usually, they can cause excessive variance [21]. The second part is a penalty function which penalizes errors larger than $+/-\varepsilon$ using a so called ε-insensitive loss function L^{ε} for each of the training points. The positive constant C determines the amount, up to which deviations from ε are tolerated. Errors larger than +/-ε are denoted with the so-called slack variables representing values above ε (ξ^+) and below ε (ξ^-), respectively. The third part of the equation represents constraints that are set to the values of errors between regression prediction f(x) and true values y_i. This constrained optimization problem is solved using the following Lagrangian form:

$$\max\ W(\alpha, \alpha^*) = \max -\frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)\langle\varphi(x_i), \varphi(x_i)\rangle + \sum_{i=1}^{l}\alpha_i(y_i - \varepsilon) - \alpha_i^*(y_i + \varepsilon) \quad (11)$$

with constraints,

$$0 \le \alpha_i, \alpha_i^* \le c \quad i = 1, \dots, l \quad \sum_{i=1}^{l}(\alpha_i - \alpha_i^*) = 0 \quad (12)$$

where α_i and α_i^* are the so-called Lagrangian multipliers, represent solutions to the above quadratic problem that acts as forces pushing predictions towards target value y_i. Only the non-zero values of the Lagrange multipliers in Eq. (12) are useful in forecasting the regression line and are known as support vectors. For all points inside the e-tube, the Lagrange multipliers equal to zero do not contribute to the regression function. Only if the requirement $|y\text{-}f(x)| \ge \varepsilon$ is fulfilled, Lagrange multipliers may be non-zero values and can be used as support vectors. By the Lagrange multipliers α_i and α_i^* calculated,

$$\bar{w} = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)\,K(x_i, x) \quad (13)$$

Now, we have solved the value of w in terms of the Lagrange multipliers. The variable b can be computed by applying Karush-Kuhn-Tucker (KKT) conditions [20] which, in this case, implies that the product of the Lagrange multipliers and constrains has to equal zero:

$$\begin{cases} \alpha_i(w.\varphi(x) + b - y_i + \varepsilon + \xi_i) = 0 \\ \alpha_i^*(y_i - w.\varphi(x) - b\varepsilon + \xi^*{}_i) = 0 \end{cases} \quad (14)$$

and

$$\begin{cases} (C - \alpha_i)\xi_i = 0 \\ (C - \alpha_i^*)\,\xi^*{}_i) = 0 \end{cases} \quad (15)$$

Since α_i, α_i^* and $\xi^*{}_i = 0$ for $\alpha_i^* \in (0, C)$, b can be computed as follows:

$$\begin{cases} b = y_i - w\,\varphi(x) - \varepsilon, \text{for } \alpha_i \in (0, C) \\ b = y_i - w\,\varphi(x) - \varepsilon, \text{for } \alpha_i^* \in (0, C) \end{cases} \quad (16)$$

Hence, the regression function is:

$$f(x) = \sum_{SVs}(\bar{\alpha}_i - \bar{\alpha}_i^*)\,K(x_i, x_j) + b \quad (17)$$

In Eq. (17) the Kernel function,

$$K(x_i, x_j) = \langle\varphi(\bar{x}_i), \varphi\bar{x}_j\rangle \quad (18)$$

can be shown that in any symmetric Kernel function, k satisfying Mercer's condition corresponds to a dot product in some feature space [22]. Several Kernel functions are named as Gaussian radial basis function (RBF) Kernel, linear Kernel and multilayer perceptron Kernel [21]. The commonly Kernel function used is the Gaussian RBF Kernel which is written as [22]:

$$k(x, y) = e^{\frac{\|x-y\|}{2\sigma^2}} \quad (19)$$

Note that σ^2 is a parameter associated with RBF function which has to be tuned. For prediction cases, any data can be regarded as an input-output system with nonlinear mechanism. For the nonlinear SVR, its generalization performance depends on a good setting of hyper-parameters C, ε and the RBF kernel parameter σ. Parameter C determines penalties to estimation errors. A large C assigns higher penalties to errors so that the regression is trained to minimize error with lower generalization, while a small C assigns fewer penalties to errors; this allows the minimization of margin with errors, hence higher generalization ability. Parameter ε controls the width of the ε-insensitive zone, used to fit the training data. The value of ε can affect the number of support vectors used to construct the regression function [22]. Here, C, σ and ε are user-determined parameters, which may affect SVR generalization performance; the selection of the parameters plays an important role in the performance of SVM. Therefore, these parameters need to be properly optimized to minimize the generalization error [18, 23].

