Evolutionary Algorithms Approach for Errors High-Precision Modeling in Single-Frequency GPS Receivers

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Abstract
The stand-alone GPS accuracy is low due to multiple error sources including multi-path effects, atmospheric effects, clock inaccuracies, unexpected interference, and weak signal applications. Because of the above mentioned error sources, GPS receivers have certain amount of errors and hence error reduction in GPS system is one of the main branches of researchers. Evolutionary Algorithms (EAs) such as Genetic Algorithm (GA), Simulated Annealing (SA), and Particle Swarm Optimization (PSO) are algorithms for optimization and learning based loosely on several features of biological evolution. In this paper, a new approach is presented for standard GPS receiver's accuracy improvement using EAs. Method validity is verified with experimental data from an actual data collection, before and after Selective Availability (S/A) error. The results are a highly effective technique for errors high-precision modeling in single-frequency GPS receivers; so that RMS error reduces to less than 0.8 m.

1. Introduction

Global Positioning System (GPS) measurements are effected by several types of random errors and biases (systematic errors). These errors may be classified as those originating at the satellites, those originating at the receiver, and those that are due to signal propagation (atmospheric refraction) (McDonald, 2002). The errors originating at the satellites include ephemeris (or orbital errors), satellite clock errors, and the effect of Selective Availability (S/A). The later was intentionally implemented by the U.S. DoD to degrade the autonomous GPS accuracy for security reasons. It was, however, switched off on May 2, 2000 (Dyke, 2000). The errors originating at the receiver include receiver clock errors, multi-path error, receiver noise, and antenna phase center variations. The signal propagation errors include the delays of the GPS signal as it passes through the atmospheric layers (mainly the ionosphere and troposphere). In fact, it is only in a vacuum (free space) that the GPS signal travels, or propagates, at the speed of light (Øvstedal, 2002). In addition to the effect of these errors, the accuracy of the computed GPS position is also affected by the geometric locations of the GPS satellites as seen by the receiver. The more spread out the satellites are in the sky, the better the accuracy obtained (Jwo et al., 2007). Modeling of GPS errors is an important research and application area. Much effect has been devoted over the past several decades to the development and improvement of GPS error models.

Well established GPS errors models include: (1) linear models, e.g., moving average, smoothing (Mosavi, 2009) and the Auto Regressive (AR) integrated moving average (Mosavi et al., 2002); (2) nonlinear models, e.g., neural network models (Mosavi, 2007), modeling using Kalman filter (Mosavi, 2006), and fuzzy system models (Mosavi, 2004); and (3) the combination of linear and nonlinear models. In this paper, Evolutionary Algorithms (EAs) such as Genetic Algorithm (GA), Simulated Annealing (SA), and Particle Swarm Optimization (PSO) are used to perform linear predictor weights optimization. GAs are inspired by the mechanism of natural selection where stronger individuals are likely the winners in a competing environment. GAs are a class of optimization procedures which are good at exploring a large and complex space in an intelligent way to find values close to the global optimum (Kim et al., 2001). Method SA simulates the annealing process in which a substance is heated above its melting temperature and then gradually cooled to produce the crystalline lattice, which minimizes its energy probability distribution. This crystalline lattice, composed of millions of atoms perfectly aligned, is a beautiful example of nature finding an optimal structure. However, quickly cooling or quenching the liquid retards the crystal formation, and the substance becomes an amorphous mass with a higher than optimum energy state. The key to crystal formation is carefully controlling the rate of change of temperature (Bryan et al., 2006). The PSO technique involves casting a population of co-operative agents, randomly in the multidimensional search space. Each agent has an associated fitness value, which is evaluated by the fitness function to be optimized, and a velocity that directs its motion. Each agent can keep track of its solution that resulted in the best fitness as well as the solutions of the best performing agents in its neighborhood. The trajectory of each agent is dynamically governed by its own and its companion's historical behavior (Chen et al., 2006). The aim of this paper is errors high-precision modeling in single-frequency GPS receivers using EAs approach. This paper is structured as follows. Section 2 presents the proposed methods. The experimental results are reported with the collected real data, before and after S/A in section 3. Finally, conclusions are given in section 4.

2. GPS Errors Modeling

Figure 1 shows the block diagram of a linear prediction, where $y(n)=\hat{x}(n)$ is the prediction made in response to inputs $x(n-1), x(n-2), \cdots, x(n-p)$. p is the prediction order. Adjustable weights are obtained using EAs.

