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Possibility of Dispensing Cycle Slips Correction Process Using Artificial Neural Networks (ANN)

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Abstract— Cycle slips may result in critical errors in the derived positions if it were not detected and treated properly. All previous works in this field concerned with detecting the occurrence of cycle slips, and hence, fixing the new value of the phase ambiguity. Then, the collected data should be re-processed to get the corrected 3-D coordinates. In this paper, a new approach was tried to dispense this traditional scenario. This approach is based on the modeling of the positional errors, resulted by cycle slips, using Artificial Neural Networks (ANN). The main reason behind the choice of ANN is its ability of relating different inputs and outputs without deciding previously the kind of relation (mathematical model) among them. The key for the successful construction of the thought ANN is the determination of the involved parameters that should be used as inputs.

In the first, seven different parameters were examined to check the existence of any dependency between each of them and the resulted positional discrepancies. Such parameters are the number of the slipped cycles, mask angle of the corrupted satellite, number of corrupted satellites, time of data acquisition, baseline length, used session length and the ratio between the uncorrupted data and the whole used session. Results showed that neither the time of data acquisition nor the length of the baseline affects the resulted positional errors, whereas the five remaining parameters exhibited different degrees of correlation with the resulted errors.

Three different Artificial Neural Networks (ANNs) were constructed using Levenberg model, Momentum model and Step model. Such constructed ANNs are capable of modeling the positional errors with the five selected parameters. For any of the constructed ANN there were about 160,000 available different outputs. Such outputs were divided into two groups. The first group (represents 90 % of the available data) was used in establishing the ANN, whereas the remaining 10% (about 16000 outputs) were used to check the reliability of the established ANN. Results showed that both the three different used ANN algorithms lead to almost the same accuracy. Each of them can be used to estimate the positional error, resulted by cycle slips, with an accuracy of few centimeters.

Index Terms— Artificial Neural Network (ANN), cycle slips, positional discrepancies, Levenberg model, Momentum model, Step model, Input/Output.

1 INTRODUCTION

In Global Positioning System (GPS), carrier phase measurements can be used to achieve very precise positioning solutions. Although these measurements are much more precise than pseudorange measurements, they are ambiguous by an integer number of cycles. When these ambiguities are resolved, a sub-centimeter level positioning can be achieved [1]. However, the GPS signal could temporarily be lost because of various disturbing factors such as trees, buildings, bridges…etc. In kinematic applications, vehicle dynamics adds to this problem as well. This signal loss causes a discontinuity of an integer number of cycles in the measured carrier phase, known as cycle slip (figure 1). Consequently, the integer counter is reinitialized, meaning that the integer ambiguities become unknown again. In this event, ambiguities need to be resolved once more to resume the precise positioning process. This is a computation-intensive and time-consuming task. Typically, it takes at least few minutes to resolve the ambiguities [2].

The ambiguity resolution is even more challenging in real time navigation due to the receiver dynamics and time sensitive nature of the kinematic solution. Therefore, it would save effort and time if these cycle slips could be detected and the phase measurements are corrected instead of waiting for ambiguity resolution. This process is known as detection and repairing of cycle slips.

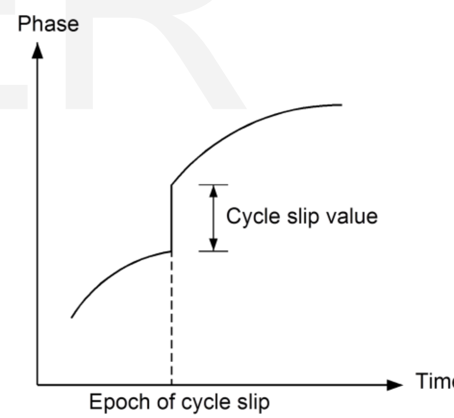

Fig. 1. Concept of cycle slip

Many previous researches were concerned with the process of detecting and repairing of cycle slips [e.g. 2, 3, 4 and 5]. In this context, all previous works worked through two different processes. First, the occurrence of cycle slips is checked (known as detection process), using certain test quantity [e.g. 4 and 6]. If a cycle slip is detected, a second process should be applied to estimate the number of the slipped cycles, which is known as the fixation process. Of course, the quality of the fixation process affects the accuracy of the derived positions very significantly [7].

