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Efficiency of adaptive neuro-fuzzy inference system in estimation of Earth's velocity field

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Abstract

The purpose of this paper is estimation of earth velocity field using adaptive neuro-fuzzy inference system (ANFIS) in north-west of Iran. For this purpose, observations of 22 GPS stations are selected from the Azerbaijan local network. At the first step, the velocity field of these stations is estimated with Bernese GNSS software. Then, observations of 20 stations used for training of ANFIS with back-propagation (BP) algorithm. It should be note that the input vector of ANFIS is considered latitude and longitude of the GPS stations and the output is the velocity field (V_e , V_n). After the training step, estimated velocity field with ANFIS in two test stations, are compared and evaluated with the velocity field obtained from GPS. For a more accurate evaluation of the new model, all results are compared with velocity field obtained from the Kriging model. To analyze the error of the models, relative error and root mean square error (RMSE) is used. The averaged relative error of ANFIS and Kriging models obtained in the two test stations for the eastern component of the velocity field is 8.61% and 18.99%, respectively. Also for northern component, the averaged relative error is 21.84% and 28.51%, respectively. The results show the high accuracy of ANFIS model compared to Kriging in estimation of velocity field.

Introduction

Today, the expansion of geodetic networks and the creation of reference points with appropriate density for geodetic applications, the study of the movement of the Earth's crust, the study of the activity of faults, etc. is one of the most important tasks of geodesy. Analyzing and evaluating the velocity of geodetic points in a specific time and framework provides very valuable information about tectonic movements of the earth's crust and faults. In active tectonic zones, the evaluation of surface displacements of the earth's crust and the study of geophysical properties can reveal valuable information about geological structures. With the advent of satellite positioning systems such as global positioning system (GPS), the creation of reference points in geodetic networks has gained high speed. The important key in creating reference points is to estimate and obtain the velocity field and the displacement of these points within a reference framework (Djamour et al. 2011; Malekshahian and Raoofian-Naeeni 2018).With the development of local and regional global navigation satellite systems (GNSS), the idea of using observations of these networks to study the crustal deformation and surface displacement field is spread. In this regard, very extensive research has been done to study the surface velocity field and geodynamic mechanisms of the crust in Iran and the world (Djamour et al. 2007; Moghtased-Azar et al. 2009; Konakoglu 2021). Accurate determination of velocity field and displacement of reference point in geodetic networks is of great importance. With the availability of information about the velocity field of GPS stations in a geodetic networks, the kinematics and dynamics of the Earth's crust in that area can be modeled (Yilmaz 2013).

In recent years, extensive efforts have been made to determine the velocity field of the Earth's crust using observations of geodetic networks. Chen (1991) modeled the 3-dimensional displacement field using geodynamic data as well as the finite element method. He finds that the strain pattern obtained is in agreement with geological structures as well as with a completely independently determined crustal uplift pattern. Voosoghi (2000) used tensor calculations to obtain a 3-dimensional curvature tensor and displacement field of the Earth's crust. He showed surface deformation tensors and their associated invariants are critical for a meaningful study of deformations and kinematics of the Earth. Hossainali (2006) used Isoparametric and Lagrangian methods to calculate the 3- dimensional displacement field. Analytical and numerical investigation of problem conditioning proved that analyzing the 3D kinematics of deformation can be an ill-posed problem. He proposed the required mathematical elements for solving this problem, including sensitivity analysis of the deformation tensor and regularization. In 2006, Vangorp et al. used the Kriging method to estimate the velocity field in Turkey. Moghtased-Azar and Zaletnyik (2009) examined the capability of artificial neural networks (ANNs) in estimating the velocity field of GPS stations. Yilmaz and Gullu (2014) applied two different types of ANN models for geodetic point velocity estimation. They constructed ANN models using the multi-layer perceptron neural network (MLPNN) and the radial basis function neural network (RBFNN). Konakoglu (2021) investigated the predictive capacity of three MLPNN, generalized regression neural network (GRNN) and RBFNN models in predicting geodetic point velocities.

Some disadvantages can be considered for previous research in modeling and predicting the crustal deformation and surface displacement fields using GPS observations. In most studies, the estimated displacement field is point-to-point and is for the location of GPS stations. In other words, in places where there is no GPS station, the displacement field cannot be accurately checked. The previously presented models are based on analytical functions and are mostly local. In other words, accurate determination of the coefficients of these models will be strongly dependent on the number of observations in the study area. In models based on analytical functions, the transformation of a continuous problem into a discrete problem leads to the production of a system of unstable equations (Hossainali et al. 2010). In these methods the use of regularization methods to solve the system of equations is inevitable.

