International Journal of Physical Sciences Vol. 5(5), pp. 401-407, May 2010
Available online at http://www.academicjournals.org/IJPS
ISSN 1992 - 1950 © 2010 Academic Journals

Full Length Research Paper

Performance of ANN in determination of unstable points in leveling networks

Cahit Tagi Celik

Department of Geodesy and Photogrammetry, Faculty of Engineering and Architecture, Nigde University, Nigde, Turkey.
E-mail: ctcelik@gmail.com. Tel: +903882252258. Fax: +903882250112.

Accepted 2 April, 2010

Deformation analysis is important for a man-made structure or a natural phenomenon like crustal movement, vertical land movements, subsidence determination, etc. Deformation analysis generally depends upon determination of stable and unstable points relative to a reference network assumed to be located outside the movement area. However, a reference network itself needs to be assured free from movements. This can be achieved conventionally by using a single point movement test. The accuracy of the results depends on the method used. This study recommends a new method of detecting stable and unstable points in a reference network designed for vertical movements. The method is based on an artificial neural network (ANN) which also enables one to measure the validity of performance of conventional method aiming at the determination of unstable points in a reference network. The presented results showed that the ANN is capable of determining unstable and stable points in a one-dimensional surveying network.

Key words: Deformation monitoring, deformation analysis, reference network, leveling network, artificial neural network, vertical movements.

INTRODUCTION

Geodesy involves repeated measurements to determine positions and rate of change in positions in the studies for monitoring deformations. Since there are no exact values of a particular distance, angels, etc., measurements are subject to errors considered sum of the three types, blunders, systematic and random errors (Caspary, 1987). While blunders or mistakes and systematic errors can be eliminated using careful observation and determining the systematic errors, random errors cannot be eliminated, but governed by statistics and probability. The statistic is a strong means if the measurements are made infinitely. However, since no measurements can be done infinitely, they can be done finitely, that is, samples from the population. In this case, some measurements, particularly in tails of normal distribution may be aberrant from the bundle and this affects the estimation of the most probable value (Maronna et al., 2006). Using these biased estimate leads to misinterpretations, particularly in deformation monitoring. Therefore, before the estimates obtained, any aberrant or outlying measurement has to be eliminated (Hekimoglu, 1999). There are a number of methods used for detection and elimination of outlying observation(s). They may be grouped into two categories; conventional methods and robust methods. While conventional methods suffer from an effected estimate if there is any outlying observation in the set, robust methods suffer from error production when the set is clean from outlying observations (Hekimoglu, 2006). Some other methods are needed for not suffering from both cases.

Deformation network analysis involves at least two epochs of estimated parameters that are free from errors as well as outliers (Caspary, 1987). There are a number of conventional deformation analysis methods described by Chrzanowski and Chen (1986). They may be put into two groups, relative network analysis and absolute network analysis (Kennie and Petrie, 1993). In absolute network analysis, which is generally used for dam deformation networks local subsidence monitoring network, etc., there are two groups of points established,

Abbreviation: ANN, artificial neural network.

object points that are subject to movements and reference points relative to which object points movements are determined. Although, the reference points are established to places where movements are not expected, they are themselves subject to movements. Before performing analysis on object points, stability of the reference points has to be assured. Conventional methods of determining the stability of the reference points varies, but most congruency tests methods are common means to be performed (Hekimoglu et al., 2002). If the congruency test fails, further investigations need to be carried out in order to determine which point(s) is moved. In a relative network, the entire object and reference points considered as reference network. Then after detecting unstable points, the remaining points constitute a reference network.

However, a question in one's mind remains unanswered. How capable is the testing procedure? Put it another way, does the testing procedure accurately find moved points in the reference network? The author recommends a new procedure to determine stable and unstable points of a reference network in a one-dimensional deformation-monitoring network using artificial neural network (ANN).