Recently, detection and repairing of cycle slips can be performed successfully for all types of GPS receivers (single and dual frequency) with a very high reliability level. Very critical cycle slips (which are of a value of only one cycle) can now be detected and fixed in real time using single frequency data [4]. However, after detecting and counting for the number of the slipped cycles, the collected phase data should be corrected (by adding the computed number of the slipped cycles) and the required position should be re-computed using the corrected data. This will, of course, require more computational effort and more time which may be restricted in many cases especially in real time applications.

In this research, a new approach will be followed to avoid the above mentioned complications associated with the correction and re-processing of the collected phase data. Such approach is based on studying all the experienced parameters that may affect the derived position in case of cycle slips occurrence. Then, all these parameters will be modeled together, using Artificial Neural Network (ANN), to get their effect on the 3-D coordinates. Finally, if a cycle slip is detected, the involved parameters will be computed and applied to the adopted ANN to get the influence of the occurred cycle slip on the obtained 3-D coordinates to correct such coordinates. Such new approach is illustrated in figure (2).

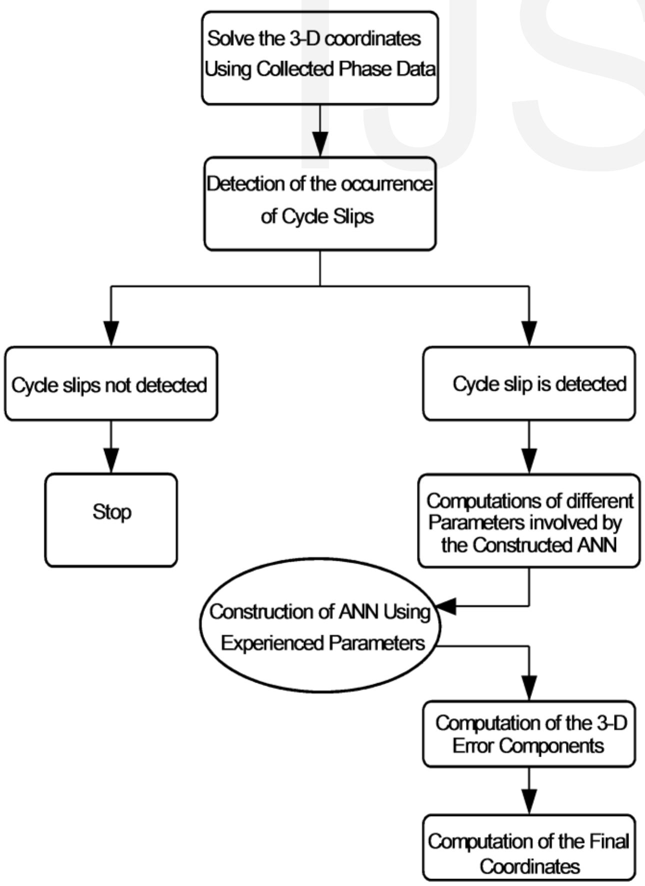

Fig.2. Proposed approach of treating cycle slips using ANN

2 Artificial Neural Networks (ANN)

The main reason behind selecting the Artificial Neural Network (ANN) to model the coordinates discrepancies resulted by cycle slips is its ability to get a solution for complicated issues, for which no mathematical models are available [8]. Furthermore, ANN has the ability of automatic updating of the weights of the involved parameters. This updating of weights is done based on the different inputs that are fed to it. Such inputs are representing the involved parameters that are expected to affect the thought outputs [9]. In our case, many parameters will be examined firstly to examine the existence of any kind of correlation between each parameter and the resulted coordinate discrepancies.

Mathematically, the mathematical basis of the ANN algorithm can be expressed as [10]:

$$O_{n1} = W_{nu} \times I_{u1} \qquad (1)$$

Where:

O	Output vector
W	Weight matrix
I	Input vector
n	Number of outputs
u	Number of inputs

In this research, the vector O will express the 3-D coordinate discrepancies and the vector I will express the involved parameters that are affect the 3-D components of the positional error resulted by cycle slips.

