Planes coordinates transformation between PSAD56 to SIRGAS using a Multilayer Artificial Neural Network

Alfonso Tierra, Ricardo Romero

Universidad de las Fuerzas Armadas-ESPE
Grupo de Investigación GITE
Av. Gral Rumiñahui s/n. Sangolquí, Ecuador. P.O.Box 171-5-31B
e-mail: artierra@espe.edu.ec; ricardo.vinromero@gmail.com

Abstract: Prior any satellite technology developments, the geodetic networks of a country were realized from a topocentric datum, and hence the respective cartography was performed. With availability of Global Navigation Satellite Systems-GNSS, cartography needs to be updated and referenced to a geocentric datum to be compatible with this technology. Cartography in Ecuador has been performed using the PSAD56 (Provisional South American Datum 1956) systems, nevertheless it's necessary to have inside the system SIRGAS (SIstema de Referencia Geocéntrico para las AmericaS). This transformation between PSAD56 to SIRGAS use seven transformation parameters calculated with the method Helmert. These parameters, in case of Ecuador are compatible for scales of 1:25 000 or less, that does not satisfy the requirements on applications for major scales. In this study, the technique of neural networks is demonstrated as an alternative for improving the processing of UTM planes coordinates E, N (East, North) from PSAD56 to SIRGAS. Therefore, from the coordinates E, N, of the two systems, four transformation parameters were calculated (two of translation, one of rotation, and one scale difference) using the technique bidimensional transformation. Additionally, the same coordinates were used to training Multilayer Artificial Neural Network -MANN, in which the inputs are the coordinates E, N in PSAD56 and output are the coordinates E, N in SIRGAS. Both the two-dimensional transformation and ANN were used as control points to determine the differences between the mentioned methods. The results imply that, the coordinates transformation obtained with the artificial neural network multilayer trained have been improving the results that the bidimensional transformation, and compatible to scales 1:5000.

Keywords: PSAD56, SIRGAS, Bidimensional transformations, Artificial Neural Network.

1. Introduction

With the development of global navigation satellite systems-GNSS all type of information of a territory has to be transformed into a new geodetic reference system to be compatible with satellite technology. With seven transformations parameters

cartesians coordinates are transformed between two references a geodetic systems topocentric to geocentric.

Latin American countries are adopting SIRGAS as official system, in order to be compatible with satellite technology such as GPS (Global Positioning System). Several works were realized to perform the transformation between systems such as the method of Helmert using cartesian coordinates (Seeber, 1993), as well as using planes UTM coordinates (E, N), by calculating coefficients of polynomials (Hussein, 1994), also using geodetic coordinates by least squares collocation (You and Hwang, 2006), finally using an artificial neural network trained for the transformation between cartesian coordinates or transformation between geodetic coordinates (Tierra, et.al, 2008), (Tierra, et.al, 2009) .

The existence of cartographic information in digital format in some countries of South America is referred to the classical system such as PSAD56 (Provisional South American Datum 1956) and must be transformed this type of cartography to a geocentric system such as SIRGAS (Sistema de Referencia Geocéntrico para las AmericaS). The parameters transformation used in Ecuador are compatible for scales of 1:25000 or less, that does not satisfy the requirements on applications for major scales. This paper demonstrates the technique of artificial neural networks as a method to transform between planes coordinates East and North (E, N) referred to PSAD56 to (E, N) referred to SIRGAS.

2. Bidimensional transformation

The bidimensional transformation also known as two-dimensional conformal transformation is a derivation of the Helmert method used to plane coordinates, in this case East and North. This transformation consists of four calculated transformation parameters, being two translations, one rotation, one scale difference (Cai and Grafarend, 2009). In equation (01) the mathematical model is showed for this transformation.

$$\begin{bmatrix} E_S \\ N_S \end{bmatrix} = \begin{bmatrix} T_E \\ T_N \end{bmatrix} + (1 + \delta) * \begin{bmatrix} cos\omega & sin\omega \\ -sin\omega & cos\omega \end{bmatrix} * \begin{bmatrix} E_P \\ N_P \end{bmatrix} \qquad (1)$$

where:

(E_S, N_S) − are planes coordinates referred to PSAD56

(E_P, N_P) − are planes coordinates referred to SIRGAS.

