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Full Length Research Paper

Effect of increasing number of neurons using artificial neural network to estimate geoid heights

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Nowadays the GPS measurements are one of the most frequently used technique in geodesy. With this technique ellipsoidal height can be reckoned. However in the engineering practice orthometric heights (height above sea level) are used. The orthometric heights are determined by levelling. Transforming the GPS-derived ellipsoidal heights to orthometric heights it is important to know the distance between the ellipsoidal and the geoid surface, called the geoid height or geoid undulation. GPS levelling method is easy to determine geoid height of related region. Geoid height calculated by soft computing methods such as fuzzy logic and neural networks has gained more popularity recently. In this study, it examined effect of increasing number of neurons in neural networks to determine geoid height. The neural network approach used in this study is based on a back propagation neural network learning the functional relationship between geographic position and geoid undulation. Thus, inputs to the neural network are geographic position (latitude and longitude), and the output from the network is the predicted geoid undulation.

Key words: Geoid height, GPS, Neural networks, neuron.

INTRODUCTION

There are two types of heights used in geodesy. These are: orthometric height which is reckoned from geoid and, the second one is ellipsoidal height reckoned from ellipsoid. Orthometric height is a physical height on the other hand; ellipsoidal height is a mathematical height. These two height systems cannot be coincided with each other. In most engineering and surveying project, orthometric heights are required because orthometric height reflects the topography better than ellipsoidal height. The difference between the two height systems are called geoid height (undulation) and can be obtained in the following simple equation:

$$N=h-H \qquad (1)$$

Where, N denotes the geoid height, h and H are the ellipsoidal and orthometric heights, respectively. The importance of accurately obtaining the geoid height has increased in recent years with the advance of quantity and quality of satellite positioning systems such as (GPS). GPS provides height information relative to a best fitting earth ellipsoid rather than the geoid. To convert ellipsoidal heights derived from GPS to conventional orthometric heights the relationship between ellipsoid and geoid mentioned Equation 1 must be known. Orthometric heights can be readily computed from (1) if the geoid and ellipsoidal height are known. Ellipsoidal heights, or ellipsoidal height differences, can be derived from GPS more economically than orthometric heights. Determination of the latter requires time-consuming leveling. More details can be found in Wellenhof and Moritz (2006), Featherstone (2001), Engelis et al. (1985), Torge (2001),Yilmaz and Arslan (2008).

GPS/levelling geoid is easy to calculate and geoid heights obtained by GPS/levelling can be used to modelling the geoid in the region of interest using polynomial coefficients (interpolation) (Yanalak and Baykal, 2001) and soft computing model such as fuzzy

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logic (Yilmaz, 2005) and Akyilmaz (2005).

In this study, we deal with Artificial Neural Network (ANN) method alternative to other geoid determination methods such as surface polynomials, fuzzy logic for the interpolation of geoid heights.

Some of these studies are Seager at al. (1999), Kuhar et al. (2001), Veronez et al. (2005), Kutoglu (2006), Kavzoglu and Saka (2005), Palencz and Volgyesi (2003). Although many studies have been performed by using ANN to determine geoid height, effect of increasing number of hidden nodes in the layer has not been studied exactly in these studies. Kavzoglu and Saka have just examined two different numbers of hidden nodes (8 and 10) in the layer. Another studies have been performed with ANN versus surface polynomial by Kutoglu (2006)), Veronez et al. (2005); Weiwei and Xiudung (2010).

METHODOLOGY

Artificial neural networks (ANNs)

Artificial neural networks (ANNs), or shortly, neural networks (NN) have been used for the structure and functionality of biological natural of human brain. Therefore, ANN is found to be more flexible and suitable than other modeling methods (Zhang et al., 1997). ANN is based on the neural architectures of the human brain (Haykin, 1994), and described as group of simple processing units, known as neurons (nodes), that are arranged in parallel layers that are connected to each other by weighted connections. By virtue of hidden layers of neurons that lie between the input and output layers of the network, and the nonlinear activation functions that are used to translate nodal input to output, ANN provides linear and nonlinear modeling without the requirement of preliminary information and assumption as to the relationship between input and output variables. This provides ANN an advantage over other statistical and conventional prediction methods such as logistic regression and numerical methods, in which nonlinear interactions between variables must be modeled in explicit functional form (Tu, 1996). ANN trained with feed-forward back-propagation algorithm has been studied extensively and applied successfully to various areas, such as automotives (Majors et al., 2002), banking (Arzum and Yalcin, 2007), electronics (Bor-ren and Hof, 2003), finance (Xiaotian et al., 2008), industry (Cheginia et al., 2008), oil and gas(Peranbur and Preechayasomboon, 2002), and robotics (Huang et al., 2008) as well as others. The most ANNs contain three layers: input, output and hidden layer. Generally, there are various types of ANN techniques for example feed forward network, radial basis network, generalized regression network and recurrent neural network.