ANN has many applications including function fitting, pattern recognition, identification, classification, speech, vision and control systems as well as solving problems that are difficult for conventional computers or human being. Some applications of ANN concerns geodetic problems including deformation modeling (Mima, 2002; Akyilmaz et al., 2004).

If one is capable of having information about moved points before performing point movement analysis, then detected movements by conventional methods can be assessed whether their analysis is accurate or not. This is impossible in practice, but one can perform a simulation containing movement scenarios.

In this study, a number of scenarios were simulated imposing to the monitoring network (leveling network) having one, two, three and four simultaneous point movements. Then these are used as inputs for an artificial neural network designed for detection of point movements in a one-dimensional network. The output of the ANN is then compared with the results obtained from conventional congruency test and point movement test.

THE LEAST SQUARE ADJUSTMENT

Least square adjustment is a well-known technique to estimate parameters in question with over determined systems (Cross, 1994). Since there are more observations than exactly needed, such systems generally have finite number of solutions. One can constrain such a system to have a minimum of sum of squared errors. Following describes observation equation model.

$$\sum v^2 = \sum (Ax-\ell)^2 = \min, \qquad \Sigma = \sigma_0^2 P^{-1} = \sigma_0^2 Q_\ell \quad (1)$$

where, l is a vector of observations, *v* is a vector of errors, *A* is a deterministic coefficient matrix consisting of values calculated from derivatives using approximate values of parameters in question and *x* is a vector of unknowns. P is the weight matrix of observations and its inverse (P^{-1}) multiplied by a priori variance (σ_0^2= unite variance of population) is the covariance matrix (Σ) of observations. Here Q_l is the cofactor matrix of observation that is an alternative way of representing P^{-1}. Solution to the above criteria leads to a system of equation to be solved for is

$$Ax=b+v \quad (2)$$

Where b is a vector-calculated observations-observations. The solution to Eq 2 is given by

$$\hat{x} = \left(A^T PA\right)^{-1} A^T Pb \quad (3)$$

It is noted here that $A^T PA$ has an invertible matrix. However, in surveying problems it is a rank deficient matrix. Rank deficiency is one for one-dimensional network as is the case in this study since it is a leveling network. One can solve Eq 3 by introducing the height of one station fixed. Then a variance-covariance matrix of parameters is given by

$$Q_x = \sigma_0^2 (A^T PA)^{-1} \quad (4)$$

Where Q_x is the variance-covariance matrix of estimated parameters. It is important that observation contains no aberrant observation.

OUTLIER TEST

In deformation monitoring networks, undetected outliers hiding in the observations are interpreted as deformation leading to a wrong decision. Therefore, any outlying observations are sought for and removed from the observation bundle before estimating parameters. There are several methods for detecting outliers including m-estimators (Hekimoğlu, 1999) and classical methods (Caspary, 1987). Before carrying out outlier test, any systematic error and blunders are determined and removed from the observations. Here a simple procedure for outlier detection is given. One can apply the free-adjustment technique (minimally constrained network) in outlier search. For one-dimensional network, free-adjustment is performed by holding only one station fixed in the leveling network (that is given above). From the results of above adjustment, one can constitute a hypothesis as

Ho: "The model is true and complete"

$$T = \frac{v^T P v}{\sigma_o^2} \sim \chi^2_{(0.025,f)} \quad (5)$$

Where $\chi^2_{(0.025,f)}$ is Chi-square percentile with significance level 0.025 and f is degrees of freedom.

$$T < \chi^2_{(0.025,f)} \quad (6)$$

If the above condition is true, the model is true and complete. If equation 6 is false, then, at least, one observation is aberrant in the observations. The next job is to find out the observation that deviates from the rest. One can compute the ratio of residuals of observations to its standard errors as follows (to find standardized residual);
Ratio of residual is

$$\bar{v}_i = \frac{v_i}{\sqrt{q_{ii}}} \quad (7)$$

Where q_{ii} is the i^{th} diagonal element of the matrix C_v ($= \sigma_0^2 P^{-1} - AQ_x A^T$) and the test value t is given by

$$t_i = \frac{v_i}{S_o \sqrt{q_{ii}}} = \frac{\bar{v}_i}{S_o} \quad (8)$$

Since σ_0^2 represent the population unite variance and it is usually not known, it is assumed to take a sample unite variance s_0^2 instead. Here t_i is compared to critical value (3.29) that is the percentile corresponds to 99.9 a level of confidence in the t-student distribution.