3.2 Genetic Algorithm

The GA is an artificial intelligence procedure based on the theory of natural selection and evolution. GA uses the idea of survival of the fittest by progressively accepting better solutions to the problems. The key feature of GA is the manipulation of a population whose individuals are characterized by possessing chromosome [24]. Therefore, GAs is distinct from many conventional search algorithms in the following ways [25]:

1. GAs considers not a single point but many points in the search space which simultaneously reduce the chance of converging to local optima.
2. GAs work directly with strings of characters representing the parameter set, not the parameters themselves.
3. GAs use probabilistic rules, not deterministic rules, to guide their search.

Two important issues in GA are the genetic coding used to define the problem and the evaluation function, called the fitness function. Each individual solution in GA is represented by a string called the chromosome [26]. The initial solution population could be generated randomly, which evolves into the next generation by genetic operators such as selection, crossover and mutation that means GAs perform the search process in four stages: initialization, selection, crossover and mutation. Fig. 3 shows the basic steps of GAs. The solutions coded by strings are evaluated by the fitness function. The selection operator allows strings with higher fitness to appear with higher probability in the next generation. Crossover is performed between two selected individuals, called parents, by exchanging parts of their strings, starting from a randomly chosen crossover point. This operator tends to enable the evolutionary process to move toward promising regions of the search space. Mutation is used to search for further problem space and to avoid local convergence of GA though the GA is less time-consuming and can obtain the optimal solution well [23, 24].

3.3 GASVR

Inspired by the natural evolution process, Holland proposed the GAs, which are organized random search techniques and which imitate the biological evolution process. The algorithms are based on the principle of the survival of the fittest which tries to retain genetic information from generation to generation. The main advantage of GAs is their capabilities to find optimal or near optimal solutions with relatively modest computational requirements [27]. In this article, GAs are used to search for better combinations of three parameters in SVMs, so each forecasting iteration yields a smaller Normalized Mean Square Error (NMSE) value. Fig. 4 shows the framework of the proposed GASVM model. The genetic algorithms for selecting the parameters of SVMs are presented as follows:

Step 1. (Initialization): Establish randomly an initial population of chromosomes.

Step 2. (Evaluating fitness): Evaluate the fitness of each chromosome. In this step, a negative NMSE is used as the fitness function as follows.

$$\text{Fitness function} = -\frac{1}{\sigma^2 N}\sum_{i=1}^{N}(d_i - y_i)^2 \qquad (20)$$

where $\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(d_i - \bar{d}_i)^2$ and N is the total number of data in the test set; d_i denotes the mean of the actual value; d_i is the actual value; and y_i is the predicted value.

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

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

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

Step 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 [26].

GAs is used to determine the values of the three parameters (σ, C and ε) in the SVM model (Fig. 4). The intervals of three parameters are [0, 250], [0, 1000] and [0, 0.1] respectively. The population size is set to 50. More bits in a gene correspond to finer partition of the search space. Parent selection is a procedure in which two chromosomes from the parent population are chosen according to fitness functions. Chromosomes with a higher fitness value are more likely to generate offspring in the next generation. The roulette wheel selection principle is used to select chromosomes for reproduction.

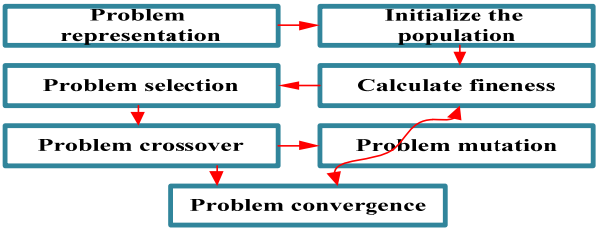

Fig. 3 Basic steps of GA.

