Scientific Research and Essays Vol. 5 (5), pp. 440-447, 4 March, 2010
Available online at http://www.academicjournals.org/SRE
ISSN 1992-2248 © 2010 Academic Journals

Full Length Research Paper

Outlier detection for geodetic nets using ADALINE learning algorithm

Mevlut Gullu and Ibrahim Yilmaz*

Department of Geodesy and Photogrammetry, Faculty of Engineering, Afyon Kocatepe University, 03200 Afyonkarahisar, Turkey.

Accepted 16 February, 2010

Developed by imitating the operation of human brain, artificial neural network applications are used in many fields such as engineering, industry, medicine, agriculture, finance, communication, meteorology, space and aeronautics. By the help of sophisticated computing technologies, the learning algorithms used in artificial neural networks allowed solving many problems that remained as undecided and defied any mathematical expression, particularly in the fields of engineering. In geodetic studies, three-dimensional geodetic networks are used for all sorts of location-based engineering measurements on earth. Numerous measurements are performed to determine the position of the points in geodetic networks. Possible errors and inconsistencies in these measurements affect geodetic network precision. Therefore, the test for outliers is implemented to eliminate measurement errors and sort out outliers. In the present study, the test for outliers was performed on a computer program developed by using ADALINE learning algorithm and the results were compared with traditional methods (data snooping, Tau, t). This new method was observed to be superior to traditional methods with regards to calculations about outliers and decision-making on the results.

Key words: Outliers, neural networks, ADALINE learning algorithm, geodetic nets.

INTRODUCTION

As in many other disciplines, improvements in computing software and hardware have also led to rapid developments in engineering, as a result of which new methods have been created, particularly in engineering calculations. Analysis of engineering systems consists of two stages in general: constructing a mathematical model that represents an existing physical system and solving the obtained mathematical equation through analytical or various approximate numerical methods. Construction of a mathematical model requires a sound mathematical background, while analysis requires a quick and extensive computer, as well as information. As a result, artificial intelligence techniques modelling the operation of the human brain have been developed. Using artificial intelligence techniques, computers can decide on any phenomenon and intuitively solve insoluble problems that cannot be expressed through any mathematical formula. Artificial Neural Networks (ANN) constitutes one of the artificial intelligence techniques developed for hard-to-program or un-programmable phenomena. Created by simulation of the operation of the human brain, ANN is a logical programming technique that aims to access through software the basic operations of the brain. Many ANN models are based on the operating principles of the brain (Haykin, 1994). ANN is used in various fields of industry, manufacturing industry, military project applications, information management, medical applications, precision farming, space and aeronautics industry, surface modelling, modelling of meteorological phenomena and various fields of engineering (Ucan et al., 2006; Sagiroglu et al., 2003; Oztemel, 2006; Kosek et al., 2001; Bodri, 2001; Bodri and Cermak, 2003). ANN is used in geodetic studies, particularly in determining the earth's gravity field, in geoid height determination from GPS/ Levelling measurements, as well as in constructing 3D numerical area models. In the present study, outlier detection was performed for geodetic networks using

*Corresponding author. E-mail: iyilmaz@aku.edu.tr. Tel: +90 272 228 14 23. Fax: +90 272 228 14 22.

ADAptive LInear NEuron (ADALINE) learning algorithm, a recent application of an ANN model in geodesy, and the results were compared with traditional methods.

OUTLIER DETECTION

High-quality geodetic networks are needed for the determination of Earth's shape and size, which is a subject of the science of geodesy, as well as for all kinds of location-based engineering measurements on Earth. Geodetic networks consist of horizontal control networks, in which x and y coordinates of certain points are determined, of vertical control networks, in which their heights (z) are determined, as well as of three-dimensional networks.

During such measurements of geodetic nets, some gross, systematic or non-systematic errors might occur depending on who performs the measurement, the device used for the measurement and environmental conditions. Gross and systematic errors can be eliminated by repeating the measurements and using a more appropriate measuring method, while non-systematic errors cannot be sorted out since their origins and time of occurrence are not known exactly (Konak and Dilaver, 1998).

The error theory assumes that non-systematic errors may occur in all measurements at any time. Therefore, even after the gross and systematic errors are sorted out, some inconsistencies can still be observed in geodetic net measurements owing to non-systematic errors. Such inconsistencies between measurements are discovered when the measurements are assessed collectively. Statistical methods are used to determine which measurement (s) should be considered as outliers according to these inconsistencies (Konak et al, 1999).