In this paper, using the observations of GPS stations in the north-west of Iran (local network of Azerbaijan), the surface displacement fields are calculated and these values are considered as the output of the ANFIS model. The desired inputs are geodetic coordinates of GPS stations. Training and modeling are performed using the ANFIS model and the results are evaluated. Also, back-propagation algorithm (BP) is used to train the ANFIS model. In order to evaluate the new model presented in this paper, the results are compared with the results of the Kriging model. Also various statistical indicators are examined for two models at test stations.

2- Adaptive neuro-fuzzy inference system

The neuro-fuzzy models developed by Jang in 1993 to combine fuzzy logic with ANNs to facilitate the learning process and adaptation. The ANFIS structure is composed of two parts. The first part is called the premise and the second part is called the consequent (inference - result), which is connected by fuzzy rules in the form of a network (Jang, 1993). ANFIS model consist of five layers in which the first layer performs fuzzification, the second layer performs the fuzzy T-norm operation for the premise part of fuzzy rules, the third layer is used for normalization, the fourth layer creates the fuzzy rules of the consequent part and finally the fifth layer calculates the final output of the system.

The ANFIS of the 5-layer network is composed of nodes and arc connector of nodes. The first layer is input data with the degree of membership that is specified by the user. All modeling operations are performed in layers 2 to 4. The last layer is the network output, which aims to minimize the difference between the output obtained from the network and the actual output. Each node in the second layer represents the firing strength for each rule. In this layer, the T-norm operator with general performance, such as the AND, is applied to obtain the output. The appropriate structure of the ANFIS is proportional to the input data, the degree of membership, the rules and functions of the output degree of membership. In the training phase, the optimum values for the membership function parameters are calculated based on the error rate. The forward equations for the network structure shown in Fig. 1 are as follows:

$$w_{jk} = \mu_{M^1{}_j}(x_1).\mu_{M^2{}_k}(x_2) \qquad j,k = 1,2,....,m \tag{1}$$

$$\overline{w_{jk}} = \frac{w_{jk}}{\sum_{i1=1}^{m}\sum_{i2=1}^{m} w_{i1i2}} \qquad j,k = 1,2,....,m \tag{2}$$

$$f_{jk} = q_{0,jk} + q_{1,jk}.x_1 + q_{2,jk}.x_2 \tag{3}$$

In the above equations, μ_M is the degree of membership function for M fuzzy set, w_{jk} represents the firing strength of each rule, $\overline{w_{jk}}$ is the normalized firing strength, m represents the number of assignment functions for each input variable and (q_0,q_1,q_2) are real numbers corresponding to linear weights in the consequent part of the ANFIS system. The final output of the ANFIS network can be calculated as follows:

$$y = \frac{\sum_{j=1}^{m}\sum_{k=1}^{m} f_{jk}\mu_{M_j^1}(x_1)\mu_{M_j^2}(x_2)}{\sum_{j=1}^{m}\sum_{k=1}^{m} \mu_{M_j^1}(x_1)\mu_{M_j^2}(x_2)} = \sum_{j=1}^{m}\sum_{k=1}^{m} f_{jk}\overline{w}_{jk} \tag{4}$$

To model complex nonlinear systems, the ANFIS model divides the input space into different parts. In other words, the input space is divided into abundant local areas. The ANFIS network uses fuzzy membership functions to divide each input dimension. These membership functions are overlapping. In other words, a single input causes simultaneous activation of at least two membership functions. The ANFIS network capability is dependent on the number of membership functions assigned for each input dimension. Usually, the associated membership functions are based on the mind and the experience of individuals. In this paper, the Gaussian bell-shaped function with an interval of [0, 1] is used. This membership function is defined as follows (Zadeh, 1965):

$$\mu_{M_i}(x) = \exp\left\{-\left(\frac{x-\bar{x}_i}{\sigma_i}\right)^2\right\} \quad (5)$$

In the above equation $(\bar{x}_i, \sigma_i)$ are parameters of membership functions. These parameters have a significant impact on the shape of the membership function.