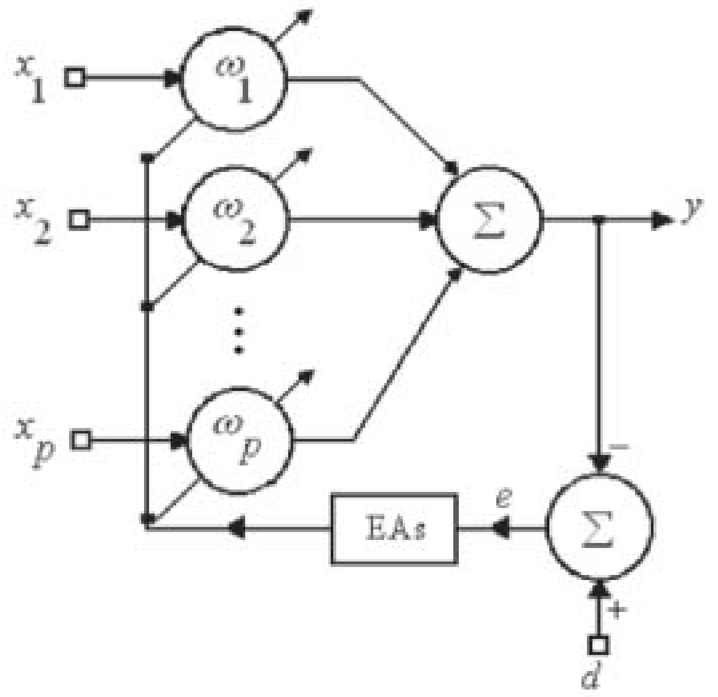

Figure 1: Block diagram of a linear prediction

The fitness function is the sum squared error and is defined as:

$$J(W) = \sum e^2$$

Equation 1

where $e = d - y$, d is the target output and $y = \sum_{i=1}^{i=p} w_i x_i$ is the predictor output. Obviously the objective is to minimize J subject to weights w_i.

2.1 Weights Adjustment using Genetic Algorithm

A GA algorithm is an iterative procedure maintaining a population of structures that are candidate solutions to specific domain challenges. During each temporal increment (called a generation), the structures in the current population are rated for their effectiveness as mutation. GAs are search algorithms based on the mechanics of the natural selection process (biological evolution). The most basic concept is that the strong tend to adapt and survive while the weak tend to die out. That is, optimization is based on evolution, and the "survival of the fittest" concept. GAs has the ability to create an initial population of feasible solutions, and then recombine them in a way to guide their search to only the most promising areas of the state space. Each feasible solution is encoded as a chromosome (string) also called a genotype, and each chromosome is given a measure of fitness via a fitness (evaluation or objective) function. The fitness of a chromosome determines its ability to survive and produce offspring. A finite population of chromosomes is maintained. GAs use probabilistic rules to evolve a population from one generation to the next. The generations of the new solutions are developed by genetic recombination operators: (1) **Biased Reproduction**: selecting the fittest to reproduce, (2) **Crossover**: combining parent chromosomes to produce children chromosomes, and (3) **Mutation**: altering some genes in a chromosome. Crossover combines the "fittest" chromosomes and passes superior genes to the next generation. Mutation ensures the entire state-space will be searched, (given enough time) and can lead the population out of a local minima. Determining the size of the population is a crucial factor. Choosing a population size too small increases the risk of converging prematurely to a local minimum, since the population does not have enough genetic material to sufficiently cover the problem space. A larger population has a greater chance of finding the global optimum at the expense of more CPU time. The population size remains constant from generation to generation. Fitness function drives the population toward better solutions and is the most important part of the algorithm (Kim et al., 2001). In this paper, a real GA has been proposed for determining of the linear predictor weights. Initial population equal 20, crossover ratio equal 0.8, and mutation rate equal 0.01 are the characteristic of the proposed GA.

2.2 Weights Adjustment using Simulated Annealing

The algorithmic analog to this process begins with a random guess of the cost function variable values. Heating means randomly modifying the variable values. Higher heat implies greater random fluctuations. The cost function returns the output J, associated with a set of variables. If the output decreases, then the new variable set replaces the old variable set. If the output increases, then the output is accepted provided that (Bryan et al., 2006):

$$r \le e^{\frac{J(p_{old}) - J(p_{new})}{T}}$$

Equation 2

where r is a uniform random number and T is a variable analogous to temperature. Otherwise, the new variable set is rejected. Thus, even if a variable set leads to a worse cost, it can be accepted with a certain probability. The new variable set is found by taking a random step from the old variable set. This control variable sets the step size so that, at the beginning of the process, the algorithm is forced to make large changes in variable values. At times the changes move the algorithm away from the optimum, which forces the algorithm to explore new regions of variable space. After a certain number of iterations, the new variable sets no longer lead to lower costs. At this point the values of T decreases by a certain percent and the algorithm repeats. The algorithm stops when $T \cong 0$. The decrease in T is known as the cooling schedule. Many different cooling schedules are possible. If the initial temperature is T_0, then the temperature at step n is given by:

$$T_n = 0.99T_0$$

Equation 3

Many other variations are possible. The temperature is usually lowered slowly so that the algorithm has a chance to find the correct valley before trying to get to the lowest point in the valley.

2.3 Weights Adjustment using Particle Swarm Optimization

The PSO conducts searches using a population of particles which correspond to individuals in EA. A population of particles is randomly generated initially. Each particle represents a potential solution and has a position represented by a position vector ω_i. A swarm of particles moves through the problem space, with the moving velocity of each particle represented by a velocity vector v_i. At each time step, a function f_i representing a quality measure is calculated by using ω_i as input.