$$\bar{v}_i > S_o.3{,}29 \quad (9)$$

If any residual meets, the condition above is considered as an outlier. After removing the outlying observations, the network is readjusted and the entire test repeated until no outlier is found.

CONGRUENCY TEST

Deformation networks have to be observed in some certain periods so that any deformation occurred between two periods is possible to be determined. In surveying problems, deformations are slow; therefore, this period requires longer time. Typically, crustal movements require six months or one year to produce a detectable amount of movements considering the observation accuracy due to the surveying equipment used.

Deformation analysis can be considered in one of the two methods; two-epoch analysis and multi-epoch analysis. Here a two-epoch analysis is given since multi-epoch analysis can also be possible considering the first epoch and next epoch.

Assume there are two epochs of observations. After adjusting each epoch of measurements and then performing outlier detection, two sets of parameters for each epoch and two covariance matrices are available. The problem is to find out whether the network between two observation epochs has changes its shape or not. A common method of testing this is to apply the congruency test.

Assume the followings are the results from two epochs of observations,

$$\hat{x}_1, \hat{x}_2, P_1, P_2, C_{\hat{x}_1}, C_{\hat{x}_2}, \sigma_{o1}^2, \sigma_{o2}^2 \quad (10)$$

Where $\hat{x}_1, P_1, C_{\hat{x}_1}, \sigma_{o1}^2$ represent estimated parameters, observation weights, variance-covariance matrix of estimated parameters and a posteriori unite variance for epoch 1 and $\hat{x}_2, P_2, C_{\hat{x}_2}, \sigma_{o2}^2$ for epoch 2.
A hypothesis Ho is as follows,

$$H_0 = E\{\hat{d}\} = 0 \quad (11)$$

Where $E\{.\}$ stands for expectation.

This implies that "the network is congruent between the two epochs".

Where,

$$\hat{d} = \hat{x}_2 - \hat{x}_1 \quad (12)$$

$$C\hat{d} = C_{\hat{x}_1} + C_{\hat{x}_2} \quad (13)$$

$\hat{x}_1, \hat{x}_2$ and $C_{\hat{x}_1}, C_{\hat{x}_2}$ are the estimated parameters and variance-covariance matrices for epoch t_1 and t_2 respectively.

$$C\hat{d} = C_{\hat{x}_1} + C_{\hat{x}_2}, \quad \Phi = \hat{d}^T C_{\hat{d}}^{-1} \hat{d} \quad (14)$$

$$T = \frac{\Phi}{h\sigma_0^2} \sim F_{h,f,\alpha}$$

$$\sigma_0^2 = \frac{f_1 \sigma_{01}^2 + f_2 \sigma_{02}^2}{f} \quad (15)$$

Where $F_{h,f,\alpha}$ is percentile value of Fisher distribution, h stands for rank of C_d and f is described as,

$f = f_1+f_2$
f_1 = degrees of freedom for epoch one
f_2 = degrees of freedom for epoch two
α = level of significance