ω − is rotation angle.

δ − is scale difference.

T_E − is translation in East

T_N − is translation in North

3. Artificial neural network-ANN

The ANN was conceived from the observation of the human brain behavior in comparison with digital computers (Yilmaz and Akhmet, 2014). Even nowadays, when digital computers execute several millions of operations per second, the human brain is able to perform most of the parallel tasks more efficiently than computers. The reason is its ability in activating millions of neuron-cells simultaneously and the flexibility of algorithms in the human brain. Therefore, it is reasonable o conduct that the human brain is a non-linear complex parallel structure that is able to process and operate information stored in the connections between neurons (Haykin, 2001).

Figure 1 reflects its showed a similitude between a biological and artificial neuron. An Artificial Neuron (AN) is a logic mathematic structure that tries to emulate the functions and behavior of a biologic one. An input layer whose links with the artificial cell body are made by connection weights develops the actions of dendrites. These weights correspond to the synapses in biologic cells. Additionally, each of the neurons is associated with a bias weight.
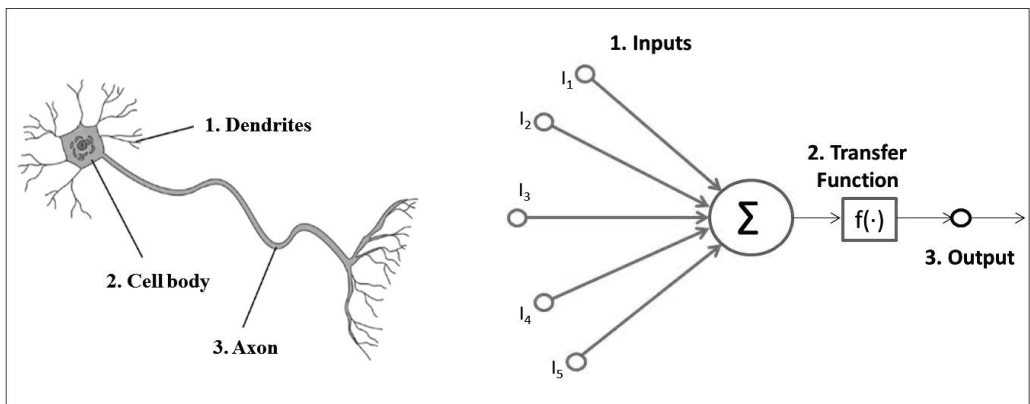

Fig. 1. Biological and artificial neuron

Inside each neuron (Figure 2), a weighted sum of the inputs is calculated, a bias weight is added, and this value is transformed by a transfer function that permits to limit the output signal in a finite interval. The transformed result is sent to neurons in the next layer.
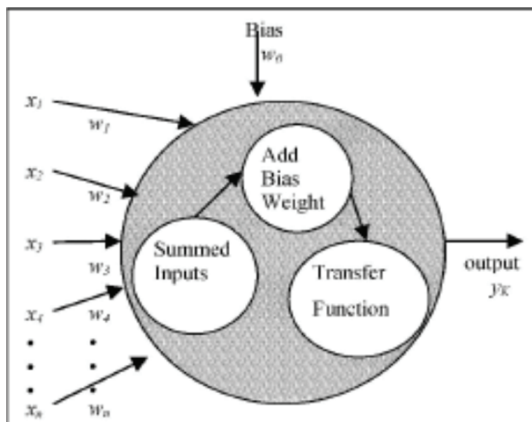
Fig. 2. Artificial neuron
Source: (Tierra, et. al., 2009)

Later, an AN structure can be modeled in the following way (Haykin, 2001), (He and Xu, 2009):

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

where:

x_i – are the input signals;

w_i – are the connection weights from the previous layer of neurons;

w_0 – is the bias weight that corresponds to an additional independent input in an ANN.