Each particle keeps track of its own best position, which is associated with the best fitness it has achieved so far in a vector p_i. Furthermore, the best position among all the particles obtained so far in the population is kept track of as p_g. In addition to this global version, another version of PSO keeps track of the best position among all the topological neighbors of a particle. At each time step t, by using the individual best position, p_i, and the global best position, $p_g(t)$, a new velocity for particle i is updated by (Chen et al., 2006):

$$v_i(t+1) = \omega v_i(t) + c1\phi_1.(p_i(t) - \omega_i(t)) + c2\phi_2.(p_g(t) - \omega_i(t))$$

Equation 4

where $c1$ and $c2$ are positive constant and ϕ_1 and ϕ_2 are uniformly distributed random number in $[0,1]$. The inertia weight ω weights the magnitude of the old velocity $v_i(t)$ in the calculation of the new velocity $v_i(t+1)$. ω is linearly decreased from 1.4 to 0. If ω_{int} and ω_{fin} represent the initial and final values of ω respectively, MAX is the maximum number of optimization steps and $iter$ represents the current iteration number, then a linearly decreasing ω is defined in equation (10):

$$\omega = \frac{(\omega_{\text{int}} - \omega_{fin}).(MAX - iter)}{MAX} + \omega_{fin}$$

Equation 5

Changing velocity this way enables the particle i to search around its individual best position, p_i, and global best position, p_g. Based on the updated velocities, each particle changes its position according to the following equation:

$$\omega_i(t+1) = \omega_i(t) + v_i(t+1)$$

Equation 6

The parameter ω_i enhances searching ability by controlling the balance between local and global exploration in the problem search space both for EA and PSO.

3. Experimental Results

The GPS receiver which we used in the present study is a Rockwell microtracker low power GPS receiver. Although there are many other higher precision GPS receivers available in the market, the approach of presented in this paper is generic. This modeling can be applied to other GPS receivers. The microtracker low power GPS receiver provides the following physical and operational features:

- Five parallel satellite tracking channels.
- Tracks and uses measurements from up to nine satellites.
- Supports true National Marine Electronics Association (NMEA)-0183 data protocol with basic and extended NMEA default messages.
- Direct, differential Radio Technical Commission for Maritime Services, Special Committee No.104 (RTCM SC-104) data capability dramatically improves positioning accuracy from 100 m to 5 m or less (in both Rockwell binary and NMEA host modes).
- Static navigation enhancements to minimize wander due to S/A.
- Designed for passive or active antennas for lowest system cost.
- Maximum navigation accuracy achievable with the standard positioning service.
- Rapid adaptation to obscuration using ephemeris collection for all visible satellites via a designed utility channel.
- Maximum operational flexibility via user commands.

To study the function of receiver, the GPS receiver was installed and setup in a fixed position. In order to data collection and connecting to computer, hardware was designed and implemented. The optimal selection of proposed methods parameters was based on the experimental results. Increasing the predictor order improves the proposed methods performance. Increasing the predictor order increases the memory for software implementation and also the structure complexity for hardware implementation. Therefore, a trade-off in selecting the order of the predictor between CPU time and accuracy of methods is required. Performances of the proposed algorithms were assessed by data sets that were collected on the building of Computer Control and Fuzzy Logic Research Lab in the Iran University of Science and Technology. Figure 2 to Figure 7 show $Dx, Dy, and\ Dz$ approximations for 1000 test data by using the proposed algorithms, before and after SA was turned off.