If T < F then, the network is congruent between the two epochs. In the opposite case, at least one of the points in the network moved and further investigation of which point making the largest contribution to Φ, is sought. One easy way of performing that is to partition the displacement vector d into d_s stable points and d_i unstable point as,

$$\hat{d} = \begin{bmatrix} \hat{d}_s \\ \hat{d}_i \end{bmatrix}, \quad and \quad C_{\hat{d}}^{-1} = \begin{bmatrix} W_s & W_{si} \\ W_{is} & W_i \end{bmatrix} \tag{16}$$

$$\Phi_i = \frac{D_i^T C_D^{-1} D_i}{h\sigma_0^2} \tag{17}$$

Where,

$$D_i = W_i^{-1} W_{si} \hat{d}_s + \hat{d}_i \tag{18}$$

Having determined which point making the largest contribution to Φ, then the significance of this can be tested as:

$$T = \frac{\hat{d}_i^T C_{\hat{d}_i}^{-1} \hat{d}_i}{\hat{\sigma}_o^2} \sim 2F_{(2,r,\alpha)} \tag{19}$$

ARTIFICIAL NEURAL NETWORK

Artificial neural networks (ANN) consist of simple elements operating in parallel. These elements are inspired by biological nervous systems. A neural network function is largely determined by the connections between these elements. An ANN can be trained to perform a particular function by adjusting values of connections (weights) between elements. An ANN can learn by one of two methods; supervised learning, unsupervised learning (Hassoun, 1995).

A typically supervised learning method involves a comparison of network outputs led by a particular input to a specified target until the output is consistent with the target.

Artificial neural networks find a wide range of applications, including function fitting, pattern recognition and identification, classification, speech, vision and control systems as well as solving problems that are difficult for conventional computers or human being. Some applications of ANN concerns geodetic problems include deformation modeling (Mima, 2002; Akyilmaz et al., 2004).

The reader is referred for the full description of ANN and training strategies to Matlab Help (Demuth and Beale, 1998).

A feed forward back-propagation network is one type of various neural networks.

FEED-FORWARD BACK PROPAGATION

Back propagation is a method of learning rule to multiple-layer networks and nonlinear differentiable transfer functions. The network is trained by using input vectors and the corresponding target vectors until it can approximate a function, associate input vectors with specific output vectors, or classify input vectors in an appropriate way as defined by the operator. The network permits the use of bias, a sigmoid layer and a linear output layer being capable of approximating any function with a finite number of discontinuities.

A gradient descent algorithm. The Widrow-Hoff learning rule is used in a standard back propagation referring to the way the gradient is computed for nonlinear multilayer networks where the network weights are moved along the negative of the gradient of the performance function. Depending on the standard optimization technique, there are a number of variations on the basic algorithm, which will not be given here. The reader needs further information on this is referred to Matlab neural network tool box help documents (Demuth and Beale, 1998).

The back propagation network that is properly trained, tents to provide a reasonable answer when it is presented with unprecedented inputs. The output of the network is similar to the correct output for input vectors used in training.

In feed forward back propagation network, a number of things to be determined can lead to different solutions. These things are the number of hidden layers and the neuron numbers in it as well as the transfer functions to be used. There is no specific method for this. This can be determined in an arbitrary way (or by experience) by the operator. The transfer functions for back propagation are limited to 'logsig' (log- sigmoid), 'tansig' (hyperbolic tangent sigmoid) and 'purelin' (linear) functions.

SIMULATION STUDY

Leveling network

A leveling reference network with five stations is considered in this study. Figure 1 shows the created network and the Table 1 depicts assumed heights. Deformation can only be determined if two or more epochs of observation are available. In a real observation campaign, measurements are not exact and contain errors due to

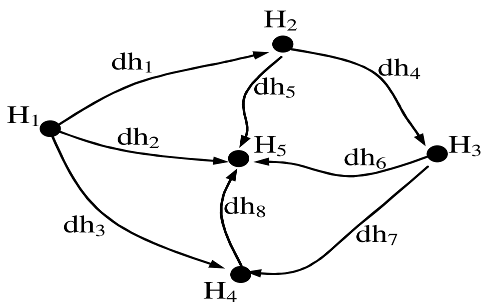

Figure 1. Designed leveling network for simulation.

Table 1. Heights and height differences for leveling network.