Outliers can sometimes markedly disrupt statistical analyses, and sometimes their effects may not be noticed. Some outliers may be the most significant measure in the measurement network. Thus statisticians have developed numerous algorithms for outlier behaviour and detection (Hampel, 2001).

Various test methods have been developed to investigate outliers in geodetic networks. Among these methods, the Data Snooping test, Tau test and t test, which are described as the conventional methods, have long been employed in determining outliers in geodetic networks (Koch, 1999; Hekimoglu and Erenoglu, 2007).

The difference among the conventional methods results from the fact that different variance factors are used to standardize the adjustments for measurements (V_i). In the Data Snooping test process, the a priori variance value (σ_0), which represents the set of measures, is used for the hypotheses. The test size is:

$$T_{DS} = \frac{|V_i|}{\sigma_0 \sqrt{Q_{v_i v_i}}}$$

Where; $\underline{Q}_{v_i v_i}$ values represent the diagonal terms of cofactor matrix $\underline{Q}_{vv}$. The critical value isp:

$$q_{DS} = N_{1-\alpha_0/2} = \sqrt{F_{1,\infty,1-\alpha_0}} = \sqrt{\chi^2_{1,\infty,1-\alpha_0}}$$

Here, α_0 is the significance level, N represents the normal distribution, F represents the Fischer table and χ^2 represents the Chi-Square table. The significance level for a single observation α_0 is computed from

$$\alpha_0 = 1-(1-\alpha)^{1/n} \cong \alpha/n$$

Where; α is the total significance level and usually chosen as 5% and n is the number of observations (Baarda, 1968; Biacs et al., 1990).

In the Tau test developed by Pope (1976), if the a priori variance cannot be known or does not yield a reliable value based on experience prior to the adjustment, the a posteriori variance m_0, which is obtained after the adjustment calculation and outliers are also used for the calculation, is used in the test for outliers (Schwarz and Kok, 1993; Gokalp and Boz, 2005).

Test size is:

$$T_{Tau} = \frac{|V_i|}{m_0 \sqrt{Q_{v_i v_i}}} \tag{4}$$

The critical value of τ table can be obtained as follows (Heck, 1981):

$$q_{Tau} = \tau_{f,1-\alpha_0/2} = \sqrt{ft^2_{f-1,1-\alpha_0/2} \Big/ \left(f-1+t^2_{f-1,1-\alpha_0/2}\right)} = \sqrt{fF_{f-1,1-\alpha_0/2} \Big/ \left(f-1+F_{f-1,1-\alpha_0/2}\right)}$$

Where; τ represents Tau table, t represents t (student) table.

If a value l_i contains a gross error that makes it an outlier, the a posteriori variance m_0 calculated by use of this measurement value will contain the same error. Therefore, the size of the Tau test calculated from Equation (4) also contains a certain degree of error. In this case, it would be more accurate to calculate the value m_0 from calculations that are cleaned of the model errors (Gokalp and Boz, 2005; Sisman, 2005).

Test size is:

$$T_t = \frac{|V_i|}{m_{0_i} \sqrt{Q_{v_i v_i}}} \tag{1}$$

Where;

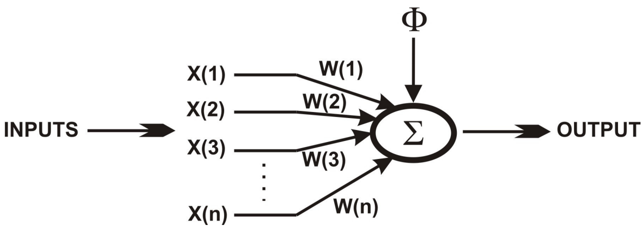

Figure 1. An ADALINE unit.