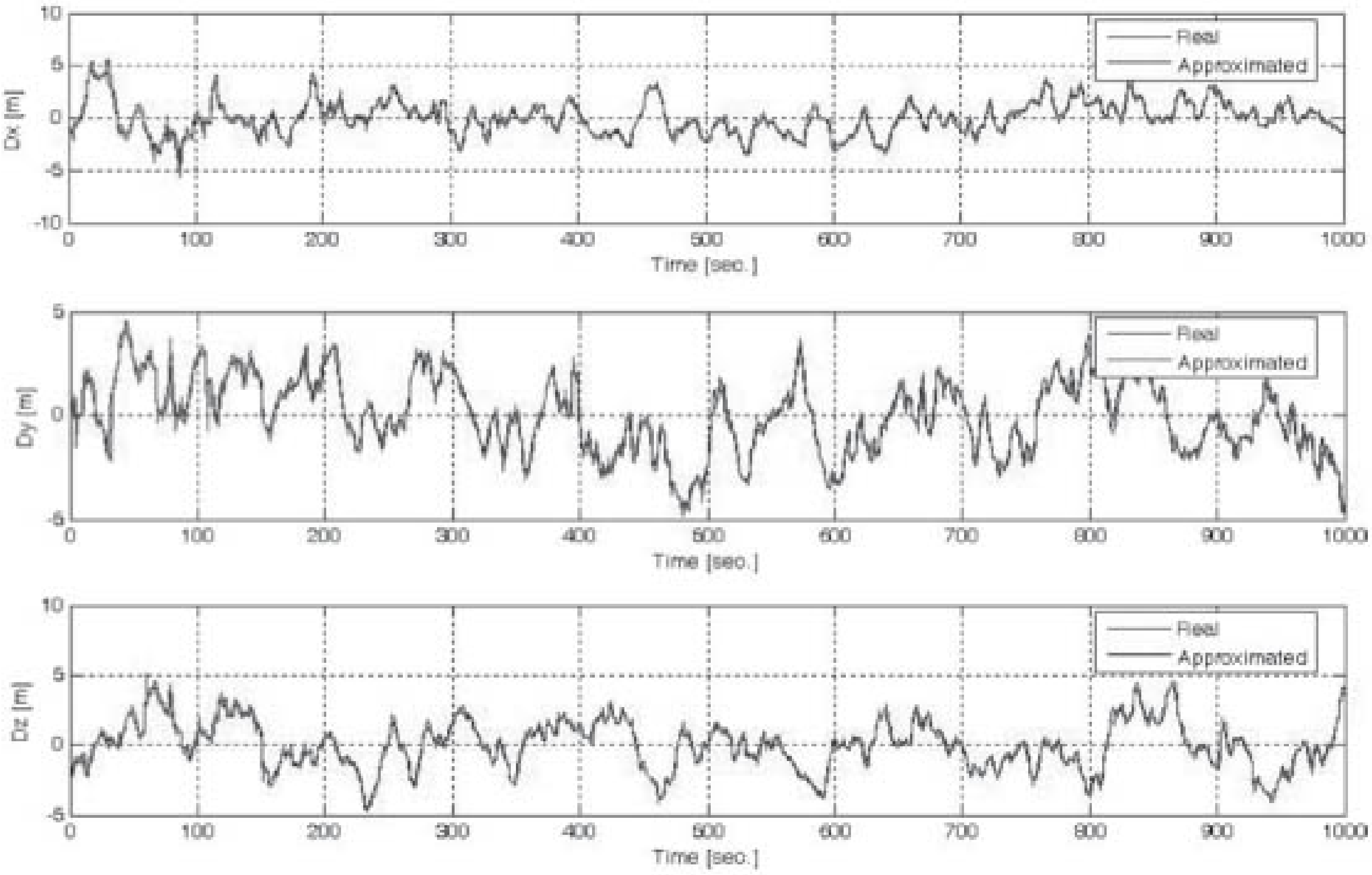

Figure 2: 1000 $Dx, Dy\ and\ Dz$ approximations by using proposed GA (S/A off)

