Scientific Research and Essays Vol. 5(20), pp. 3141-3146, 18 October, 2010
Available online at http://www.academicjournals.org/SRE
ISSN 1992-2248 ©2010 Academic Journals

Full Length Research Paper

Coordinate transformation by radial basis function neural network

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Accepted 20 September, 2010

The Turkish National Geodetic Network (TNGN) datum (ED50) was changed to the Turkish National Fundamental GPS Network (TNFGN) datum (WGS84) in 2001 in parallel with the increasing use of GPS technology. Due to this reference frame change it became necessary to transform the existing coordinate information between ED50 and WGS84. The two-dimensional (2D) affine transformation is widely used for coordinate transformation. The objective of this study is proposing a radial basis function neural network (RBFNN) that has been more widely applied in function approximation as an alternative coordinate transformation method. 2D affine transformation (Affine) method and RBFNN are evaluated over a study area, in terms of the root mean square error (RMSE). The results showed that RBFNN transformed the plane coordinates (Y, X) of the check points with a better accuracy (± 0.011 m, ± 0.013 m, respectively) than Affine method and pointed out that RBFNN can be used for coordinate transformation.

Key words: Coordinate transformation, artificial neural network, radial basis function, affine transformation.

INTRODUCTION

The coordinate information about location can be provided anywhere on the earth with a high accuracy by the Global Positioning System (GPS) in satellite positioning applications. Nowadays, GPS is a standard technique for establishing geodetic networks because of its accuracy and efficiency. The GPS measurements are frequently used in mapping applications for determining the coordinates which are the basis of large-scale mapping and geographic information systems. The datum being used in GPS is the World Geodetic System 1984 (WGS84). To fully utilize this system, countries using different datum's for their own coordinate bases have to either make a datum transformation platform between their datum and the global geodetic datum or change the datum to the global one (Kwon et al., 2005). Therefore, the Turkish National Geodetic Network (TNGN) was changed to the Turkish National Fundamental GPS Network (TNFGN) in 2001.

General Command of Mapping had established TNGN with traditional techniques between 1934 and 1954. TNGN was condensed by lower order geodetic networks and its relative accuracies are within the range of 10-20 ppm (Eren and Uzel, 2006). TNGN was based on the international Hayford ellipsoid. The datum of TNGN was the European Datum 1950 (ED50) and it was realized by connecting to eight geodetic control stations of the European network. The tectonic structure of Turkey was ignored while establishing TNGN. Scientific investigations show that positions change by almost 2 cm every year because of crustal movements (Celik et al., 2004). Because of the crustal movements and the displacements based on earthquakes since 1954, TNGN was not suitable for modern geodetic applications. TNFGN has been established in 2001 and some of the stations have been re-surveyed due to the earthquakes that happened in 1999 (Mw = 7.5 Izmit, Mw = 7.2 Duzce), 2000 (Mw = 6.1 Cankiri-Cerkes), 2002 (Mw = 6.5 Sultandagi), and 2003 (Mw = 6.4 Bingol). The total number of stations is about 600, of which 145 were resurveyed in 2003 and 172 in 2004 together with reconnaissance of about 210 points in western Anatolia for the purpose of improvement and maintenance of TNFGN in 2005. For each station, 3D coordinates and their associated velocities were computed in ITRF2000. Positional accuracies of the stations are about 1 - 3 cm whereas the relative accuracies are within the range of

0.1 - 0.01 ppm. Besides, the network has been connected to the Turkish Horizontal and Vertical Control Networks through overlapping stations and time-dependent coordinates of all stations which are computed in the context of the maintenance of the network with repeated GPS observations (Caglar, 2005). Up to the year 2001, all cartographic products and coordinate information produced nationwide have been in the ED50 datum. There are more than 300 000 maps produced in the ED50 datum in the General Directorate of Land Registry and Cadastre. The legal rights of people are based on TNGN. Due to the reference frame change and the existence of coordinate information based on different reference systems, the constructed coordinate data need to be transformed to WGS84.