$$m_{0_i} = \pm\sqrt{\frac{V^T PV - \frac{V_i^2}{Q_{v_i v_i}}}{f-1}} \tag{7}$$

The critical value of *t* table is:

$$q_t = t_{f-1,1-\alpha_0/2} \tag{8}$$

ADALINE LEARNING ALGORITHM

The literature on ANN includes many learning algorithms, most of which are mathematics-based and are used for weight updating. Most have been derived from the Hebb (1949) rule. The Delta rule is a different version of the Hebb rule. The Widrow-Hoff delta rule for ADALINE is one of the most popular learning rules for mapping neural networks. Like the McCulloch-Pitts neuron and Rosenblatt's perception, ADALINE is one of the earliest neural-network models. Widrow and Hoff proposed the ADALINE model and developed one of the most important learning algorithms, now often referred to as the Widrow-Hoff delta rule or simply delta rule (McCulloch and Pitts, 1943; Rosenblatt, 1958; Widrow and Hoff, 1960). This rule is based upon an idea that reduces the difference between the actual output and desired output of the neuron, reinforces and continuously changes its input connections. It is grounded on the principle of reducing mean square error by changing the connection weight values. The error reduces through a simultaneous back-propagation from one layer to the preceding layers. The process of reducing the errors of the network continues from the output layer to the input layer (Sagiroglu et al., 2003). ADALINE is only a linear model, and hence its capability is very limited. Its learning algorithm, the delta rule, is not only extremely simple but also linear, which makes learning fast and easy. The ADALINE has become a powerful tool in some areas, such as adaptive signal processing, even with its limited modelling capability (Widrow and Stearns, 1985; Wang et al., 2000; Kavak et al., 2005).

In general terms, ADALINE is a network consisting of a process element (ADALINE unit). This network is based on the square of the least mean squares method. The basis of the learning rule is the principle of regulating the weights to minimise the network output error when compared with the desired output value. Figure 1 shows the constitution of an ADALINE unit.

In Figure 1, X_i indicates n number of inputs, W_i the weights that represent the effect of each input on the ADALINE unit, and Φ the threshold value that gives the output of ADALINE unit a non-zero value. Calculation is based on the following equation:

$$I = \sum_{i=1}^{n} W_i X_i + \Phi$$

Output *O* will be

$$\begin{aligned} OUTPUT\,(O) &= 1 \; IF \; I >= 0 \\ OUTPUT\,(O) &= -1 \; IF \; I < 0 \end{aligned} \tag{10}$$

$$E = B - O$$

Since the aim is to find the values to minimize value *E*, errors are calculated by presenting the network with different samples each time, and weights are adjusted to reduce the error. The result is calculated by obtaining the final weights when value *E* reaches its minimum.

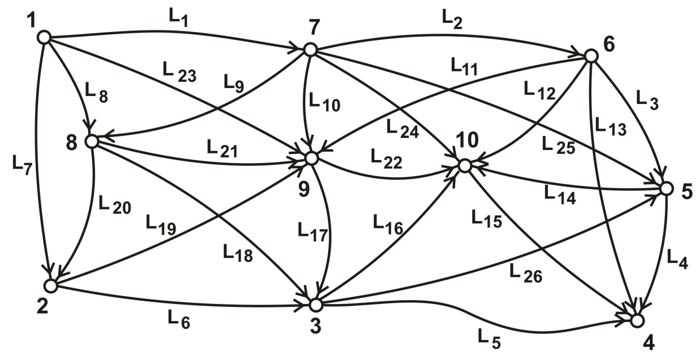

Figure 2. Levelling net.

APPLICATION AND PROGRAMMING

In order to investigate outlier detection in geodetic nets using ADALINE learning algorithm, the levelling net in Figure 2 and the triangulation net in Figure 3 were established and measures were performed in Ahmet Necdet Sezer Campus area at Afyon Kocatepe University (Turkey).

The levelling net consists of 10 points, among which 26 height differences were measured. The weights of all these measures are equal and were taken as 1. Approximate heights of all the points in the levelling net were taken as unknown and the height differences between the points were adjusted through free levelling

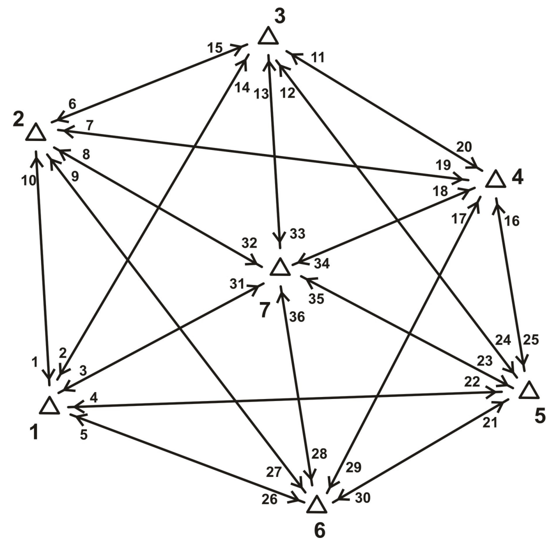

Figure 3. Triangulation net.