Heights (m)		Height differences (m)	
H_1	100.0000	dh_1	0.0204
H_2	100.0201	dh_2	0.6650
H_3	101.0045	dh_3	1.5537
H_4	101.5543	dh_4	0.9840
H_5	100.6647	dh_5	0.6453
		dh_6	0.5498
		dh_7	-0.3400
		dh_8	-0.8902

systematic and random errors assuming that no blunders occurred. After determining and removing the systematic errors, the measurements contain only random errors (assumed to be random). It is important here to note that remaining errors, after elimination of systematic errors, are randomly distributed and reside within the 95% of normal probability distribution. This paper concerns only outlier-free data further treatment will not be given here. Simulated observations were obtained using,

$$l = AH + randn * 0.001 \tag{20}$$

Where A is a deterministic matrix that is known from the geometry of the leveling network and H is a vector of heights given in Table 1. To make the height differences like real, random noise are added to height differences using ‘randn’ function in Matlab. The equation 20 produced stable height differences implying that no point within the network is moved. Later, movements were also imposed to the leveling network leading to inputs and targets to be used in training the ANN.

Preparation of inputs to artificial neural network

Inputs prepared for the ANN can be described in two steps. The first step involves clean data, which are height differences estimated from the least square adjustment along with congruency test applied to simulated height differences with added noises using a random number generator having 1 mm standard deviations. The second step involves deformed data, which are again estimated height differences from simulated data. At this point, a congruency test is also applied to make sure the data possesses point movements. The movements are imposed to posses all possible scenarios. The scenarios applied are as fallows:

First, only one station assumed to move, for example, H_2. Therefore, H_2 was increased and decreased by the amount starting from 1 to 5 mm with added random noise having 1 mm standard deviation. Then this scenario was applied to H_3, H_4 and H_5. Because H_1 kept fixed for all epochs in the least square adjustment, it is intended to have no movements.

Second, two simultaneous point’s movements were imposed to the leveling network. The same simulation was applied as above. The point’s pairs possessing movements were H_2-H_3, H_2-H_4, H_2-H_5, H_3-H_4, H_3-H_5 and H_4-H_5. Then triple points were introduced to the leveling network. These were all combined into an input file to train the designed ANN. At the same time, target file is created. The target file consists of four elements. Each indicates whether a point(s) possess movements, a '0' for no movements and a '1' for a movement. For example, if H_2, H_4 posses movements the target file is a vector as (1, 0, 1, 0). If there is no movement at that epoch, then the target file is a zero vector as (0, 0, 0, 0). By carrying out this procedure all possible movements considered and taken into account.

RESULTS AND DISCUSSION

An artificial neural network has been designed to detect which reference point/points moved. The designed neural network was an artificial feed forward back-propagation network with three hidden layers each having 20, 20 and 10 neurons respectively and finally an output layer with four neurons (Figure 2). This figure shows the designed ANN architecture having the hidden layers and the output layer. It is noted here that several ANN architecture was tried and finally above-mentioned network gave ‘best’ results.

The ANN network was trained using all possible deformation scenarios described above due to first station kept fixed in the least square adjustment process and therefore, no movements expected in the fixed station. Therefore, the station one was not included in the results presented. ANN performance is shown in Figure 3.

Table 2 has three blocks consisting of four columns each. The first block represents the ANN results, which is exactly the case imposed to be in the training process. The second block represents the results of conventional method and finally third block is the difference of the first two. As mentioned above each block has four columns, now each column represents detected movement for the point named at the title of each column. These rows are height differences calculated as the second epoch minus the first epoch. Each row represents a different scenario such as in the first row and in the second epoch, H_2 has increased 1 mm and in the second row again, in the third epoch, H_2 increased 2 mm and so on., up to 5 mm while other points in the leveling network kept unchanged relative to the first row. Here H_2 alterations are only four rows due to second row proved to be congruent in the training stage while H_3, H_4 and H_5 alterations are five rows. Therefore, in these column 1’s represent significant movement and 0’s represents no movement of the point at the title of each column. Here in the first row, to make it clear, dh_2 moved by an amount of 1 mm and no movement imposed for other