Artificial neural networks (ANNs) have been applied in many fields of geodesy and geoinformatics (Miima et al., 2001; Schuh et al., 2002; Lin, 2007; Gullu and Yilmaz, 2010; Yilmaz et al., 2010), including coordinate transformation, and remarkable accomplishments were obtained with ANNs. Zaletnyik (2004) carried out a coordinate transformation between geographical and plane coordinates with ANN, Lin and Wang (2006) transformed the cadastral coordinates between two different coordinate systems and Tierra et al. (2008) made a comparison of the ability of artificial neural networks and official transformation parameters for coordinate transformation. In this paper, a radial basis function neural network (RBFNN) is evaluated for 2D coordinate transformation between WGS84 and ED50 as an alternative coordinate transformation method. The plane coordinates of the check points that are estimated from Affine method and RBFNN are compared to the known plane coordinates of the check points over a study area in terms of the root mean square error (RMSE) of the coordinate differences.

THEORETICAL BACKGROUND

The 2D coordinate transformation between WGS84 and ED50 can be carried out as a coordinate conversion: (YED50, XED50) → (YWGS84, XWGS84). The plane coordinates associated with the initial reference system must be converted to plane coordinates associated with the desired reference system. Affine method and RBFNN are used to transform these plane coordinates between the initial and the new reference systems in the evaluation procedure.

Affine method

There are a number of ways for defining the coordinate transformation between two reference systems. A coordinate transformation model can be optimized so that it is easy to perform and gives the highest accuracy. The Large Scale Map and Map Information Production Regulation (Turkish Chamber of Survey and Cadastre Engineers, 2008) has required the coordinate transformation between WGS84 and ED50 by several transformation methods and one of them is Affine method. Affine method is widely used for the local coordinate transformation, which has two different scale factors on Y and X axis (Wolf and Dewitt, 2000).

Affine method is used for converting or transforming a coordinate reference system possibly with non-orthogonal axes and possibly different units along the two axes. Therefore, it involves a change of origin, differential change of axis orientation and a differential scale change. Affine method is composed of two translations of the coordinate origin, two scale factors and two rotation parameters. If coordinates from two coordinate systems are available for some common points, those transformation parameters can be estimated. In theory, three common points from two different coordinate frames are enough to estimate those seven parameters, but more common points are used in a least squares sense to eliminate the biases and achieve high precision of the estimates (Kwon et al., 2005). Affine method is applied to plane coordinates between WGS84 and ED50 by:

$$YWGS84 = a\ YED50 + b\ XED50 + c \quad (1)$$

$$XWGS84 = d\ YED50 + e\ XED50 + f \quad (2)$$

Where a, b, c, d, e and f are 6 coordinate transformation parameters that can be estimated by the least squares adjustment. The detailed information about the least squares adjustment for estimating the coordinate transformation parameters can be found in Wolf and Ghilani (1997).

Radial basis function neural network

ANN is a complex processing system which is structured by interconnected artificial neurons or simply by neurons that are a highly simplified model of the decision-making processes of a human brain. There are several ANN models that can be formed with various architectures, depending on the number of additional layers and neurons, training algorithms and activation functions. In this study the RBFNN model was selected because of its function approximation features among several kinds of ANNs. RBFNN has a feed-forward structure consisting of one input layer, one or more hidden layers, and one output layer, and it is trained by supervised learning. Figure 1 shows the architecture of an RBFNN model.

The input layer is constituted by the input data that are given to the network. The input data are transferred to the hidden layer by a non-linear activation function. The response of the network is obtained in a linear type