Table 1. Adjustment data (1st adjustment).

Adjustment parameters	Levelling	Triangulation
Number of points, u	10	7
Number of measures, n	26	36
Datum defect, d	1	4
Degree of freedom, f	17	19
A posteriori variance, m_0 (±)	0.038667 m	3.532536^{cc}

Table 2. Statistical table values and outlier data.

Levelling			Triangulation		
q_{DS}	q_{Tau}	q_t	q_{DS}	q_{Tau}	q_t
3.1000	2.7970	4.0300	3.1970	2.8923	4.0850
Outlier height differences			**Outlier direction angles**		
L_6, L_{20}	L_6, L_{20}	L_6	L_{15}	L_{15}	L_{15}

network adjustment. The triangulation net consists of 7 points, on which 36 direction angles were measured. Direction weights are equal and were taken as 1. By taking approximate coordinates of all points in the traingulation net as unknown, free triangulation net adjustment was made and the direction angles between the points were adjusted. Table 1 presents the data on the adjustment results for the levelling net and triangulation net.

To detect the outliers in the levelling and triangulation nets by conventional methods, the correction values (V_i) for the measures as a result of the 1st adjustment were used. For this purpose, by using Equations 1, 4 and 6 were for each measure, the test size values T_{DS}, T_{Tau} and T_t were compared with the statistical table values q_{DS}, q_{Tau} and q_t, which are computed by equations 2, 5 and 8, respectively. As a result of the comparison, measure(s) of the test size value greater than the statistical table value were taken as outliers. Table 2 shows the data on the statistical table values and outliers used in the outlier test performed for the levelling and triangulation nets by conventional methods.

Height difference measures L_6 and L_{20} in the levelling net and direction angle L_{15} in the triangulation net were excluded from the measure set as they were identified to be outliers by conventional outlier detection methods, and

Table 3. Adjustment data (2nd adjustment).

Adjustment parameters	Levelling	Triangulation
Number of points, u	10	7
Number of measures, n	24	35
Datum defect, d	1	4
Degree of freedom, f	15	18
A posteriori variance, m_0 (±)	0.019792 m	1.989293^{cc}

Table 4. Statistical table values and outlier data (according to the results of the 2nd adjustment).

Levelling			Triangulation		
q_{DS}	q_{Tau}	q_t	q_{DS}	q_{Tau}	q_t
2.7430	3.0800	4.1200	3.1880	2.8709	4.1200
Outlier height differences			**Outlier direction angles**		
-	-	-	-	L_{24}	L_{24}

a second adjustment was performed and the outlier test was repeated with the remaining measures. The results of the second adjustment are given in Table 3, and Table 4 presents the statistical table values and outlier data computed by using the correction values obtained with the results of the second adjustment. Since conventional outlier detection methods carried out by using the values obtained as a result of the 2nd adjustment for the levelling net did not reveal any outliers; that is, all measures were found to be consistent, the adjustment process was ended and the points' exact heights were calculated by using the adjusted height differences obtained in the final adjustment process. However, according to the conventional outlier detection methods performed on the values obtained in the 2nd adjustment for the triangulation net, direction angle L_{24} was identified to be an outlier. Direction angle L_{24} was excluded from the measure set in the triangulation net and a 3rd adjustment and outlier test was performed with the remaining measures. Table 5 shows the data on the 3rd adjustment for the triangulation net and Table 6 presents the statistical table values and outlier data calculated using the correction values obtained according to the results of this adjustment process.

Since conventional outlier detection methods carried out by using the values obtained as a result of the 3rd adjustment for the triangulation net did not reveal any outliers; that is, all measures were found to be consistent, the adjustment process was ended and the points' exact coordinates were found by using the adjusted direction angles obtained in the final adjustment process. As clearly seen in Tables 1 - 6, in detecting the outliers in geodetic nets by conventional methods, differences might be observed among methods with regard to the results obtained. Furthermore, in outlier detection using conventional methods, the outlier detection test should be repeated until there are no outliers in the geodetic net. Therefore, multiple adjustments and outlier tests are often performed in a geodetic net. In order to overcome this drawback, or to detect all possible outliers in geodetic nets at the first stage and to eliminate the need for numerous mathematical operations, a software program was developed in VİSUAL BASIC language by using ADALINE learning algorithm for outlier detection by the artificial neural network method.