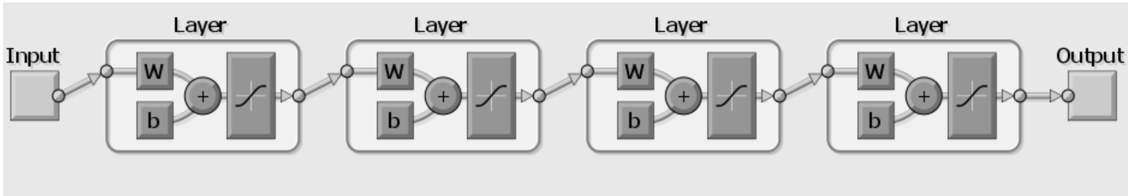

Figure 2. Designed artificial neural network.

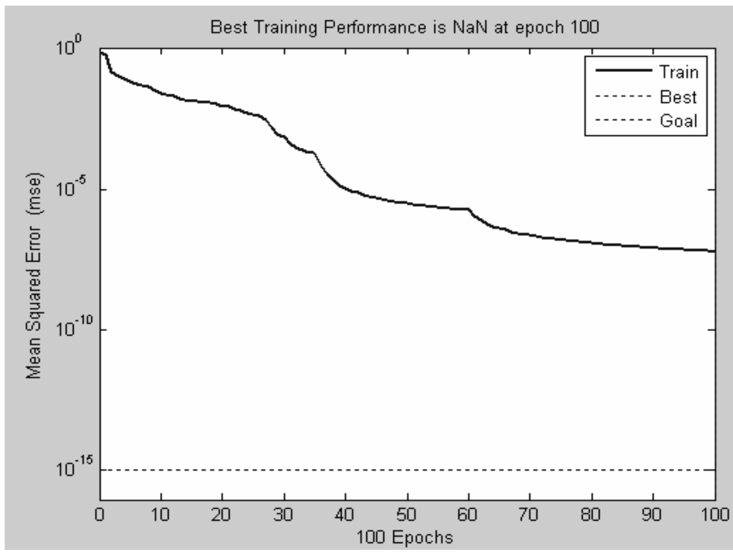

Figure 3. Training performance of artificial neural network.

points (dh_3, dh_4 and dh_5) that correspond to (1, 0, 0, 0). In this table, it is noted here that only one point movement is considered for each epoch.

In Table 2, ANN results are the same as the scenario imposed while the results from conventional method have some errors. In the first and the second rows, conventional method produced false movements at station 5 while imposed movements are on the station 2. However, conventional method and the ANN produced the same results for third and fourth row. This may be explained as conventional method capability of finding moved point is inadequate for small movements like 1 - 2 mm. Since all the possible scenarios were considered, the movements from the fifth to ninth rows were imposed on the station 3. The results from the ANN and the conventional method were incompatible. While the ANN produced the true results, the conventional method gave false results pointing the movements on the station 2 again. This and the other results from the tenth to nineteenth rows are not compatible either. This shows that the conventional method is not fully capable of identifying the moved points accurately. The author of this article thinks that the random errors added to the first epoch of measurements in the simulation stage along with the imposed movements (to produce the second, the third epochs and so on.,) make it difficult for the conventional method to identify the moved points.

Table 3 shows two or more points movements in one epoch. The Table produced for only ANN results because conventional methods work only for one point movements at a time. Here it is clear that the ANN found the moved point accurately.

Clearly, ANN proved to be a candidate method for detection of unstable/stable points in a reference network designed for detection of vertical movements (that is, one-dimensional network). It is noted here that ANN approach requires training data. When preparing the training data, all possible scenarios must be considered. In two and three dimensional deformation network, obtaining training data might take a considerable amount of time.

Conclusion

The ANN is trained and tested using simulated data considering all possible movement scenarios including one-point, simultaneous two-point and three-point movements. A comparison of conventional method to the ANN approach showed that the conventional method is

Table 2. Comparison of the results from ANN and conventional method.