Feed-forward back-propagation and radial basis ANN the most often used of networks type. They have been utilized to solve a number of real problems, although they gained a wide use, however the challenge remains to select the best of them. In other words, there are no perfectly clear methods to determine the best network type. In this paper, geoid heights are calculated using feed-forward back-propagation.

A Feed forward neural network

Multi-layer feed-forward network was first established by Rumelhart (Rumelhart et al., 1986). Among the existing several neural networks such as recurrent networks, Hopfield networks, etc. the feed-forward is most popular, primarily due to their simplicity from the viewpoint of structure and ease of mathematical analysis, good representational capabilities. Feed forward network has been applied successfully to various application domains, such as prediction, controlling, system modeling and identification, signal processing and patter classification (Bilski, 2005). Overall, feed-forward architecture as shown in Figure 1 demonstrates an arrangement of interconnected nodes called neurons by sets of connections weight organized into three groups called layers, that is, input, hidden, and output layers (Abdalla et al., 2010).

In feed forward network each neuron in a layer receives weighted inputs from a previous layer and transmits its output to neurons in the next layer. The sums of weighted inputs are computed by Equation (2) and this sums is transferred by an activation function shown in Equation (3). The output values of network are compared with the actual output and the error of network is computed with Equation (4). The training process continues until this error met acceptable value.

$$y_{net} = \sum_{i=1}^{n} x_i . w_i + w_0 \tag{2}$$

$$y_{out} = f(y_{net}) = \frac{1}{1+e^{-y_{net}}} \tag{3}$$

$$E = \frac{1}{2}\sum_{i=1}^{k}(y_{obs} - y_{out})^2 \tag{4}$$

where x_i is input neuron, w_i is weight coefficient of each input neuron, w_0 is bias, y_{net} is the summation of weighted inputs, y_{out} is the response of system, $f(y_{net})$ is the nonlinear activation function, y_{obs} is the observed output value, E is the error between output observed value and network result. Furthermore, in the Figure 1, N is the number of input patter and M is number of neurons in hidden layer (Abdalla et al., 2010).

The back-propagation algorithm for training of feed-forward network was inspired by Rumelhart 1986. The training process adjusts the connection weight and bias of network in order to minimize the error function (that is, instantaneous sum squared error) defined in Equation 4.

The adjustment of connection weight are conducted by back-propagating the errors to the network. To achieve this, the connection weight is adjusted by an amount proportional to the gradient of error with respect to the weight, shown as follows:

$$\Delta w = -\eta \frac{\partial E(w)}{\partial w} \tag{5}$$

where η is the learning rate parameter which is used to controlling the convergent speed of the training algorithm and $E(w)/w$ the local gradient of $E(w)$.

The BP algorithm presents a better performance with a second-order term referred to as the momentum coefficient α, which introduces the old connection weight change as a parameter for the calculation of the new connection weight change.

$$\Delta w_{k+1}^{new} = -\eta \frac{\partial E(w)}{\partial w} + \alpha \Delta w_k^{old} \tag{6}$$