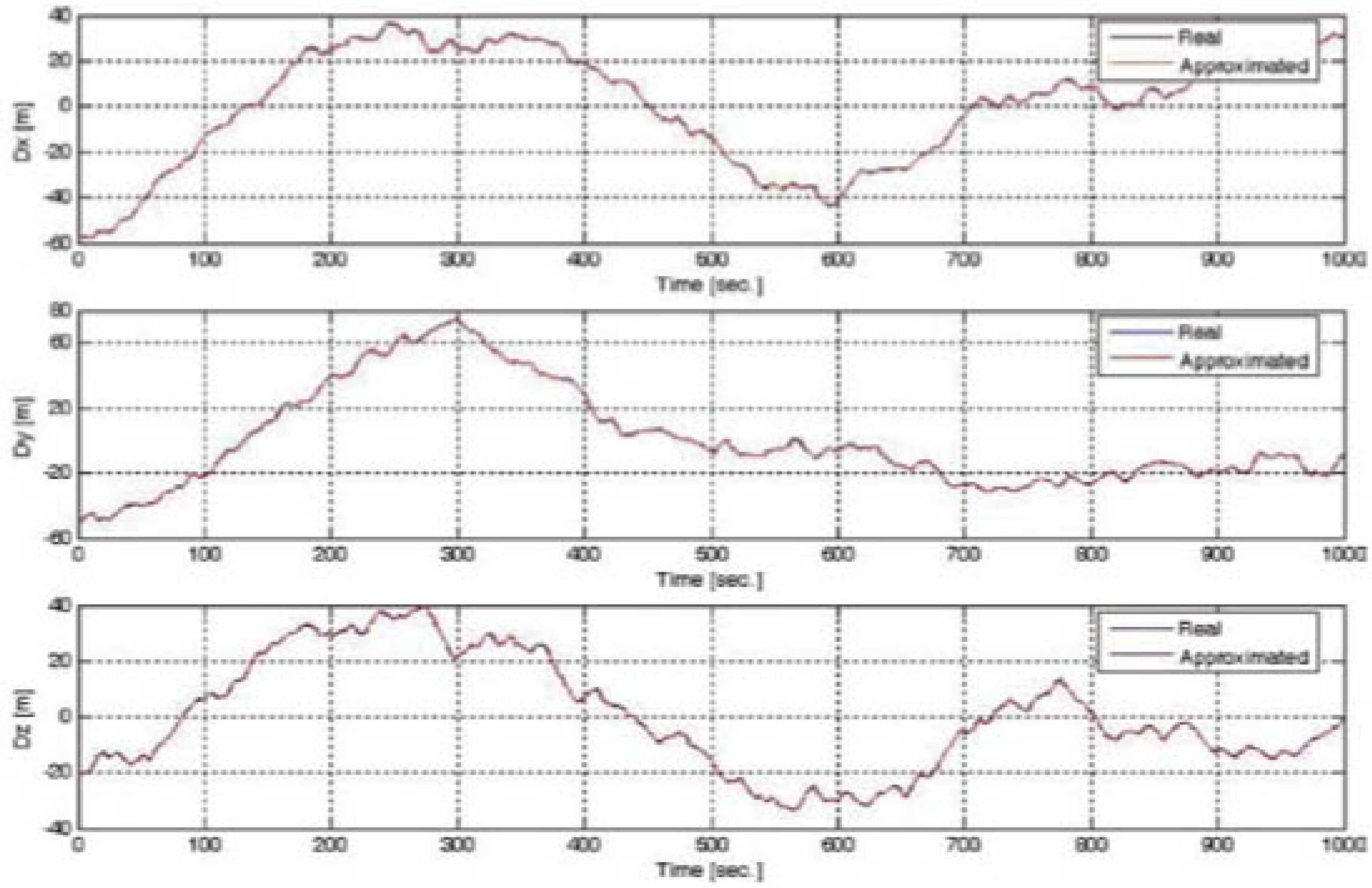

Figure 3: 1000 $Dx, Dy\ and\ Dz$ approximations by using proposed GA (S/A on)

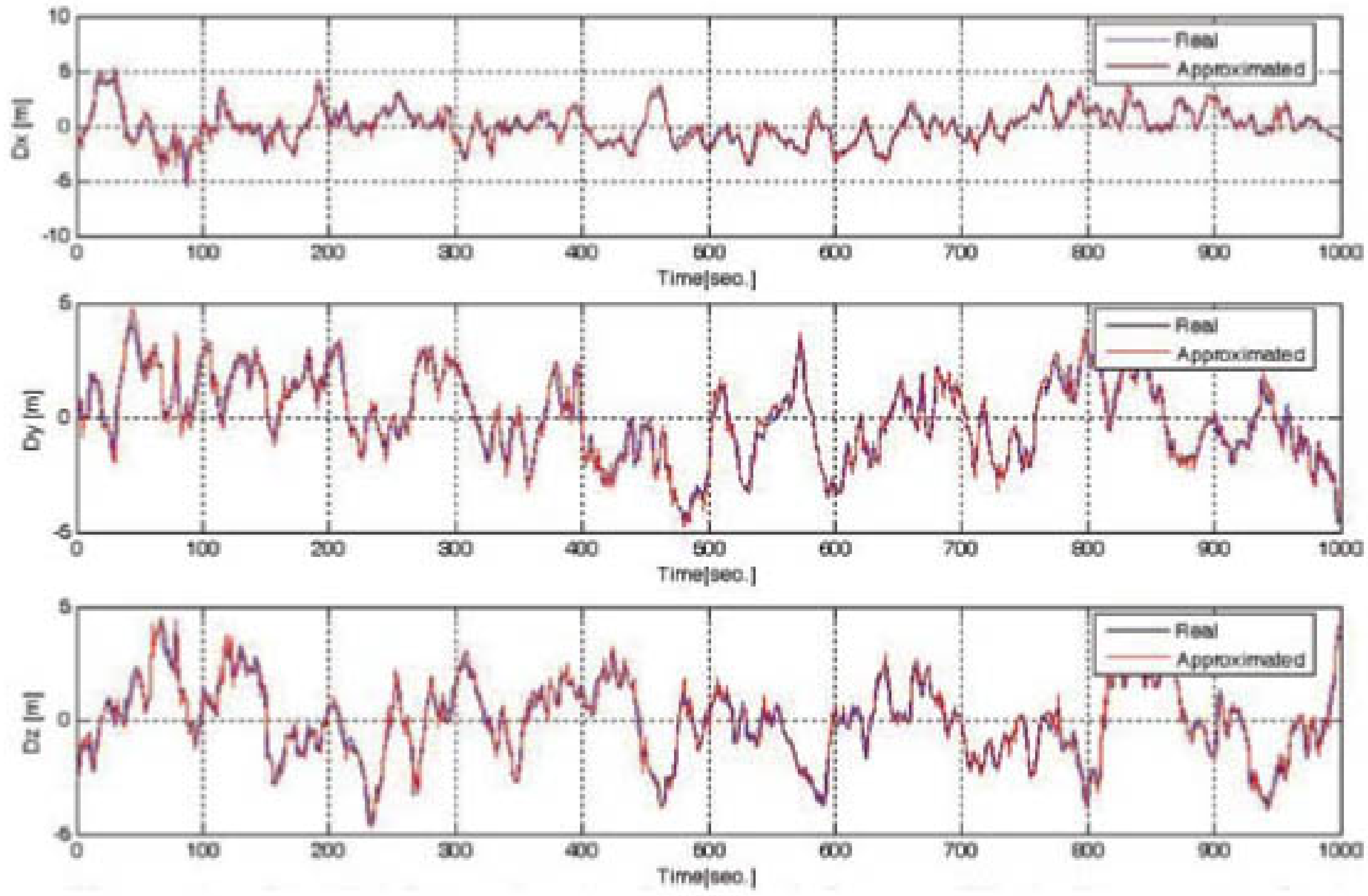

Figure 4: 1000 $Dx, Dy\ and\ Dz$ approximations by using proposed SA (S/A off)