3. Kriging Interpolation

Kriging is probably the most widely used technique in geostatistics to interpolate data. It was formalized in the sixties by a French engineer George Matheron (1963) after the empirical work of Danie G. Krige (1951). Kriging interpolation is a two-step process: first a regression function f(x) is constructed based on the data and a Gaussian process Z is constructed through the residuals (Couckuyt et al., 2013):

$$Y(x) = f(x) + Z(x) \quad (6)$$

Where f(x) is a regression function and Z is a Gaussian process with mean 0, variance σ^2 and a correlation matrix ψ. Depending on the form of the regression function, Kriging has been prefixed with different names. Simple Kriging assumes the regression function to be a known constant, f(x) = 0. A more popular version is ordinary Kriging, which assumes a constant but unknown regression function $f(x)=\alpha_0$. In universal Kriging, more complex trend functions such as linear or quadratic polynomials are used (Couckuyt et al., 2013):

$$f(x) = \sum_{i=1}^{p} \alpha_i b_i(x) \quad (7)$$

Where $b_i(x)$ are i = 1 … p basis functions and $\alpha = (\alpha_1, \ldots, \alpha_p)$ denotes the coefficients. The idea is that the regression function captures the largest variance in the data and that the Gaussian process interpolates the residuals. In fact, the regression function f(x) is actually the mean of the broader Gaussian process Y. However, selecting the correct regression function is a difficult problem, hence; the regression function is often chosen to be constant. Consider a set of n samples, $X = (x^1, \ldots, x^n)$ in d dimensions and associated function values; $Y = (y^1, \ldots, y^n)$ essentially, the regression part is encoded in the n×p model matrix F:

$$F = \begin{pmatrix} b_1(x^1) & \ldots & b_p(x^1) \\ \vdots & \ddots & \vdots \\ b_1(x^n) & \ldots & b_p(x^n) \end{pmatrix} \quad (8)$$

While the stochastic process is mostly defined by the n×n correlation matrix ψ:

$$\Psi = \begin{pmatrix} \psi(x^1, x^1) & \ldots & \psi(x^1, x^n) \\ \vdots & \ddots & \vdots \\ \psi(x^n, x^1) & \ldots & \psi(x^n, x^n) \end{pmatrix} \quad (9)$$

In which $\psi(x^n, x^n)$ is the correlation function. $\psi(x^n, x^n)$ is parameterized by a set of hyper parameters θ which are identified by maximum likelihood estimation (MLE). Subsequently, the prediction mean and prediction variance of Kriging are derived respectively, as:

$$\mu(x) = M\alpha + r(x) \times \Psi^{-1} \times (y - F\alpha)$$

(10)

$$s^2(x) = \sigma\left(1 - r(x)\Psi^{-1} r(x)^T + \frac{\left(1 - F^T \Psi^{-1} r(x)^T\right)}{F^{/} \Psi^{-1} F}\right)$$

(11)

where, $M=(b_1(x), b_2(x), \ldots, b_p(x))$ is the model matrix of prediction point x, $\alpha=(F^T\psi^{-1}F)^{-1}F^T\psi^{-1}y$ is a p×1vector denoting the coefficients of the regression function, determined by generalized least squares (GLS), and $r(x)=(\psi(x,x^1), \ldots, \psi(x,x^n))$ is an 1×n vector of correlation between the point x and the sample X.

4- Error evaluation

In order to analyze the efficiency of the two interpolation models presented in this paper, the observations of the local network of Azerbaijan (north-west of Iran) have been used. Observations of 22 GPS stations are used. Out of 22 GPS stations, 20 stations are considered for training and determining coefficients and 2 stations used for testing the obtained results. The accuracy of the obtained results is evaluated based on the relative error and RMSE as follows:

$$\mathrm{Re} = \frac{\left|V_{\mathrm{mod}\,el} - V_{GPS}\right|}{\left|V_{GPS}\right|}$$

(12)

$$RMSE = \sqrt{\frac{1}{Q}\sum_{q=1}^{Q}\left(V_{\mathrm{mod}\,el}^{q} - V_{GPS}^{q}\right)^2}$$

(13)

Where, V_{GPS} is the velocity values obtained from GPS observations and $V_{\mathrm{mod}\,el}$ is the velocity values estimated from ANFIS and Kriging models.

5- Study area and error analysis

In this paper, the aim is to interpolate the velocity of geodetic points on the Iranian plateau. For this purpose, part of north-west of Iran has been selected. There are several GPS stations in this area. Also, this area is tectonically active and there are many active faults in it. The existence of numerous large and devastating earthquakes indicates the seismicity of this region. For this reasons, the study and analysis of crustal deformation and its displacement is of special importance in this region. Observations of 22 GPS stations in 2007 have been prepared by the Iranian national cartographic center (NCC). The modeling area is between 36^0N to 40^0N and 44^0E to 49^0E. Figure (1) shows the spatial distribution of 22 GPS stations of the Azerbaijan network with their velocity vectors. In this figure, the circles represent the stations used as inputs to the ANFIS and Kriging models, and the red squares represent the test stations.