Table 5. Adjustment data (3rd adjustment).

Adjustment parameters	Triangulation
Number of points, u	7
Number of measures, n	34
Datum defect, d	4
Degree of freedom, f	17
A posteriori variance, m_0 (±)	0.874294^{cc}

Table 6. Statistical table values and outlier data (according to the results of the 3rd adjustment).

Triangulation		
q_{DS}	q_{Tau}	q_t
3.1800	2.8424	4.1610
Outlier direction angles		
-	-	-

In line with the rule of least mean squares, to train the geodetic network with ADALINE learning algorithm, it was

Table 7. Values obtained with ADALINE learning algorithm.

Levelling			Triangulation		
$V_k = V_{15}$	Φ	O	$V_k = V_{16}$	Φ	O
1.3178 mm	2.7970	4.0300	0.0478	-0.4491	2.1670
Outlier height differences			**Outlier direction angles**		
L_6, L_{20}			L_{15}, L_{24}		
L_6, L_{20}			L_{15}		
L_6			L_{15}		

Table 8. Values obtained with ADALINE learning algorithm (2nd Test).

Levelling			Triangulation		
$V_k = V_{23}$	Φ	O	$V_k = V_{35}$	Φ	O
0.0009 mm	-0.9802	0.0228	-0.0079	-0.5170	1.0335
Outlier height differences			**Outlier direction angles**		
-			-		
L_6, L_{20}			L_{15}		
L_6			L_{15}		

assumed that the measure with the lowest correction value obtained through free geodetic network adjustment cannot be an outlier. Thus, in accordance with the principle of the ADALINE learning algorithm, the following equation was developed by using the $(\underline{Q}_{vv})$ values of inverse matrix of weight coefficients for the corrections.

$$I_i = \sum_{i=1}^{n} \sum_{j=1}^{n} W_{(j)} Q_{vv}(i,j) + \Phi \tag{12}$$

By taking as consistent the value I_k obtained from value with the lowest correction rate V_k, the network was trained using Equation (12) with the help of matrix $Q_{vv}(k,j)$ and outliers were detected by applying the obtained weights to the entire geodetic network (Table 7).

In order to check the accuracy of the outliers in Table 7 detected by the artificial neural network method using ADALINE learning algorithm, measures L_6 and L_{20} in the levelling net and measures L_{15} and L_{24} in the triangulation net were removed from the measure set and a second outlier detection process was performed both for the levelling net and the triangulation net by using ADALINE learning algorithm. Table 8 presents the results obtained from this checking process.

CONCLUSION

Adjustment calculations for geodetic nets that could often not be performed or could only be approximately performed previously owing to computational difficulties can be carried out in accordance with the error theory today, thanks to the vast and quick calculation opportunities offered by computers. To this end, the measures used in the adjustment of geodetic nets should be examined and cleaned of outliers, if any. Researchers should work meticulously to identify outliers, investigate their reasons, and remove the outlier from the measure set or repeat the measurement if necessary. At this stage, it should be remembered that the root mean square will increase since each measure removed from the measure set will decrease the number of redundant measures; and, in contrast, the adjustment performed for the measure set containing the outlier will not follow the rule of minimum sum of squares of the corrections, a rule that forms the basis of network adjustment.

Studies on conventional outlier detection methods refer to their disadvantages of being directly affected by the errors in correction, propagating these errors and containing iterative solutions, besides their advantage of statistical evaluation in outlier detection. These studies conclude that:

1. The data snooping test could be preferred if a reliable a priori variance is obtained prior to the adjustment.
2. Tau or t tests could be used if there is no information on the a priori sensitivity of the network and if either Tau or t test is preferred, t test will be more appropriate as it uses the a posteriori variance cleaned of model errors.
3. It would be more appropriate to use more than one test method and interpret the common results in any decision about outliers.

In this study, the possibility of outlier detection by ADALINE learning algorithm, which is used to detect outliers in geodetic nets and involves fewer process stages than conventional methods, was tested both in levelling and triangulation nets.