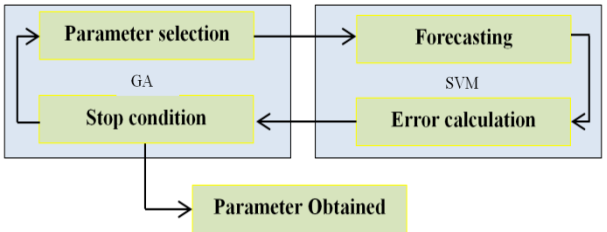

Fig. 4 The architecture of a GASVM model.

In crossovers, chromosomes are paired randomly. The single-point-crossover principle is employed here in. Segments of paired chromosomes between two determined break-points are swapped. Mutations are performed randomly by converting a 1" bit into a 0" bit or vice versa. The rates of crossover and mutation are determined by probabilities. Mating rate has a probability of 0.7, mutation rate is 0.01 and the number of generations is considered to be 40.

4 PRC Predictions Topology

Fig. 5 shows the topology provided for PRC prediction; it consists of two major parts.

(A) Hardware (Fig. 6): It consists of a low-cost GPS receiver and a module to convert TTL to RS232.

(1) (MOTOROLA (M12)) (Fig. 6): The technically significant features of the GPS receiver used in data collection process include a 12-channel GPS receiver capable of: keeping track of up to 9 satellites, position measuring with maximum accuracy in SPS mode (25m), selecting satellites and making satellite's view angle narrow, updating information in each second. M12 receiver is supporting invers DGPS and RTCM input at 9600 baud rate (Base station and Rover) [28].

(2) (TTL to RS232): The PC serial port protocol is RS232; therefore we designed and applied a ''TTL-to-RS232'' converter between USART and personal computer (PC).

(B) Software (MATLAB): it contains comment unit, store data unit, prediction unit and result unit.

(1) Comment unit: In order to generate the most accurate corrections, the M12 being used as a Base Station must be put in position-hold mode. Once the @@BH command is invoked, the base station will start issuing @@Ce correction messages at the requested rate.

(2) Store unit data: After receiving the pseudo-range correction input (@@Ce); now parse the 6 sat data slots in this message and store PRC data by using software MATLAB. Table 2 shows @@Ce message format.

(3) Prediction unit: The architecture of the GASVM for predicting the PRC is shown in Fig. 7. For the prediction of the DGPS corrections at time t+1 (denoted as prc (t+1)), a series of the DGPS corrections prc (k), prc (k-1), …, prc (k-n), will be used, where n is the number of data point used as the input to the network. The GASVM predictor receives a set of past PRC values and infers the one at next epoch. The time intervals between epochs are six seconds, thus time step of the prediction was 6 second.

5 Experimental Results

The experiments on the GASVM were performed using real data for PRC predictions. An experiment was conducted to evaluate the system performance. Simulation was performed on an 2.5 GHz CORE™ i5 CPU. The computer code was constructed by MATLAB 10.1 version software. The measurement update rate was 1sec and six GPS satellites were used in the experiment. Fig. 8 shows the original DGPS corrections of 6 satellites.

Table 2 Pseudo-range Correction Data Input.

@@Cettt ippprrd ippprrd ippprrd ippprrd ippprrd ippprrdC<CR><LF>		
Title	**Explanation**	**No. Byte**
Ttt	GPS time reference	3
I	Satellite id	1
Ppp	Pseudo-range correction input	3
Rr	Range Rate PRC	2
D	Issue of data ephemeris	1
C	Checksum	1

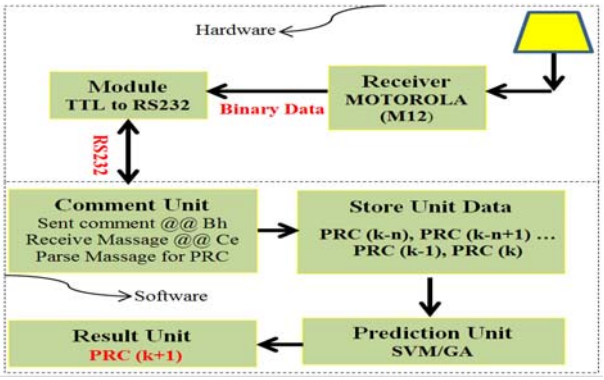

Fig. 5 Topology for PRC Prediction.