The result from equation 02 is applied in a transfer function $f(S)$ that gives an output Y_k according the model:

$$Y_k = f(S) \tag{3}$$

The activation function determines the amplitude of the signal coming from the previous layers of the neural network, the same that is responsible for activating or deactivating the signal that is being issued to subsequent layers of the network. Although many different functions could be successful transfer function, usually a differentiable and bounded function is used (Haykin, 2001). The used transfer functions in this study were the linear (equation 04)

$$f(S) = S \tag{4}$$

and the hyperbolic tangent (equation 05)

$$f(S) = \frac{e^S - e^{-S}}{e^S + e^{-S}} \qquad (5)$$

3.1. Multilayer Artificial Neural Network – MANN

The usual Multilayer Artificial Neural Network form (MANN) permits only backward and forward flux, with different forms of connection. The MANN with supervision and training by an algorithm called back-propagation has been developed in the 1980s, and were used to solve successfully several problems. The neurons in an MANN are connected with all the neurons of neighbor layers but without connections in the same layer.

An MANN is formed by three kinds of layers (Figure 3): **Input layer** formed by *n* input units with the function of distributing the external signals to the next layer; **Hidden layer** formed by the processing elements (neurons) without external contacts. The number of hidden layers is not dependent on the ANN type, but from the problem to be solved; **Output layer** is singular and formed by *m* processing elements (neurons) from that emerge output vectors to form the output of the MANN. This kind of structure with progressive signal flux without direct or indirect lateral connections is called feed forward (Krasnopolsky, 2013).
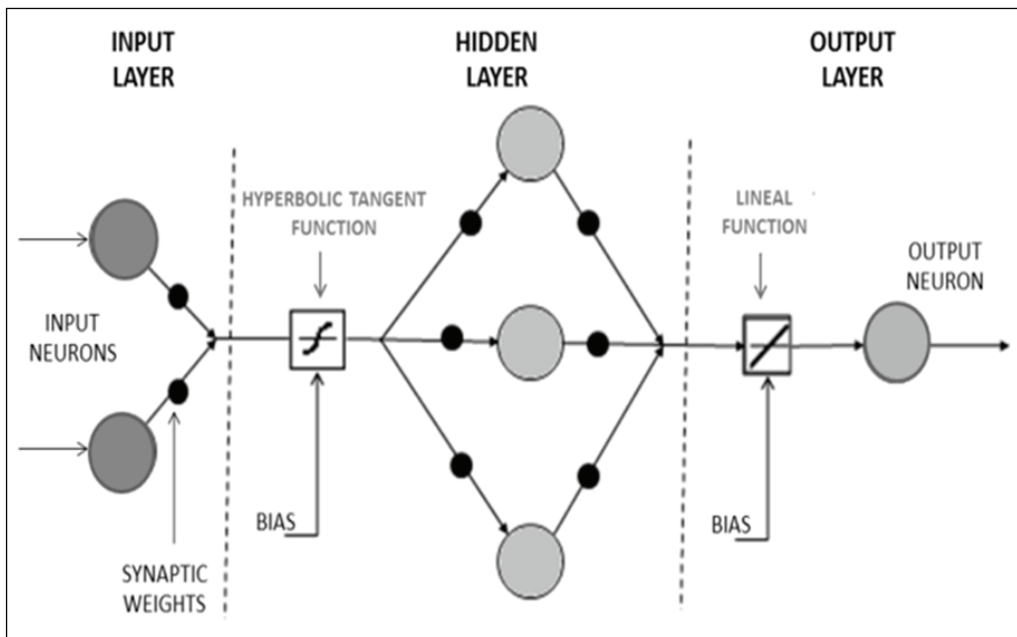

Fig. 3. Multilayer Artificial Neural Network

The MANN is trained by using an algorithm called back-propagation that is based on learning by error correction (Haykin, 2001). The backpropagation is used as base for supervised learning. In this sense, it is necessary to have input data for training and output reference data as basis for controlling the connection weights. In synthesis, the learning by back-propagation consists in finding adequate weights to solve the problem.