To this end, free network adjustment (1st adjustment) was first performed in the levelling and triangulation nets by using all the measures for the network (Table 1). The conventional outlier detection methods employed by using the correction value obtained from free network adjustment revealed that the only outliers in the levelling net were height differences L_6 and L_{20} in the Data Snooping and Tau method and height difference L_6 in the t-test method (Table 2). And in the triangulation net, direction angle L_{15} was identified as the outlier in all of the three methods (Table 2). These different results found in the levelling net revealed a critical drawback of the conventional outlier detection methods, which suggests that there may be advantages and disadvantages among the conventional outlier detection methods and thus, different results might be obtained. Another drawback of outlier detection by conventional methods is the repetition of the process until there is no outlier left in the geodetic net. For this purpose, the outliers in Table 2 were removed from the measure set and the second adjustment (Table 3) and a second outlier test were performed by using the correction values obtained from the second adjustment. These tests showed that all the measures in the levelling net were consistent, while measure L_{24} in the triangulation net was an outlier direction angle (Table 4). Since there was no outlier left in the levelling net, no other adjustment was made and the points' exact heights were computed according the results of the 2nd adjustment. Nevertheless, in the triangulation net, direction angle L_{24} was removed from the measure set and a third adjustment (Table 5) was performed. A third outlier test was carried out by using the correction values obtained from the third adjustment and all the remaining measures in the triangulation net were identified to be consistent (Table 6). Thus, the exact coordinates of the points in the triangulation net were computed in accordance with the adjustment results in Table 5.

Outlier detection in geodetic nets using conventional outlier detection methods has numerous drawbacks, such as the difficulties about which method to select and whether the result obtained from the selected method is accurate, the difficulty in identifying the critical values used to calculate statistical table values, and the need to repeat testing until there is no outlier left in the network. In order to eliminate these drawbacks, the possibility of outlier detection in geodetic nets by ADALINE learning algorithm using artificial neural network techniques was tested both in levelling and triangulation nets.

Thus, by assuming that of the correction values (V_i) obtained as a result of the free network adjustment (1st adjustment), the measure of the smallest correction value as an absolute value (V_k) cannot be an outlier, each correction value was taken as an input value for the artificial neural network and the geodetic net was trained with ADALINE learning algorithm. At the end of training, the expected value (B) was calculated for each output value (O) and the values were sought that would make Equation (11) have the minimum value. Bu using the weight and output values resulting in minimum values, height differences L_6 and L_{20} in the levelling net and direction angles L_{15} and L_{24} in the triangulation net were identified to be outliers, as seen in Table 7. It was observed that these detected outliers are consistent with the results of the conventional methods and in the triangulation net in particular, measure L_{24} was found to be inconsistent without the need for a second adjustment and thus without performing a second outlier test.

In order to check whether there was any other outlier both in the levelling net and the triangulation net, measures L_6 and L_{20} in the levelling net and measures L_{15} and L_{24} in the triangulation net were excluded from the measure set and the adjustment was repeated. The net was trained by ADALINE learning algorithm in accordance with the results obtained from the new adjustment. As a result, no outlier was detected, as is clear from Table 8. This demonstrates that all outliers in geodetic nets can be detected with the 1st adjustment by using ADALINE learning algorithm and there is no need for a 2nd or 3rd adjustment or outlier test.

The superiority of detecting outliers through the ADALINE learning algorithm over conventional methods lies in the fact that statistical tests are not used, which is accepted as an advantage of conventional outlier detection methods because there is a possibility of committing errors to an extent close to the size of the test used or at levels exceeding the threshold value. In particular, according to the table threshold value, there is a possibility that a measure that is actually an outlier could be identified as consistent since the measure identified as an outlier is very important for the measure plan and strongly affects the internal and external sensitivity of the network, or the table value to be used is high, a case that occurs in geodetic networks with insufficient number of redundant measures. The method developed here eliminated this problem. Another advantage of this method is that it does not use the a priori and a posteriori variance values that the conven-tional outlier detection methods use. Thus, inconsistent measures in the measure set used to calculate a priori and a posteriori variances can be avoided.

REFERENCES

Baarda W (1968). A testing procedure for use in geodetic network. Publication on Geodesy, New series Delft/Netherlands 2(5): 97.