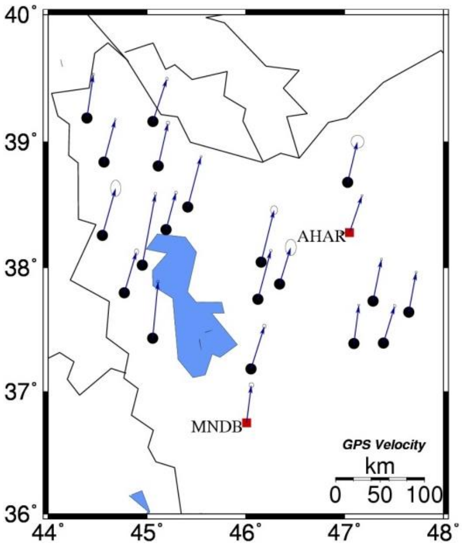

Fig. 1: Distribution of the GPS stations used in this paper (circles represent the GPS stations used for the training of models; red squares represent the test stations). Blue vectors shows the velocity field with 95% error ellipse obtained from GPS processing compared to the Eurasian plane.

Out of 22 stations, 2 stations (AHAR and MNDB) have been selected as test stations. The spatial distribution of these two stations is such that it can provide a correct assessment of the accuracy of the results obtained from the two models. Also in this figure, the velocity vectors in the north-west region relative to the Eurasian plate with an error ellipse of 95% are shown (velocity vectors are calculated by Bernese GNSS software). According to Figure (1), it can be seen that the presented velocity vectors are related to the location of stations in the local network of Azerbaijan. It is important to note that in the absence of a station from a geodynamic network in a particular area, such as near an active fault, it is necessary to use methods that can estimate the velocity field at those points.

The stations used in this paper are divided in two groups: 20 stations are used for training the ANFIS and 2 stations used for testing the results obtained from the models. In the first step, in order to obtain the optimum structure of the ANFIS model, the training is done using the observations of 20 training stations and then the RMSE are calculated. Based on the minimum RMSE in training step, the optimal structure is selected for the ANFIS model. Table (1) shows the results of this study for both the northern and eastern components of the velocity field.

Table 1: RMSE values for training step of ANFIS model and selection the optimal structure.

ANFIS model structure (Input-number of rules-output)	RMSE for the training step (mm/yr)	
	Ve	Vn
2-4-1	0.0194836	0.0235489
2-5-1	0.0078936	0.0081369
2-6-1	0.0060129	0.0063291
2-7-1	0.0084967	0.0087574
2-8-1	0.0095476	0.0109752

Based on the results of Table (1), with the structure of 2-6-1, the value of RMSE for the training step in both the northern and eastern components of the velocity field has the minimum value. Therefore, this structure has been selected as the optimal structure for the ANFIS model.

After the training step of the ANFIS model and selecting the optimal structure for it, in this step, with the trained model, the amount of velocity field in the test stations can be estimated and compared with GPS velocity. In Tables (2) and (3), the velocity field obtained from the ANFIS and Kriging models in the two test stations is estimated and compared with the velocity field obtained from GPS. In other words, the GPS velocity field is considered as the reference.

Table 2: Relative error (%) of ANFIS model in comparison with GPS velocity at the two test stations and for northern and eastern components.

station name	Latitude (deg)	Longitude (deg)	GPS Velocity (m/yr)		ANFIS. Velocity (m/yr)		Relative Error (%) (GPS-ANFIS)	
			Ve	Vn	Ve	Vn	Ve	Vn
AHAR	38.281	47.049	0.0267	0.00904	0.0238	0.00803	10.86	11.17
MNDB	36.745	46.009	0.02736	0.00343	0.0291	0.00251	6.36	26.82

Based on the results of Table (2) in 2 test stations and for the eastern component of the velocity field, the highest relative error is obtained in AHAR test station and it is 10.86%. Also in 2 test stations and for the northern component of the velocity field, the highest relative error is in the MNDB test station and is 26.82%. For better and more accurate evaluation, the results of the Kriging model are compared with the results of GPS velocity and the results are given in Table (3).

Table 3: Relative error (%) of Kriging model in comparison with GPS velocity at the two test stations and for northern and eastern components.

station name	Latitude (deg)	Longitude (deg)	GPS Velocity (m/yr)		Kriging. Velocity (m/yr)		Relative Error (%) (GPS-Kriging)	
			Ve	Vn	Ve	Vn	Ve	Vn
AHAR	38.281	47.049	0.0267	0.00904	0.0313	0.00623	17.23	31.08
MNDB	36.745	46.009	0.02736	0.00343	0.0346	0.00254	26.46	25.95

Based on the results of Table (3) in 2 test stations and for the eastern component of the velocity field, the highest relative error value is obtained in the MNDB test station and it is 26.46 %. Also in 2 test stations and for the northern component of the velocity field, the highest relative error value is in AHAR test station and is equal to 31.08%.