The error (ε) in the output layer of a neuron j is given by:

$$\varepsilon_j = d_j - y_j \tag{6}$$

where:

d_j – is the value ideal
y_j – is the obtained value in output neuron

The training process is made iteratively until one obtains the cost function MSE (Mean Square Error) is a minimum, given by:

$$MSE = \frac{1}{M} \sum_{k=1}^{M} \left(\frac{1}{2} \sum_{j=1}^{nn} \varepsilon^2 \right) \tag{7}$$

where:

nn – is the number of neurons in output layer
M – is the total number of samples

Then:

$$\frac{\partial MSE}{\partial w_i} = 0 \tag{8}$$

Where, w_i is the connection weight between neurons

That is, it is necessary to solve a numerical optimization problem, to minimize the cost function with respect to the weight vector (w). The class of unconstrained optimization algorithms used for neural network training was the Levenberg-Marquart

4. Test

The study zone has been in an area of the city of Quito with available digital cartography with planes coordinates east (E) and north (N), both referred to as the SIRGAS and PSAD56. For calculating bidimensional transformation parameters, the coordinates E, N were obtained from the digital map at the four corners, as seen in Table 1, and the parameters calculated are showed in the Table 2.

Table 1. Points coordinates to calculate the transformation parameters

Coordinates E,N referred in PSAD56		Coordinates E,N referred in SIRGAS	
EAST (m)	NORTH (m)	EAST (m)	NORTH (m)
501500	9982800	501263.3395	9982432.4923
503900	9982800	503663.3139	9982432.4943
503900	9981600	503663.3084	9981232.5010
501500	9981600	501263.3340	9981232.4988

Table 2. BIDIMENSIONAL transformation parameters

Parameters	Value	Standard deviation
Translation East	-234.00 m	±15.024 m
Translation North	-271.23 m	±15.024 m
Rotation angle	0.0447 "	±0.3101"
Scale Difference	-9.6 ppm	±1.5 ppm

In order to train MANN 77 points were used from digital cartography coordinates E, N referring to SIRGAS (see Figure 4) and they were divided into three data sets as follows:
− 38 points for network training (triangle)
− 20 points for network validation (cross)
− 19 points determine the generalization of the network (circle)

Fig. 4. Distribution of the points for the training of the ANN

The artificial neural network used for the training was a multilayer. Several training were made, by changing the number of neurons and the transfer function in the hidden layer, and in the output layer the transfer function. The MANN structure trained was a [2_8_2] (Figure 5); i.e. two coordinates planes (E,N) referred to PSAD56 in the input layer; eight neurons in the hidden layer with hyperbolic tangent transfer function according to the equation (05); and two neurons in the output layer with the linear transfer function , according to the equation (04), and the outputs of the network were the two coordinates planes (E,N) referred to SIRGAS.
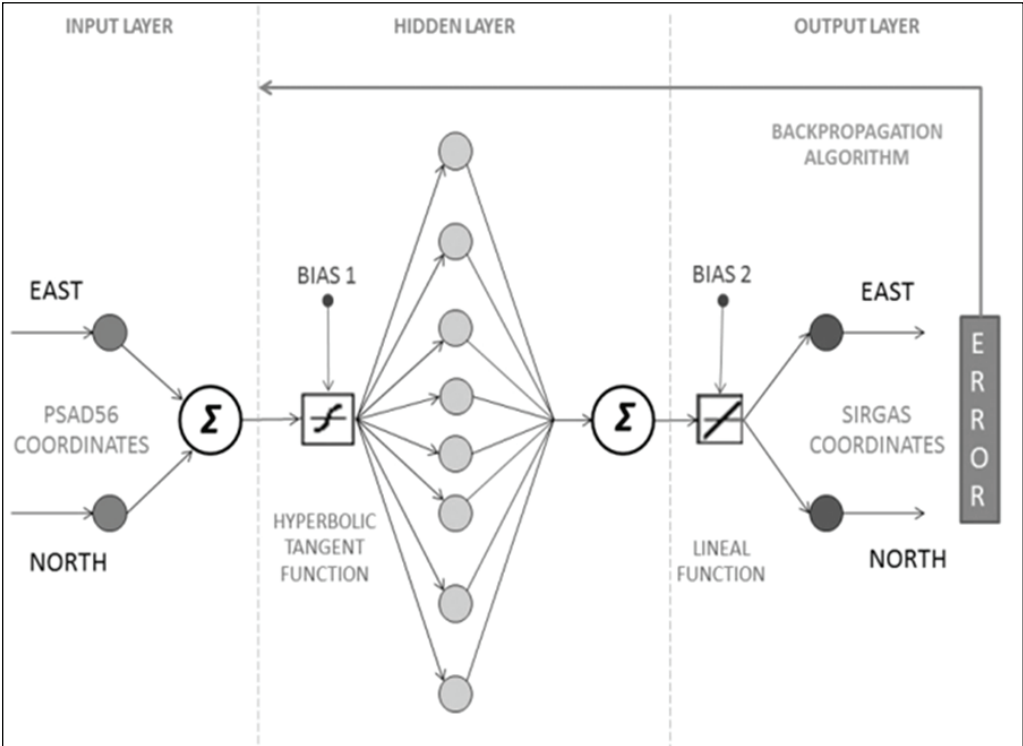