Biacs ZF, Krakiwsky EJ, Lapucha D (1990). Reliability analysis of phase observations in GPS baseline estimation. J. Surv. Eng. 116(4): 204-224.

Bodri L (2001). Neural network prediction of monthly precipitation: Application to summer flood occurrence in two regions of central Europe. Stud. Geophy. Geodaetica 45: 155-167.

Bodri L, Cermak V (2003). Prediction of surface air temperatures by neural network, example based on three-year temperature monitoring at Sporilov Station. Stud. Geophys. Geodaetica 47: 173-184.
Gokalp E, Boz Y (2005). Outlier detection in GPS Networks with Fuzzy Logic and Conventional Methods. FIG Working Week and GSDI-8, April 16-21, Cairo, Egypt, http://www.fig.net/cairo/
Hampel F (2001). Robust Statistics: A brief introduction and overview. In: First International Symposium on Robust Statistics and Fuzzy Techniques in Geodesy and GIS, March 12-16, Zurich/Switzerland, pp.1-5.
Haykin SS (1994). Neural Networks: A Comprehensive Foundation. McMillan Press, New York/USA, p. 223.
Hebb DO (1949). The Organization of Behavior. John Wiley, New York/USA. p. 378.
Heck B (1981). Der einfluss einzelner beobachtungen auf das ergebnis einer ausgleichung und die suche nach ausreissern in den beobachtungen (Examining the effects of observations to the adjustment results and analysis of outliers). AVN 88: 17-34.
Hekimoglu S, Erenoglu RC (2007). Effect of heteroscedasticity and heterogeneousness on outlier detection for geodetic networks. J. Geod. 81: 137-148.
Kavak A, Yigit H, Ertunc HM (2005). Using adaline neural network for performance improvement of smart antennas in TDD wireless communications. IEEE Trans. Neural Networks 16(6): 1616-1625.
Koch KR (1999). Parameter Estimation and Hypothesis Testing in Linear Models. 2nd Edition. Springer Verlag. New York/USA, p. 333.
Konak H, Dilaver A (1998). The methods used in outlier localization in geodetic networks and their behaviors. Bull. Chamber Surv. Eng. Turk. 85: 91-109.
Konak H, Dilaver A, Kurt O (1999). The Fuzzy Logic approach in the process of outlier detection. In: UCTEA Chamber of Survey and Cadastre Engineers, 7th Council of Mapping, March 1-5, Ankara/Turkey, pp. 213-227.
Kosek W, McCarthy DD, Luzum BJ (2001). El Nino impact on polar motion prediction errors. Stud. Geophys. Geodaetica 45: 347-361.
McCulloch WS, Pitts W (1943). A logical calculus of the ideas immanent in nervous activity. Bull. Math. Biophys. 5: 115-133.
Oztemel E (2006). Artificial Neural Networks. Papatya Press, Istanbul/Turkey, p. 232.
Pope AJ (1976). The statistics of residuals and the outlier detection of outliers. NOAA Technical Reports, NOS 65, NGS 1, Rockville, Maryland/USA, p. 256.
Rosenblatt F (1958). The perceptron, a probabilistic model for information storage and organization in the brain. Psychol. Rev. 65: 386-408.
Sagiroglu Ş, Besdok E, Erler M (2003). Applications of Artificial Intelligence in Engineering – 1: Artificial Neural Networks. Ufuk Press, Kayseri/Turkey, p. 425.
Schwarz CR, Kok JJ (1993). Blunder detection and Data Snooping in LS and Robust Adjustment. J. Surv. Eng. 119(4): 127-136.
Sisman Y (2005). The methods used for determining outliers. J. Gen.l Command of Mapping 133: 74-89.
Ucan ON, Osman O, Albora AM (2006). Image Processing Techniques and Engineering Applications. Nobel Press Ankara/Turkey, p. 210.
Wang ZQ, Manry MT, Schiano L (2000). LMS learning algorithms: Misconceptions and new results on convergence. IEEE Trans. Neural Netw. 11(1): 47-56.
Widrow B, Hoff ME (1960). Adaptive switching circuits. IRE WESCON Conv. Rec. 4: 96-104.
Widrow B, Stearns SD (1985). Adaptive Signal Processing. Prentice-Hall, Englewood Cliffs, New Jersey/USA, p.528.