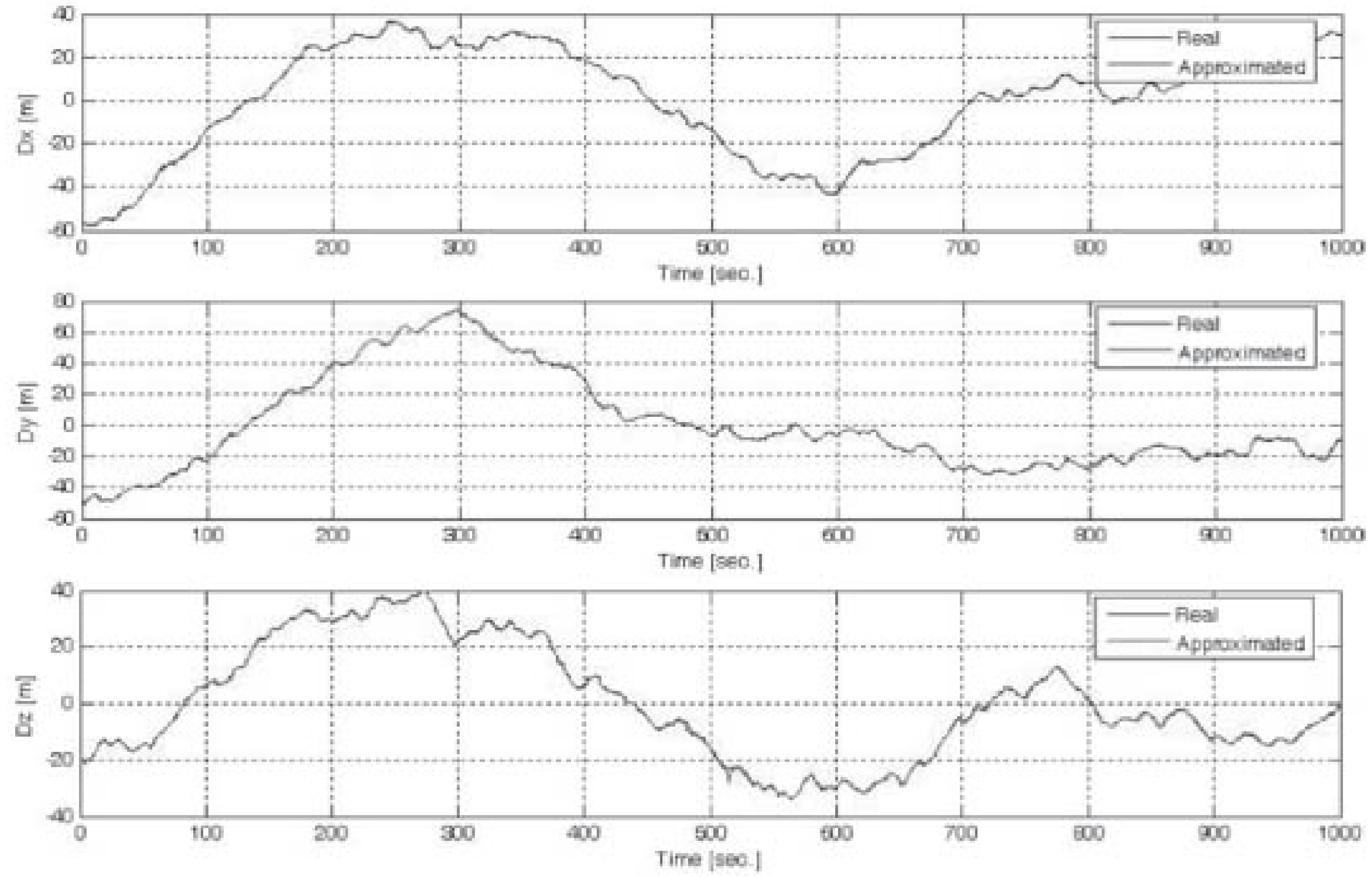

Figure 5: 1000 $Dx, Dy\ and\ Dz$ approximations by using proposed SA (S/A on)