As mentioned before, Artificial Neural Network (ANN) is a useful tool for solving nonlinear problems that involve mapping input data to output data without having any prior knowledge about the mathematical process involved. When input and output information exist, ANN established the inter-related model among them with its internal structure is tuned to mimic the human brain [11]. ANN is composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. ANN can be trained to perform a particular function by adjusting the values of the connections (weights) between elements so that a particular input leads to a specific target output. The ANN is adjusted, based on a comparison of the output and the target, until the network output matches the target. Given an unknown model or an unknown functional relationship with its inputs and observed outputs, ANN learns to fit the unknown model or functional relationship by comparing the output from a neural network with the observed outputs. It then adjusts the value of its internal weighted links iteratively until the error between the outputs and observed outputs meet a predefined accuracy [12].

In the algorithm of ANN, many different models are used to construct and update the weight matrix (W). Among these models, the most famous three models are Levenberg model, Momentum model and Step model [13]. Such three models will be tried in this work as will be seen later.

3 Testing Different Parameters Affecting Position in Case of Cycle Slips Occurrence

Before going through the thought ANN, it is of great importance to experience and decide firstly its involved parameters (Inputs). In our case, such parameters should be these factors which are expected to have some kind of correlation (dependency) with the resulted coordinate discrepancies in case of cycle slip occurrence. To accomplish this task, GPS real data are used. Such data consists of 24 hours of observations, collected at eleven stations, surrounding Great Cairo City, in a single frequency format. Such data are checked against the existence of any cycle slips. Here, seven different parameters will be examined to check the existence of any type of correlation between each of them and the resulted 3-D coordinate discrepancies. Each parameter will be varied, separately, using some different trials with fixing other parameters and so on. Such examined parameters are summarized in table (1).

Table 1
Examined Input Parameters for the Adopted ANN

No.	Examined Parameter	Symbol	No. of Trials
1	Number of the slipped cycles	N_{SC}	9
2	Mask angle of the corrupted satellite.	MA	7
3	Number of corrupted satellites	N_{sat}	7
4	Time of cycle slip	T_{CS}	24
5	Length of baseline	L	10
6	Length of session	SL	11
7	Percentage of clear time through the session*	$\%_{clear}$	11

* $\%_{clear}$ indicates the ratio between the non-infected session to the whole session

In the following, the dependency of the components of the positional discrepancy on each of the seven parameters will be examined. To verify such dependency, only one parameter will be considered in each test with fixing the remaining six parameters. This will be done in order to select the input parameters that will be involved by the thought ANN. In each test, a certain baseline is processed twice. Firstly, using the original data (which is free of cycle slips), then, a simulated cycle slip will be introduced and the baseline is re-processed to get the thought coordinate discrepancies. Only one central point is selected as a reference point in each test.

3.1 Examination of the Number of the Slipped Cycles (N_{SC}):

Here, one baseline (with a length of 17.5km) is considered for a session of only 30 minutes. Different simulated cycle slips are introduced at the rover station (for the same satellite) with values of 1, 2, 5, 10, 25, 50, 100, 500 and 1000 cycles. This will result in different 9 trials (represented by the last column in table 1). Results are depicted in figure (3).

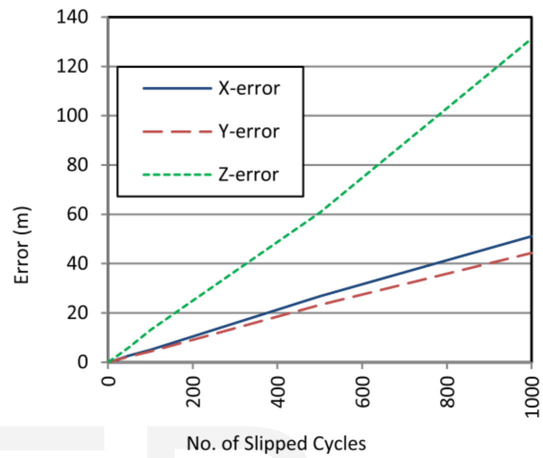

Fig. 3. Coordinate discrepancies using different numbers of slipped cycles

3.2 Examination of the Mask Angle of the Corrupted Satellite (MA):

For the same processed baseline in test (1) and the same session length, cycle slips of 10 cycles are introduced separately for each one of the seven tracked satellites. This resulted in 7 different trials. The obtained coordinate discrepancies are drafted in figure (4).