Fig. 6 Hardware structure.

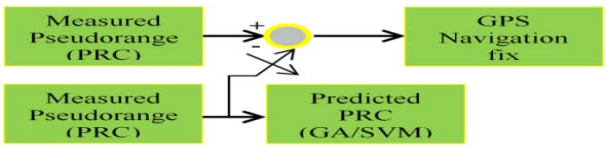

Fig. 7 Architecture for predicting the PRC.

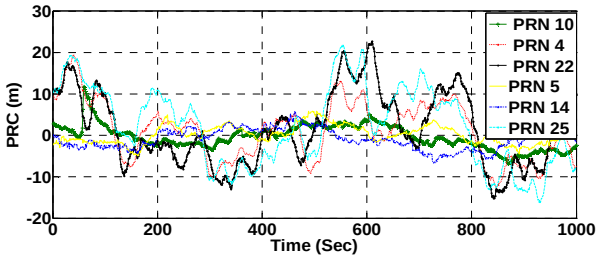

Fig. 8 DGPS PRC of PRN's 4, 22, 25, 14, 10 and 5.

The GASVM was trained to predict the DGPS corrections six second ahead of the current epoch. Fig. 9 shows the one-step prediction PRC (PRN10). As shown in Fig. 9, the GASVMs, have been successful in approximated real value. Fig. 10 shows PRC prediction for PRN22. Figs. 11 (PRN 10) and 12 (PRN 22) shows the 6sec ahead PRC prediction error, respectively. It is found from Figs. 11 and 12, that GASVMs have great approximation ability and suitability in DGPS corrections prediction. Figs. 13 (Time step 5) and 14 (Time step 10) shows the predicted PRC value of the GASVM for PRN 12. This time limitation is equal to 30sec and 60sec because the step time is 6 sec.

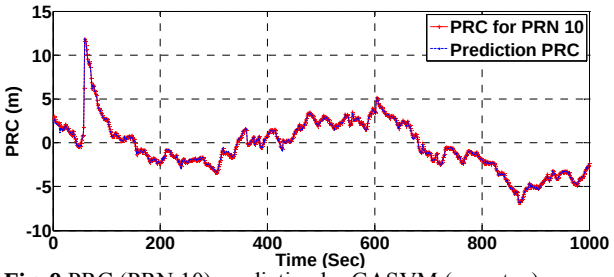

Fig. 9 PRC (PRN 10) prediction by GASVM (one step).

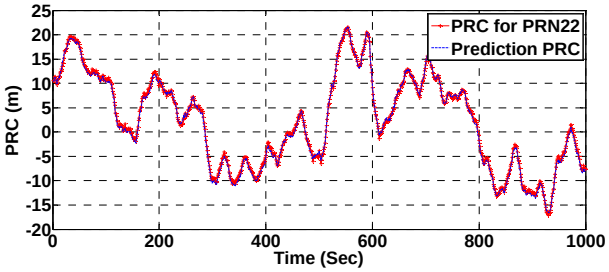

Fig. 10 PRC (PRN 22) prediction (one step).

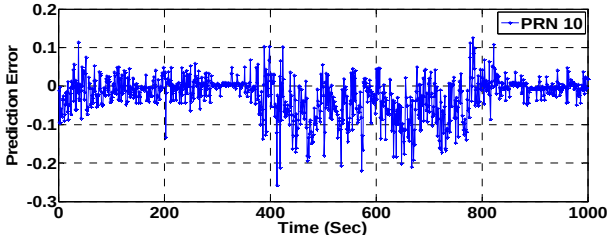

Fig. 11 6s ahead PRC prediction error for PRN 10.