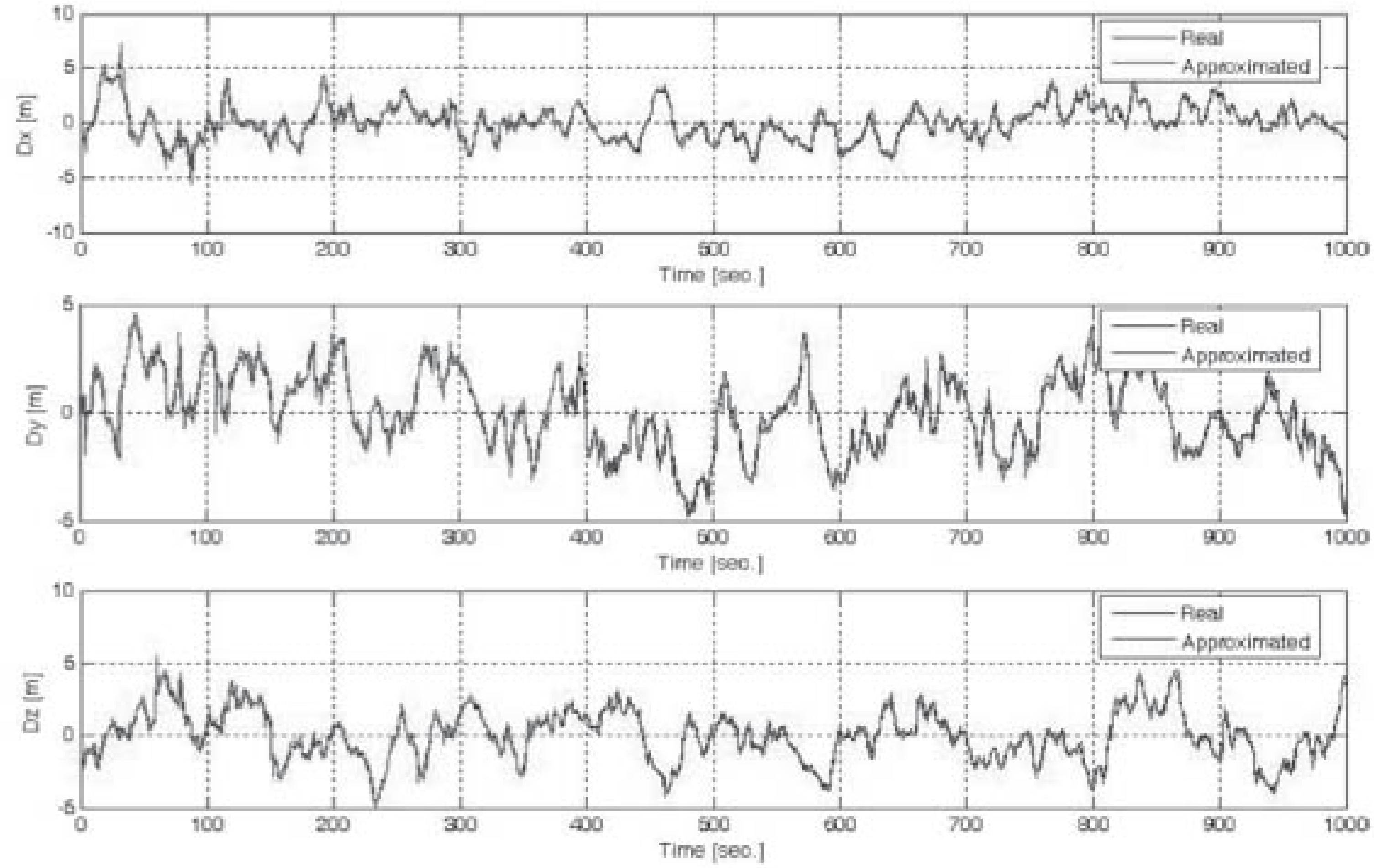

Figure 6: 1000 $Dx, Dy\ and\ Dz$ approximations by using proposed PSO (S/A off)