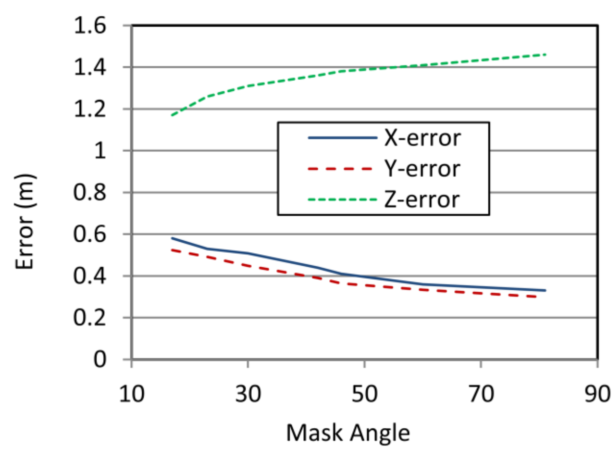

Fig. 4. Coordinate discrepancies using different mask angles

3.3 Examination of the Number of Corrupted Satellites (N_{sat}):

For the same processed base line in the previous test, seven different trials are performed by applying a slip of 10 cycles to the 1st satellite, then to the 1st and 2nd satellites and so on till corrupting all the involved seven satellites. Then, the computed coordinate discrepancies are drafted against the number of the corrupted satellites as shown in figure (5).

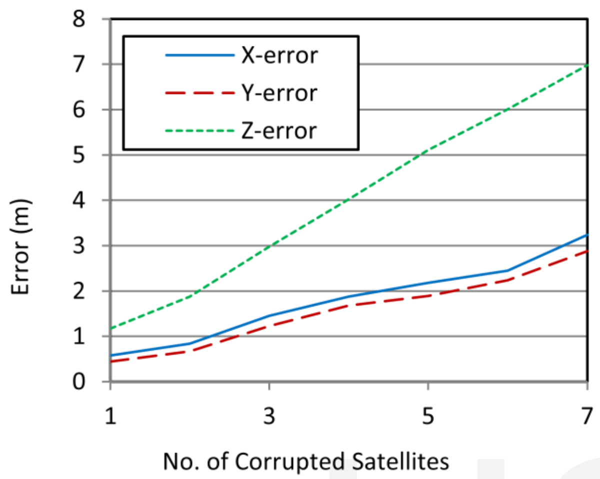

Fig. 5. Coordinate discrepancies using different number of corrupted satellites

3.4 Examination of the Cycle Slip Occurrence Time (T_{CS}):

For the same baseline, only one satellite is corrupted by 10 cycles using a session of 30 minutes. However, this process was performed every one hour during one complete day. This resulted in 24 trials covering the whole day. In the same previous manner, the 3-D positional discrepancies are computed for each trial and drafted against time in figure (6).

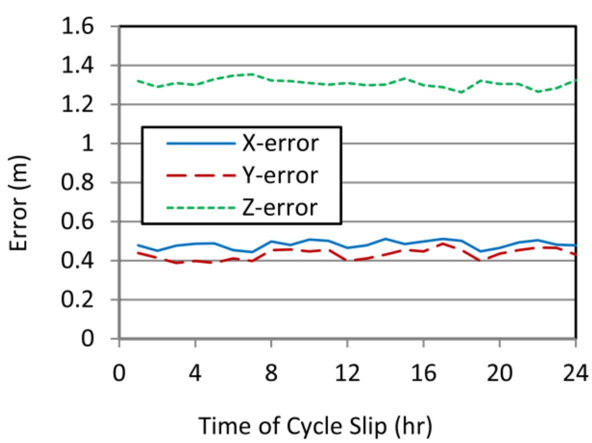

Fig. 6. Coordinate discrepancies throughout a whole day

3.5 Examination of the Baseline Length (L):

As mentioned before, the used GPS data consists of 11 stations. So, with fixing the pre-selected reference station, there will be 10 different baselines with different lengths ranging from 17.5 km to 96.9 km. For each baseline, one satellite is slipped with 10 cycles using all the other fixed parameters. Coordinate discrepancies are computed at the rover station for each one of the ten lines. The resulted discrepancies are drafted against length in figure (7).