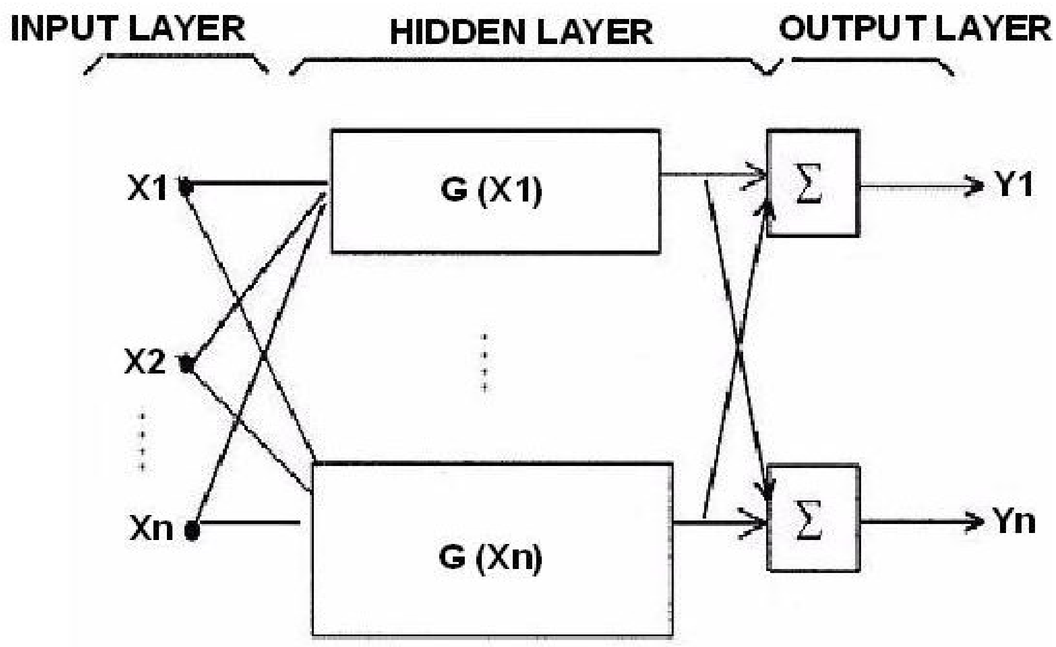

Figure 1. Radial basis function neural network.

output layer. Several types of non-linear activation functions can be used to transfer the input data to the hidden layer. The Gaussian function is used as the activation function in this study and it is defined by:

$$G_j(X) = \exp\left(-\frac{\|X - u_j\|^2}{2\sigma_j^2}\right) \tag{3}$$

Where X is the input vector, and uj and σj are the centre values of the basis function G and the width parameter, respectively, associated with the jth hidden neuron. $\|\cdot\|$ denotes the Euclidean distance. The hidden neuron is activated whenever X is close enough to its corresponding u in RBFNN. The response of each hidden neuron is scaled by its connecting weights and to the output neurons. The output layer of RBFNN consists of between I and k output neurons and the response of RBFNN is calculated by:

$$Y_k = \sum_{j=1}^{P} W_{jk} a_j + W_0 \tag{4}$$

Where W_{jk} is the weight coefficient between the jth hidden neuron and the kth output neuron, W_0 is the bias, and p denotes the number of hidden neurons. The location of neurons, the weight coefficients, and the bias are defined during the training process of RBFNN.

The training of RBFNN requires a set of data samples called the training set for which the corresponding network outputs are known (Tierra et al., 2008). Mathematically, the training can be considered as an optimization problem where the network parameters are to be solved while the error of the network output must be minimal (Barsi, 2001). The iterative supervised training procedure defines the parameters, calculates the error, and updates the parameters by propagating back the effect of the error to every parameter. The training process continues until the network error reaches an acceptable value. The network error is defined by:

$$E = \frac{1}{n}\sum_{k=1}^{n}(Y_{act} - Y_{pred})^2 \tag{5}$$

Where Y_{act} denotes the actual output value and Y_{pred} denotes the predicted output value.

STUDY AREA, DATA ACQUISITION AND METHODOLOGY

The application of the coordinate transformation based on Affine method and RBFNN between WGS84 and ED50 was performed over a study area that is located internal Anatolia region of Turkey within the geographical boundaries: 37.55° N ≤ φ ≤ 38.10° N, 32.30° E ≤ λ ≤ 32.75° E defining a total area of 2700 km^2 (60 x 45 km). The source data set comprises 47 control points that belong to the Turkish National Triangulation Network with known plane coordinates in WGS84 and ED50 (Figure 2).

The plane coordinates of these points have been determined as a part of the Digital Cadastre Project by the General Directorate of Land Registry and Cadastre. The evaluation of the performance of