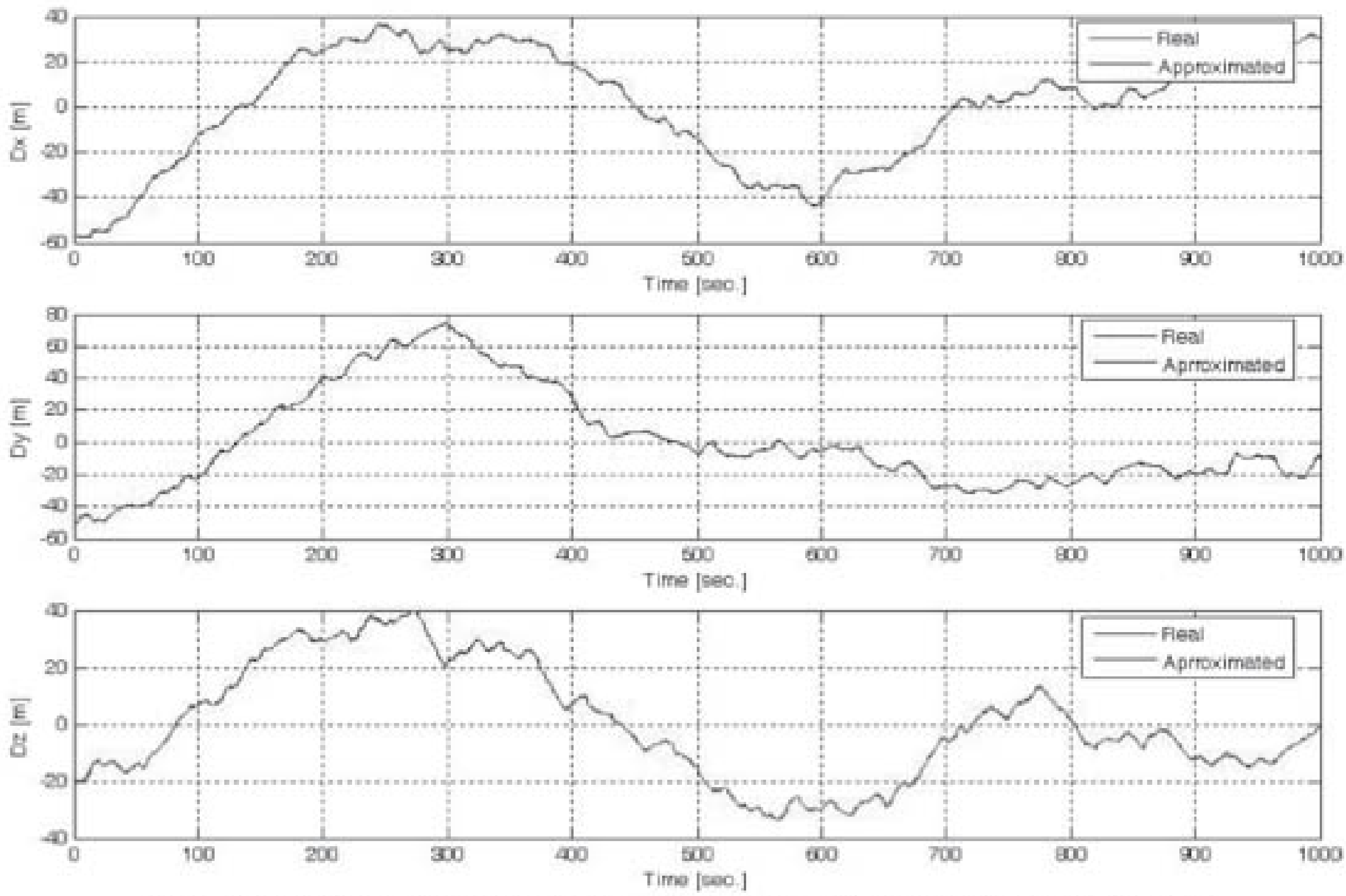

Figure 7: 1000 Dx, Dy *and* Dz approximations by using proposed PSO (S/A on)

The obtained results from Figure 2 to Figure 7 presents that the proposed methods can be highly effective tools to model the positioning errors. Table 1 to Table 6 show approximation errors (the difference between the approximated and real values) statistical significance characteristics for 1000 test data by using the proposed methods (before and after S/A error). The objective function used in the Root Mean Square Error (RMSE) (Indriyatmoko et al., 2008):

$$RMSE = \sqrt{\frac{1}{M}\sum_{i=1}^{i=M}(y_1^i - y_2^i)^2}$$

Equation 7

where M is number of tests and y_1^i and y_2^i denote the target output and model output, respectively.

Table 1: Maximum, minimum, average, and RMS of approximation errors using GA (S/A off)

Parameters	X Component	Y Component	Z Component
Max	2.4602	1.7928	2.2458
Min	-2.5411	-2.9226	-1.7463
Average	0.0005	0.0068	0.0175
RMS	0.4722	0.4537	0.4138
Total RMS	**0.7746**		

Table 2: Maximum, minimum, average, and RMS of approximation errors using GA (S/A on)

Parameters	X Component	Y Component	Z Component
Max	1.6219	1.7771	1.4959
Min	-1.5481	-2.3182	-1.8779
Average	0.0151	0.0127	0.0219
RMS	0.4301	0.5080	0.3966
Total RMS	**0.7748**		

Table 3: Maximum, minimum, average, and RMS of approximation errors using SA (S/A off)

Parameters	X Component	Y Component	Z Component
Max	2.4154	2.3054	1.9593
Min	-2.2701	-2.2261	-1.7565
Average	-0.0057	0.0033	0.0204
RMS	0.4864	0.4482	0.4247
Total RMS		**0.7860**	

Table 4: Maximum, minimum, average, and RMS of approximation errors using SA (S/A on)

Parameters	X Component	Y Component	Z Component
Max	1.3919	1.3128	2.3319
Min	-1.4551	-2.4524	-4.7701
Average	-0.0006	-0.0075	-0.0215
RMS	0.3989	0.4521	0.4544
Total RMS		**0.7550**	

Table 5: Maximum, minimum, average, and RMS of approximation errors using PSO (S/A off)

Parameters	X Component	Y Component	Z Component
Max	4.1065	1.5887	2.6684
Min	-2.5563	-2.9226	-1.6239
Average	-0.0027	-0.0065	0.0150
RMS	0.4750	0.4522	0.4172
Total RMS		**0.7773**	

Table 6: Maximum, minimum, average, and RMS of approximation errors using PSO (S/A on)

Parameters	X Component	Y Component	Z Component
Max	1.4081	1.9203	1.0321
Min	-1.2258	-1.4931	-1.0205
Average	0.0179	0.0104	0.0137
RMS	0.4140	0.5219	0.3340
Total RMS		**0.7452**	

Tables 1 to Tables 6 demonstrate that the total RMS error is reduced to less than 0.8 m with and without S/A by using the proposed methods.

4. Conclusions

During past several years, accuracy improving or error decreasing in GPS time and position measurement have been greatly considered as the most important topic for researches. EAs are derivative-free stochastic optimization methods based on the features of neural selection and biological evolution. They are less likely to get trapped in local minima and their flexibility facilitates both structure and parameter optimization in complex models. In this paper, it was shown that machine learning techniques such as GA, SA, and PSO could be useful in errors high-precision modeling of single-frequency GPS receivers. Experimental results from an actual data collection showed the effectiveness of the proposed approach for GPS receiver's errors approximation; so that RMS error reduced to less than 0.8 m.

Acknowledgment

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