Data

In this study 1005 points whose latitude, longitude, ellipsoidal height

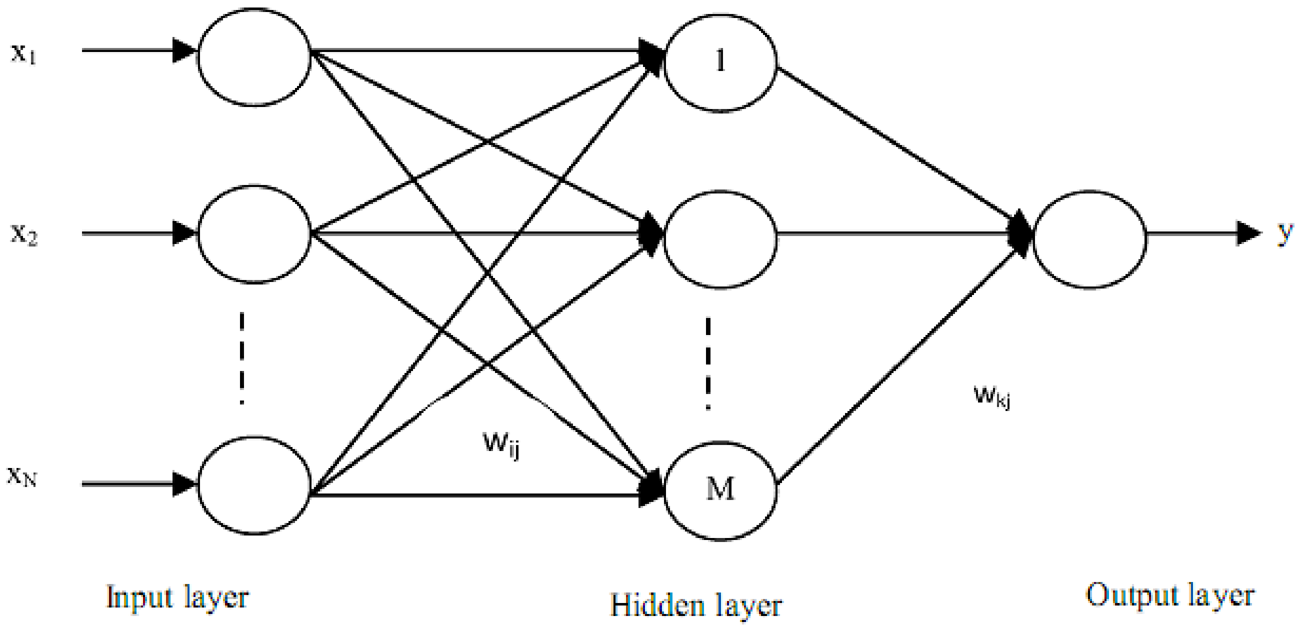

Figure 1. General structure of feed forward network.

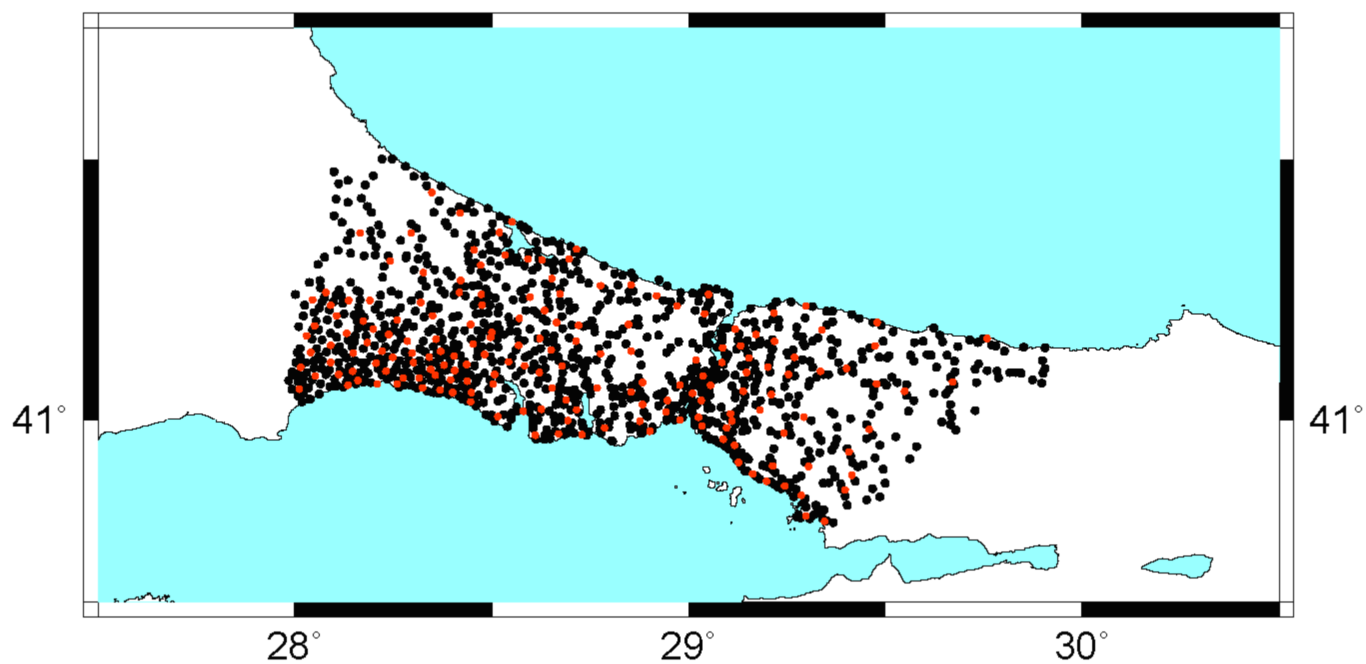

Figure 2. Distribution of model and test points in Istanbul (black dot shows model and red dot show test points).

and orthometric height are known were used to construct neural network models in the region. The points are homogenously distributed and randomly selected in Istanbul; the point density is nearly one point in 10 km^2. The data covers the region between 41° 30´2.79″ > φ > 40° 48´13.75″ and 29° 54´ 24.24″ > λ > 27° 59´ 3.05″. The standard deviation of the ellipsoidal heights after the adjustment of the network has been found to be ± 2.56 cm (Ayan et al., 2006). To construct the neural network models latitude and longitude are taken as inputs and geoid heights of the points are taken as outputs. To check for the calculation, randomly selected 178 points which had not been included in the preparation of the neural network models are used. The distribution of the 1005 model points and the 178 test points used in the ANN can be seen in Figure 2.