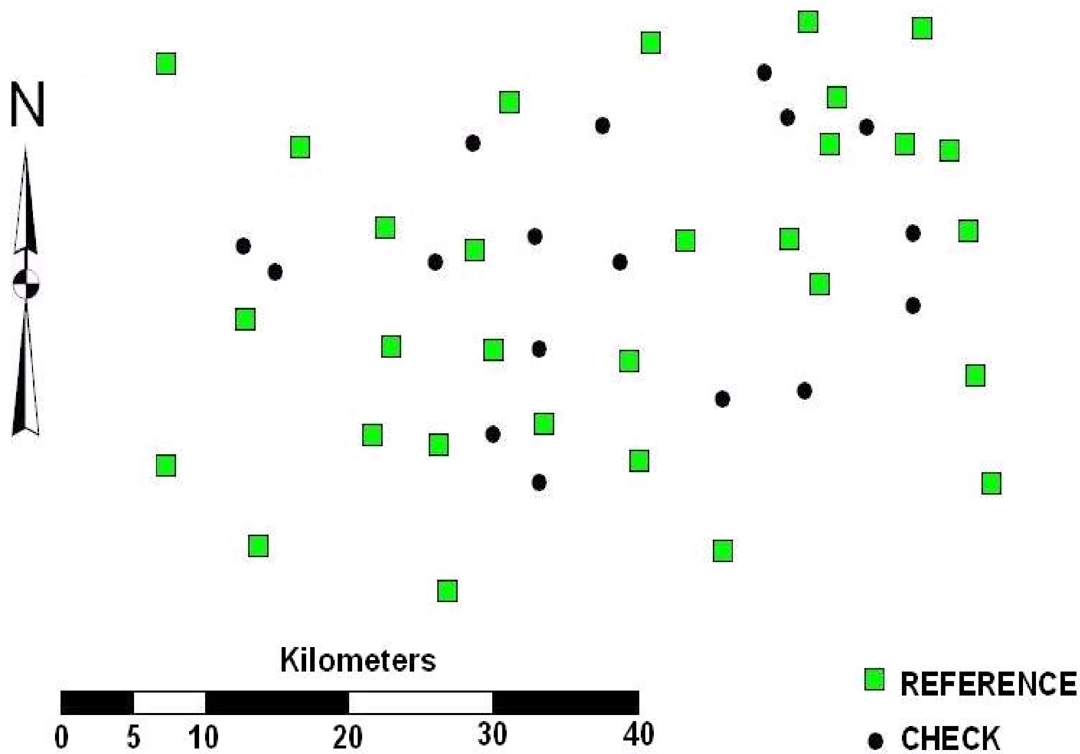

Figure 2. Reference and check point distribution over the study area.

the coordinate transformation focused on the differences between the known planes coordinates and the plane coordinates estimated by Affine method and RBFNN, using the equation below:

$$\Delta Y,X = (Y,X)\text{known} - (Y,X)\text{estimated} \tag{6}$$

For the statistical analysis of the plane coordinate residuals (ΔY, X), the maximum negative error, maximum positive error were determined and mean error (ME) and RMSE values were calculated by:

$$\text{ME} = {}^{1}\!/_{n} \sum_{i=1}^{n} \Delta_{Y,X} \tag{7}$$

$$\text{RMSE} = \sqrt{{}^{1}\!/_{n} \sum_{i=1}^{n} (\Delta_{Y,X})^{2}} \tag{8}$$

ΔY,X are investigated by RMSE value in the evaluation process of the coordinate transformations based on Affine method and RBFNN between WGS84 and ED50 because RMSEs are sensitive to even small errors, which is good for comparing small differences between estimated and observed discharges on models (Abghari et al., 2009).

CASE STUDY

The source data set is classified into two groups as the reference data set and check data set (Figure 2). The reference data set consists of 30 points that cover the study area from the outside and the check data set consists of 17 points that can be considered as densification points in the study area. The reference points are used for the RBFNN training process in the neural network approach and for determining the transformation parameters in Affine method approach. The check points are used for evaluating the performance of the coordinate transformations by comparing the known plane coordinates with the estimated plane coordinates in both coordinate transformation approaches.

The proposed RBFNN has two neurons in the input layer and output layer. The plane coordinates (Y, X) of the point in the ED50 datum are selected as input values and the corresponding (Y, X) in the WGS84 datum are used as output values for the training and testing procedure in the neural network approach. After a trial-and-error strategy, the optimal number of neurons in the hidden layer was selected as 19, which produced the smallest network error. Thus, the optimum structure of RBFNN was determined as [2:19:2]. The plane coordinates (Y, X) of the check points in the WGS84 datum are estimated by the trained RBFNN in the neural network approach and by the transformation parameters based on the reference data set in Affine method approach. The differences between the known plane coordinates (in WGS84) and the estimated plane coordinates of the check points were computed. RMSE is used for investigating the coordinate residuals of the check data set. The statistical values and RMSE value of the check data set's coordinate residuals are presented in Table 1. The ME and RMSE values of the check points' coordinate residuals based on Affine method and RBFNN are shown together in Figure 3.

RESULTS

When the maximum negative error, maximum positive error and ME values given in Table 1 are analysed, it can

Table 1. Statistics of check data sets coordinate residuals based on Affine method and RBFNN over the study area (units in m).