6- Velocity estimation

After evaluating the accuracy of the results of the ANFIS model and comparing it with the results of GPS observations as well as the results of the Kriging model, it is now possible to estimate the velocity field variations in north-west of Iran at any desired geodetic points using two models. Figures (2) and (3) shows the velocity field from the ANFIS model (green vectors) and the Kriging model (red vectors) for the north-west region and is shown in the figure along with the velocity vectors from GPS observations (blue vectors).

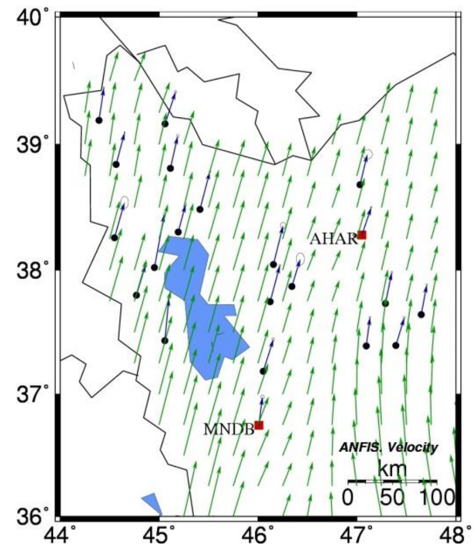

Fig. 2: Estimated velocity field using ANFIS model (green vectors) and comparison with GPS velocity (blue vectors).

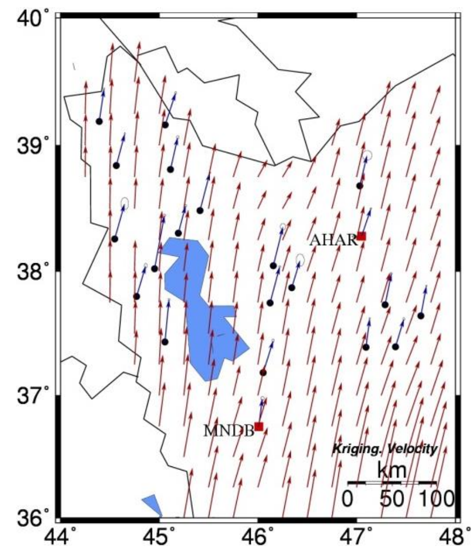

Fig. 3: Estimated velocity field using Kriging model (red vectors) and comparison with GPS velocity (blue vectors).

Based on the results of Figures (2) and (3), it can be clearly seen that GPS velocity vectors are only related to the location of GPS stations and the number of stations in the north-west of Iran is very low (it is a tectonically active region and requires more stations to analyze crustal deformation). As a result, it is very difficult to study the surface deformation of the Earth's crust in the north-west of Iran, especially near active faults. While using ANFIS model, it is possible to model and analyze velocity fields for any specific geodetic point with high accuracy and precision.

7- Conclusion

The main purpose of this paper was to use the adaptive neuro fuzzy inference system (ANFIS) to model the surface displacement field in the north-west of Iran. To do this, GPS observations related to the local GPS network stations of Azerbaijan were used and the velocity fields related to GPS were calculated by Bernese GNSS software after processing. Then these velocity vectors were introduced as the output of the ANFIS model and also the geodetic position of these vectors as the input of the model. However, the observations of the two stations were selected as test stations and were not used in the training step of the ANFIS model. The amount of error in the training step was an important factor in determining the number of fuzzy rules in the ANFIS model. After achieving the optimum number of fuzzy rules as well as the consequent minimum error rate, the trained model is used and the velocity fields in other geodetic points is estimated. Also, for better and more accurate study, the results have been compared with the Kriging model. The type and number of test and training stations in the Kriging model is considered the same as the ANFIS model. In ANFIS model, the averaged relative error computed at the test stations was + 8.61% for the eastern component and + 18.99% for the northern component of the velocity field. For the Kriging model, the relative error calculated at the test stations was + 21.84% for the eastern component and + 28.51% for the northern component. Comparison of the results of both methods indicates the relative superiority of ANFIS mode in estimating the velocity field in the north-west of Iran. It is important to note that in both models, the number and distribution of stations in the results can have a significant impact.

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