Movement imposed to be and the result from ANN				Movement determined from contributions to Phi				Difference			
dh_2	dh_3	dh_4	dh_5	dh_2	dh_3	dh_4	dh_5	dh_2	dh_3	dh_4	dh_5
1	0	0	0	0	0	0	1	1	0	0	-1
1	0	0	0	0	0	0	1	1	0	0	-1
1	0	0	0	1	0	0	0	0	0	0	0
1	0	0	0	1	0	0	0	0	0	0	0
0	1	0	0	1	0	0	0	-1	1	0	0
0	1	0	0	1	0	0	0	-1	1	0	0
0	1	0	0	1	0	0	0	-1	1	0	0
0	1	0	0	1	0	0	0	-1	1	0	0
0	1	0	0	1	0	0	0	-1	1	0	0
0	0	1	0	1	0	0	0	-1	0	1	0
0	0	1	0	0	1	0	0	0	-1	1	0
0	0	1	0	1	0	0	0	-1	0	1	0
0	0	1	0	1	0	0	0	-1	0	1	0
0	0	1	0	0	1	0	0	0	-1	1	0
0	0	0	1	0	1	0	0	0	-1	0	1
0	0	0	1	0	1	0	0	0	-1	0	1
0	0	0	1	0	1	0	0	0	-1	0	1
0	0	0	1	0	1	0	0	0	-1	0	1
0	0	0	1	0	1	0	0	0	-1	0	1

Table 3. ANN results for simultaneous two and tree point movements.

dh_2	dh_3	dh_4	dh_5
1	1	0	0
1	0	1	0
1	0	0	1
0	1	1	0
0	1	0	1
1	1	1	0
1	1	0	1
1	0	1	1
1	1	1	0
1	1	0	1
1	0	1	1

not accurate in finding the moved point(s). The author recommends that ANN can be used in a determination of stable/unstable points in a one-dimensional leveling network designed for deformation monitoring.

REFERENCES

Akyilmaz O, Celik RN, Apaydin N, Ayan T (2004). GPS Monitoring of The Fatih Sultan Mehmet Suspension Bridge By Using Assesment Methods of Neural Networks. ISPRS, Vol. 34, Part XXX.

Caspary WF (1987). Concepts of Network and Deformation Analysis. School of Surveying Monograph 11.

Chrzanowski A, Chen YQ (1986). Report of ad-hoc committee on the analysis of deformation surveys. 18th FIG Int. Congr. Toronto 19.

Cross P A. (1994). Advanced Least Square Applied to Position-Fixing. School of Surveying University of East London, Working Paper no. 6, London.

Demuth H, Beale M (1998). Neural Network Toolbox User's guide. The Mathworks inc.

Hassoun MH (1995). Fundementals of Artificial Neural Networks. London -511.

Maronna R, Ricarda A, Dougles Martin, Victor J, Yohai (2006) Robust statistics: Theory and Methods. John Wiley & Sons, England.

Kennie TJ, Petrie G (1993). Engineering Surveying Technology. London.

Mima JB (2002). Adapting Neural Networks for Modeling Geodetic Deformations. In Kahmen/Neimeier/Retscher(eds), Procedings of the 2nd symposium on Geodesy for Geotechnical and Structural Engineering. Berlin, Germany, May 21-24 pp. 186-194.

Hekimoglu S (1999). Robustifying Conventional Outlier Detection Procedure. J. Surv. Eng., Vol. 125, No. 2, May.

Hekimoglu S, Hüseyin D, Cuneyt A (2002). Reliability of the Conventional Deformation Analysis Methods for Vertical Networks, Deformation Measurement and Analysis III, FIG XXII International Congress Washington, D.C. USA, April 19-26.

Hekimoglu S (2006). Kaba Hataların Belirlenmesindeki Sorunlar. Harita Dergisi, Sayi=135, Ocak.