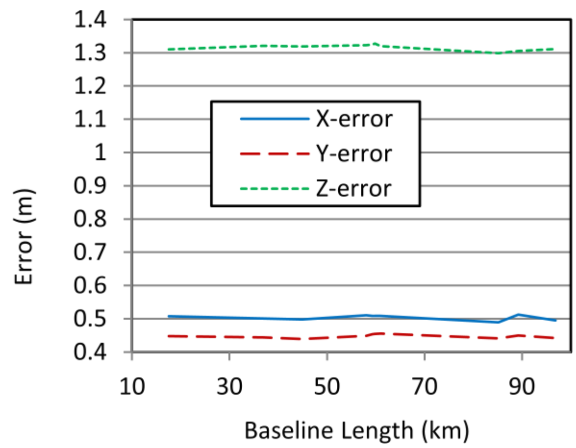

Fig. 7. Coordinate discrepancies for different baseline lengths

3.6 Examination of the Session Length (SL):

For the same baseline, a cycle slip of 10 cycles is introduced at the rover station for the same satellite. Here, the duration of the considered session is changed. The tested session lengths start from 30 minutes up to 3 hours, with increasing the session by 15 minutes each time (i.e. sessions of 30, 45, 60…..180 minutes are considered). So, 11 different session durations are tried in this test. Figure (8) gives the behavior of the resulted discrepancies.

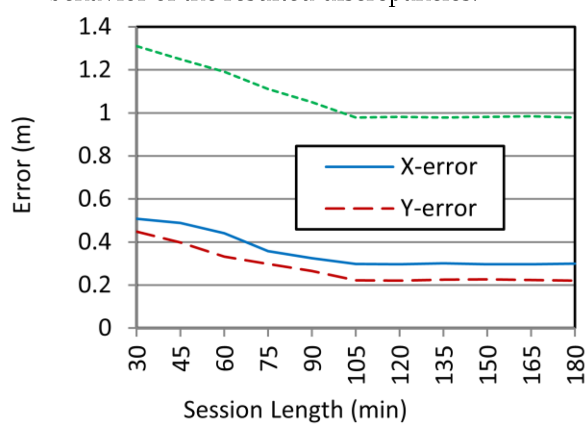

Fig. 8. Coordinate discrepancies for different session durations

3.7 Examination of the Percentage of Session Clear Time ($\%_{clear}$):

In this test, only one baseline is considered using a session of 30 minutes. Also, one satellite is slipped by 10 cycles. Here, the epoch of the introduced cycle slip is changed many times through the same session. Firstly, the cycle slip was introduced at the start of the used 30 minutes. So, all the 30 minutes are infected, which corresponds to a percentage of clear time of zero. In the second trial, the cycle slip was introduced after 3 minutes. This resulted in a percentage of clear time 10% (0.1). This process was repeated every 3 minutes (11 trials) till reaching a percentage of clear time 100%. Behavior of the resulted discrepancies with the percentage of clear time is given in figure (9).

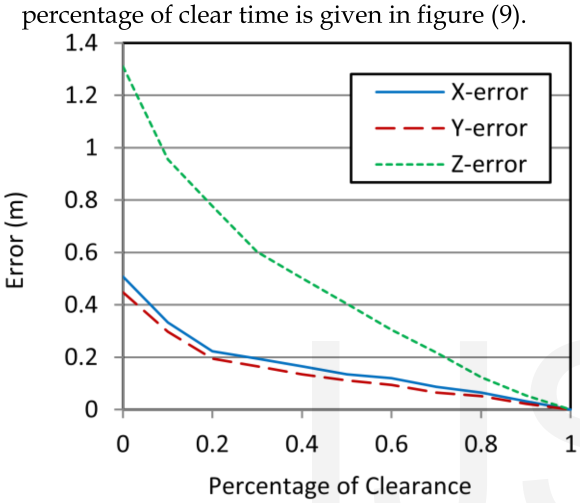

Fig. 9. Coordinate discrepancies for different clear session percentages

4 Selection of the Involved Parameters for the Used ANN

Based on the above performed seven tests, and referring to figures (3 to 9) it can be seen that, some of the tested parameters have some kind of correlation with the resulted coordinate discrepancies. Such correlation can be observed clearly in figures (3, 4, 5, 8 and 9), which correspond to parameters number (1, 2, 3, 6 and 7) in table (1). On the other hand, parameters number (4 and 5) did not exhibit any correlation with the resulted positional discrepancies. This can be obviously seen by the random fluctuations in figures (6 and 7). So, parameters number 4 and 5 will be filtered out from the input data that will be fed to the thought ANN. So, only five parameters will be considered. Such parameters, as well as the type of their correlation with each component of the resulted positional discrepancies are given in table (2). In this table, positive correlation (denoted by +) means that the considered parameter and the error component are directly proportional, and vice versa for negative correlation (denoted by -)