Transformation		Max (-)	Max (+)	ME	RMSE
Affine	ΔY	0.021	0.016	-0.007	0.019
	ΔX	0.021	0.019	-0.009	0.022
RBFNN	ΔY	0.010	0.009	0.004	0.011
	ΔX	0.009	0.012	0.005	0.013

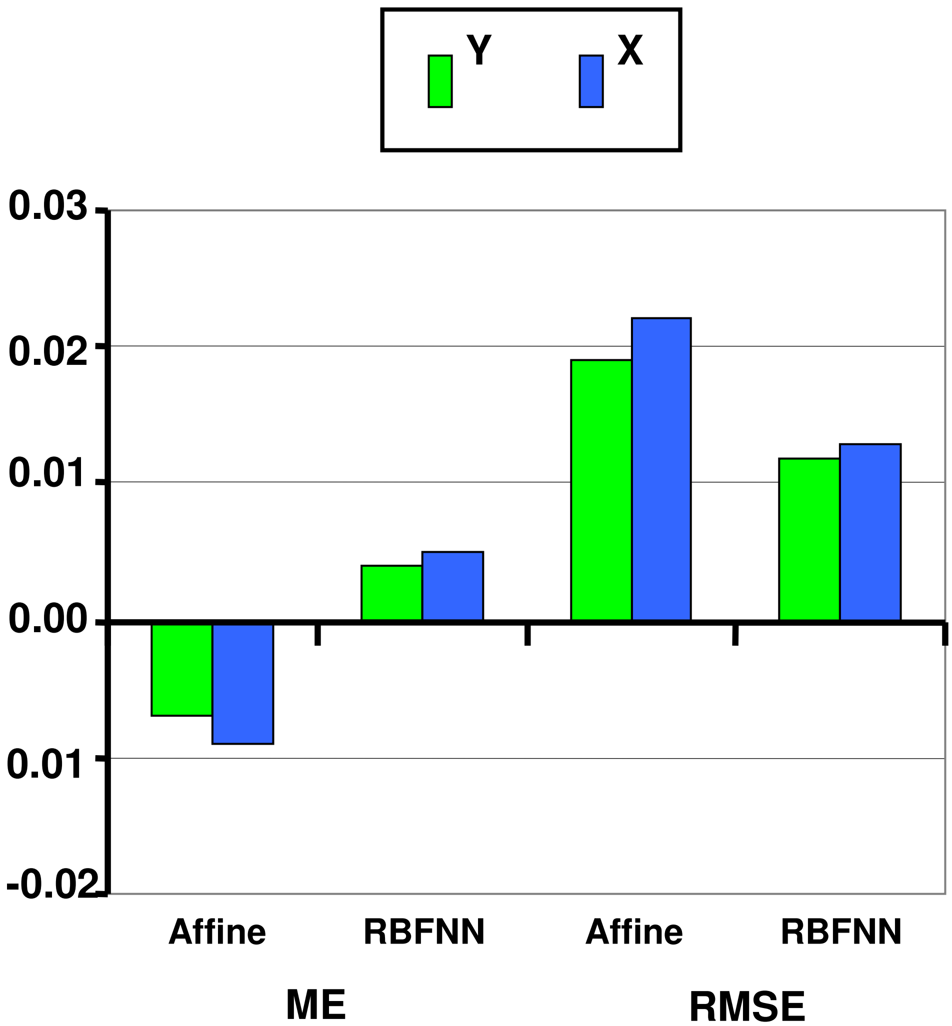

Figure 3. The check data set's ME and RMSE values based on Affine method and RBFNN (units in m).

be seen that the mean values are about two times better than the maximum values in the neural network approach. The evaluation of the results presented in Table 1 and Figure 3 shows that RBFNN estimated the plane coordinates (Y, X) of the check points with a significantly better accuracy than Affine method in terms of RMSE. RBFNN gave the smaller RMSE values (± 0.011 m, ± 0.013 m, respectively) of the coordinate residuals.

CONCLUSIONS AND FUTURE REMARKS

The following conclusions can be made from the results of this study:

(1) The employment of RBFNN estimated the plane coordinates with a better accuracy than Affine method for coordinate transformation, in terms of RMSE.
(2) The adaptation of an ANN that is properly formed and trained can be used for coordinate transformation as an alternative method.
(3) More accurate results based on ANN can be expected with high quality coordinate information data and with improved geographical coverage.

The evaluation of RBFNN and the other ANN models with various architectures (e.g., different activation functions, additional hidden layers) may be conducted for coordinate transformations with a huge quantity of coordinate information data in future works.

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