Table 1. Summary of results at model and test points obtained by neural networks using different numbers of neuron.

Number of neuron	Model points			Test points		
	Maximum Error (cm)	Minimum Error (cm)	RMSE (cm)	Maximum Error (cm)	Minimum Error (cm)	RMSE (cm)
5	20.49	-15.71	4.769	10.25	-10.34	4.403
10	12.44	-13.78	4.083	12.57	-3.96	3.814
15	11.89	-12.60	3.523	8.55	-5.49	3.496
20	11.61	-12.80	3.517	7.88	-7.13	3.508
25	13.80	-12.05	3.444	8.30	-5.11	3.419
30	10.52	-12.05	3.310	10.11	-5.27	3.259
35	11.39	-13.60	3.238	9.39	-4.62	3.300
40	11.76	-11.83	3.206	9.11	-6.06	3.303

Table 2. Number of points that error values greater than +7 cm and lower than -7 cm at both model and test points.

Number of neuron	Number of points error values greater than +7 cm		Number of points error values lower than -7 cm	
	Model points	Test points	Model points	Test points
5	56	8	75	9
10	63	4	39	7
15	34	5	27	5
20	29	6	22	6
25	22	3	17	5
30	20	1	19	3
35	21	3	13	4
40	18	5	18	5

RESULTS AND DISCUSSION

In this study, geoid height is calculated by neural network with taking eight different numbers of neurons. Models are constructed by starting at neuron number 5 and each time neuron number is increased in 5 and last models are finished neuron number reached at 40. Therefore, eight different neural network models are set up. It is aimed to show both neural network method can be used in geoid height calculations and effect of increasing number of neurons. Summary of obtained results are shown in Table 1.

When Table 1 is examined, the highest RMSE value is 4.769 cm obtained using 5 neurons, the lowest RMSE value is 3.206 cm obtained using 40 neurons in neural network calculations at model points. On the other hand, the highest RMSE value is 4.403 cm obtained using 5 neurons, the lowest RMSE value is 3.259 cm obtained using 30 neurons in neural network calculations at test points. It can be seen that RMSE values are decreasing as the neuron numbers are increased until number of neuron is 30 at both model and test points. After neuron number is 30, RMSE value is still decreasing at model points, however, it cannot be said same thing at test points. Because After neuron number is 30 RMSE values is getting increasing at test points. This indicates that if neuron number is selected larger than 30, neural network model is over fitting.

Maximum and minimum error values are varied between -15.71 and +20.49 cm at 5 neurons and maximum and minimum error values are varied between -11.83 and +11.76 cm at 40 neurons at model points.

Number of points that error values greater than +7 cm and lower than -7 cm are examined at both model and test points and results about this are given in Table 2. If these points are carefully searched, it is seen that some points have large error values at all neural models. Points numbered at 735, 747, 858, 898, 179 and 874 have generally large minimum error values and at 730, 1033, 736, 567 and 132 huge maximum error values at model points. Because these points have large errors at all neural models, it can be inferred that either height of these points are defective or incompatible. Therefore, heights of these points must be checked or throw away from neural model to get better results. Same thing has done at test points and points numbered at 458, 683, 840 have generally huge minimum error values and at 130, 873, 819, 91 have big maximum error values.

Conclusion

This study shows that neural network can be used as calculation method in geoid height determination. Changing number of neuron numbers affects the geoid height results. To find suitable number of neuron is a trial and error task. If appropriate number of neuron is not selected, model can be overfitting and these leads to wrong results. This means neural network model gives better result at model points but it also gives worse results at test points. RMSE value is used to validate neural network model. If RMSE values are close at both model and test points, constructed neural model can be used (as it happen neuron number from 5 - 30), otherwise neural model cannot validate (as it happen in neuron number 35 and 40).

It is also important to keep in mind the number of points used in neural network. If selected points are represented the study area well enough, precision of neural network and other calculation methods of geoid height will be high. And lastly, quality of points also effect precision of geoid height results.

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