Table (2)
Selected Input Parameters of the Adopted ANN

Selected Input Parameter	No. of Trials	Exhibited Correlation		
		X	Y	Z
NSC	9	+	+	+
MA	7	-	-	+
Nsat	7	+	+	+
SL	11	-	-	-
%clear	11	-	-	-

5 Establishment of the Used Artificial Neural Network (ANN)

After deciding the five parameters that will be involved by the thought ANN, a data base should be constructed and fed to such ANN. To achieve this goal, different combinations among all the selected parameters were done. Referring to the number of trials (in table 2), this will result in a total number of trials equals the product of number of performed trials of each selected parameter. As a result, 53361 different trials are done. Recall that each trial has three different outputs (for the three coordinate components), this will lead to 160083 different outputs.

To judge the quality of the established ANN, the available 160083 outputs are divided into two groups. The first group, denoted as used output, will be assigned as 90% of the available outputs (particularly 144075 outputs), while the remaining 10% (which will be 16008 outputs) will be used as check points. Such check outputs were selected randomly to cover different values of all involved parameters (inputs).

Concerning the inputs of the used ANN, it will be the different values of the selected five parameters. So, its number will be the same as of the conducted trials. As a result, there will be 53361 different inputs. In this paper, three different algorithms of ANN are used which are Levenberg model, Momentum model and Step model [13]. All computations were performed using NeuroSolutions Software Package. In this software, the required model is selected firstly. Then, the known inputs and outputs are entered to the software. At this stage, the software processes these data and constructs the required weight matrix.

6 Validation of the Three Constructed (ANNs)

After constructing the three ANNs (using the three mentioned models), it is of great importance to judge their ability in modeling the positional errors resulted by cycle slips in different field conditions. To achieve this goal, each of the adopted three ANNs is applied, using the resulted weight matrix, at the check points. This was done by applying such ANN, using its own generated weight matrix and the different values of the selected five parameters, to get the output vector. Then, values contained by this vector are compared, absolutely, with the check outputs as:

$$\delta_X = \left|(X - error)_{chk} - (X - error)_{out}\right| \quad (2)$$

$$\delta_Y = \left|(Y - error)_{chk} - (Y - error)_{out}\right| \quad (3)$$

$$\delta_Z = \left|(Z - error)_{chk} - (Z - error)_{out}\right| \quad (4)$$

Where:

δX, δY and δZ	ANN estimation errors
$(X, Y \text{ and } Z\text{-error})_{chk}$	Known discrepancies at the check points
$(X, Y \text{ and } Z\text{-error})_{out}$	Estimated discrepancies at the check points using ANN

Equations (2, 3 and 4) are applied for each of the three used ANN models. Statistical information of the resulted estimation errors are summarized in table (3).

Table (3)
Statistics of the Resulted ANN Estimation Errors

Estimation Errors (cm)		Used ANN Model		
		Levenberg	Momentum	Step
X	Max	4.1	4.3	3.9
	Min	0.5	0.2	0.7
	Mean	2.1	1.9	2.1
	RMS	0.92	0.89	1.01
Y	Max	3.9	3.7	3.9
	Min	0.2	0.0	0.1
	Mean	1.7	1.8	1.6
	RMS	0.64	0.88	0.81
Z	Max	5.3	5.3	5.2
	Min	0.0	0.1	0.3
	Mean	2.5	2.6	2.4
	RMS	0.89	0.88	0.93

Based on the obtained estimation errors in table (3) it is very evident that each of the three established ANNs is capable of estimating positional errors, resulted by cycle slips, with a high degree of reliability. This can be verified by the obtained relatively small estimation errors. Also, no model among the three tested models was found to be superior over the others. This can be seen by the clear proximity between the resulted estimation errors for the three adopted ANN models.