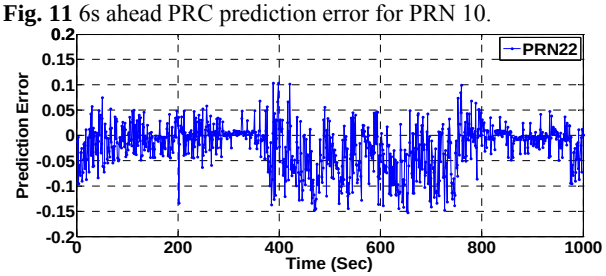

Fig. 12 6s ahead PRC prediction error for PRN 22.

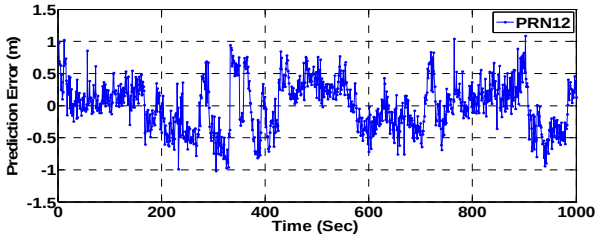

Fig. 13 30s ahead PRC prediction error for PRN 12.

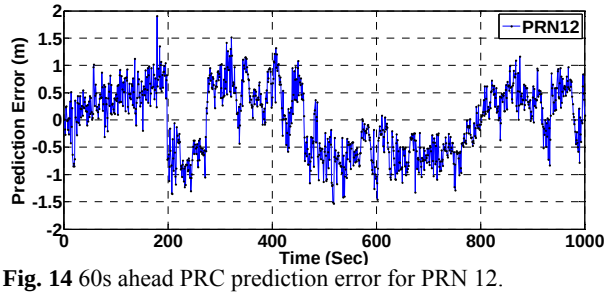

Fig. 14 60s ahead PRC prediction error for PRN 12.

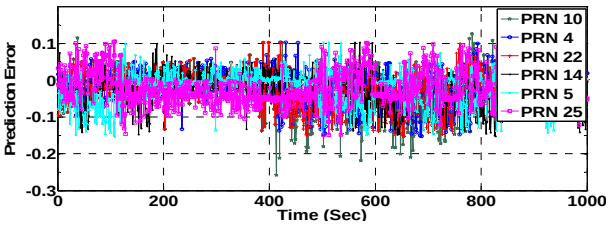

Fig. 15 One step ahead PRC prediction error of 6 satellites.

Table 3 Comparison prediction errors statistical significance characteristics.

Time	Parameters	MAX	MIN	Ave	VAR	RMS
6 s	PRN 10	0.33	0	0.12	0.22	**0.186**
	PRN 22	0.21	0	0.11	0.21	**0.183**
30 s	PRN 7	0.6	0.056	0.23	0.53	**0.587**
60 s	PRN7	2	0.1	0.36	0.761	**0.867**

From above figures, it can be seen that the accuracy of the PRC prediction has dramatically improved with the proposed approach. In prediction unit, PRC for six satellites simultaneously and real-time was predicted. Fig. 15 shows the DGPS PRC prediction error for PRN 10, 4, 22, 14, 5, 25. Table 3 shows prediction errors statistical significance characteristics for 1000 test data using GASVM. It is found that the maximum prediction error is less than 0.3 m; also total RMS prediction errors for algorithm is 0.186m for one step ahead. A comparison of the accuracy prediction results between the ARMANN and GASVM was carried out. The NN was trained using the BP algorithm and it took 3 minutes to train the ARMANN before it was ready to provide DGPS corrections.

Once the NN was trained, the constructed ARMA model was used to predict a time series with a step length of 6S. The neural network was trained to predict DGPS corrections 6S ahead of the current correction. The RMSE prediction accuracy of the ARMA (9, 8) mode was 0.2472m. However, the PSOSM method accuracy with time step equal is about 1.8m.

6 Conclusion

A GASVM that can effectively be employed to predict the pseudo-range differential corrections online has been presented. When the PRC signal was temporarily lost, the GASVM predicted PRC correction data with a significant accuracy improvement. In summary, conventional algorithms have difficulties in precisely predicting the DGPS corrections online.

It uses for improvement RTDGPS accuracy. A comparison between the ARMANN and GASVM shows that the GASVM requires less network training time and in equal time step GASVM prediction RMSE is less than ARMANN.

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