Fig. 5. Structure of the MANN trained

5. Results

For the evaluation of both techniques the checkpoints to determine the respective differences have been used. Using the equation (01) and the transformation parameters calculated in Table 2 the coordinates (E,N) referred to SIRGAS were obtained. Similarly, transformation MANN trained according to the figure (5) has been realized. The results obtained with the two methods are showed in Table 3.

Table 3. Errors obtained with transformation parameters and artificial neural network multilayer

Variable	Results with Transformation Parameters	Results with a MANN
Mean (m)	0.806	0.705
Standard deviation (m)	1.238	0.534
Minimum difference (m)	0.003	0.035
Maximum difference (m)	3.300	2.436

According to table 3, the mean of the errors obtained with MANN are lower that obtained with transformation parameters, and the standard deviation improvement in more than 100% approximately. The interval of the error with transformation parameters has been 3.3 m and the MANN 2.4 m , approximately. Figure 6 indicates the error vectors obtained with MANN in which it is demonstrated that in most points the error is less than 1.5 m in black color, and only six points the errors are higher than 1.5 m in gray color

Fig. 6. Errors vector of the points with MANN

6. Conclusions

With the results obtained the conclusions are summarized as follows:
– Using the technique of multilayer artificial neural networks improving the transformation between planes coordinate systems related to two different systems.

- The results demonstrate than the ANNM technique allow to transform the digital cartography from classic network (topocentric) to modern network (geocentric).
- Using trained ANNM is possible to transform the digital cartography compatible to 1:5000 scale

Acknowledgments

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Transformacja współrzędnych płaskich pomiędzy PSAD56 to SIRGAS z wykorzystaniem wielowarstwowej sieci sztucznej inteligencji

Alfonso Tierra, Ricardo Romero

Universidad de las Fuerzas Armadas-ESPE
Grupo de Investigación GITE
Av. Gral Rumiñahui s/n. Sangolquí, Ecuador. P.O.Box 171-5-31B
e-mail: artierra@espe.edu.ec; ricardo.vinromero@gmail.com

Streszczenie

Dostęp do nowoczesnych technologii, w tym GNSS umożliwiły dokładniejsze zdefiniowanie systemów odniesień przestrzennych wykorzystywanych m.in. w definiowaniu krajowych układów odniesień i układów współrzędnych. W Ekwadorze wykorzystywany jest system PSAD56 (Provisional South American Datum 1956), ale w ostatnim czasie zaszła konieczność zdefiniowania wewnętrznego(krajowego) systemu SIRGAS (SIstema de Referencia Geocéntrico para las AmericaS). Do transformacji pomiędzy oboma systemami powszechnie wykorzystuje się metodę Helmerta, stosując układ siedmioparametrowy. Transformacja taka pozwala na zachowanie dokładności wystarczającej do opracowania map topograficznych w skalach 1:25 000 lub mniejszych. W artykule do transformacji zastosowano sieci neuronowe, co umożliwiło podniesienie dokładności do skali 1:5 000.