7 Conclusions

Based on the performed tests and the obtained results, many important conclusions can be extracted concerning the behavior of the positional errors caused by cycle slips and the modeling of such errors using Artificial Neural Networks (ANN). Such conclusions can be enumerated as:

- If any cycle slip is detected in any GPS phase data, its influence on the derived positions should be considered. Otherwise, the resulted coordinates will be certainly biased.
- Coordinate discrepancies resulted by cycle slips are affected by five parameters. Such parameters are the number of the slipped cycles, mask angle of the corrupted satellite, number of corrupted satellites, used session length and the percentage of clear data with respect to the whole session.
- Coordinate discrepancies resulted by cycle slips are independent on both the time of data acquisition process and the length of the considered baseline.
- Although the resulted positional discrepancies exhibited a clear correlation with the above mentioned five parameters, it can not be modeled with such parameters using any pre-defined mathematical model. This is due to the variable exhibited trend of these discrepancies with each parameter. This makes the Artificial Neural Network (ANN) is the best solution for such modeling.
- Artificial Neural Networks (ANN) can be used to model the positional discrepancies, resulted by cycle slips, with the selected five parameters due to its ability in updating itself based on the given input/output data.
- The used three ANN models, which are Levenberg, Momentum and Step models, resulted in positional discrepancies with nearly the same degree of reliability.
- ANN can be used to model the positional errors, resulted by cycle slips, with a relatively high accuracy. In the worst case, an accuracy of few centimeters can be reached. This accuracy is acceptable in many GPS surveying operations especially kinematic applications which suffer from many sources of cycle slips.
- Treatment of the effect of the cycle slips on 3-D coordinates can be dispensed by using ANN in modeling such effect.

References

[1] B. Hofmann-Wellenhof, H. Lichtenegger and J. Collins , "Global Positioning System- Theory and Practice". 5th Revised edition, Springer, Verlag, New York, USA, 2001.

[2] M. Karaim, T. Karamat, A. Noureldin and A. El-Shafie, " GPS Cycle Slip Detection and Correction at Measurement Level". British Journal of Applied Science and Technology, Vol. 4, No. 29, pp 4239-4251, 2014.

[3] M. El-Tokhey, T. Fath-Allah, A. Ragheb and M. Moursy, "GPS cycle slips detection and repair through various signal combinations". International Journal of Modern Engineering Research (IJMER), Vol. 4, Iss.11, No. 2, Nov. 2014.

[4] T. Fath-Allah, "A new approach for cycle slip repairing using GPS single frequency data," World Applied Sciences Journal, vol. 3, no. 8, pp. 315–325, 2010.

[5] M. Moursy, "Different Techniques for Detecting and Repairing GPS Cycle Slips". M.Sc. Thesis, Public Works Department, Faculty of Engineering, Ain Shams University, Egypt, 2015.

[6] S. Banville and R. Langley, "Cycle-Slip Correction for Single-Frequency PPP". 25th International Technical Meeting of the Satellite Division of the Institute Of Navigation (ION), Nashville TN, September 17-21, 2012.

[7] G. Seeber "Satellite Geodesy: foundations, methods, and applications". Walter de Gruyter, Berlin, New York, 1993.

[8] S. Tafazoli and M. Mosavi "Performance Improvement of GPS GDOP Approximation Using Recurrent Wavelet Neural Network". Journal of Geographic Information System, Vol. 3, pp 318-322, 2011.

[9] W. MAO "GPS Interference Mitigation Using Derivative-free Kalman Filter-based RNN". Journal of RADIO ENGINEERING, VOL. 25, NO. 3, SEPTEMBER 2016.

[11] S. Kumar1, R. Sharma and E. Vans "Localization for Wireless Sensor Networks: A Neural Network Approach". International Journal of Computer Networks & Communications (IJCNC) Vol.8, No.1, 2016.

[12] Y. Xiao-kui and Y. Jian-ping "Neural Network-based GPS/INS Integrated System for Spacecraft Attitude Determination". Chinese Journal of Aeronautics, Vol.19 No. 3, 2006.

[12] N. El-Sheimy and W. Abdel-Hamid "An adaptive neuro-fuzzy model to bridge GPS outages in MEMS-INS/GPS land vehicle navigation". GNSS , ION, Long Beach, California, USA, 2004.

[13] J. Song, G. Xue and Y. Kang "A Novel Method for Optimum Global Positioning System Satellite Selection Based on a Modified Genetic Algorithm". Journal of PLOS ONE, DOI:10.1371, journal.pone.0150005, March 2016.