RECTIFICATION OF REMOTELY SENSED IMAGES WITH ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Raw digital images can not be used as maps because they contain geometric distortions which stem from the image acquisition process. To supply the same geometric integrity as a map, original raw images must be geometrically corrected and the distortions, such as variations in altitude, and earth curvature, must be compensated for. There are two techniques that can be used to correct the various types of geometric distortions present in digital image data: one is orbital geometry modelling and the other one, rather used in many image processing, is the transformation based on ground control points.

In the last few years there has been a significant resurgence of interest in using artificial neural network algorithms for different image processing procedures. In this study besides the conventional image processing procedures, an artificial neural network algorithm for the rectification of the SPOT- P image of the study area in □stanbul was developed and applied for generating both new grids and corresponding brightness values. The rectification results were compared with those from the polynomials, and their merits and weakness were addressed.

1 INTRODUCTION

When image data is recorded by sensors on satellites and aircraft, it can contain errors in geometry and in the measured brightness values of pixels. The latter are referred to as radiometric errors and can result from the instrumentation used to record the data and from the effect of the atmosphere. Image geometry errors can arise, for example, from the curvature of the earth, uncontrolled variations in the position and attitude of the platform, and sensor anomalies.

Before using an image, it is frequently necessary to make corrections to its brightness and geometry. There are essentially two techniques that can be used to try to minimise these geometric distortions. One is to model the nature and magnitude of the distortion and thereby establish a correction, the other is to develop a mathematical relationship between the pixel coordinates on the image and the corresponding points on the ground (Richards, J.A., 1986; Lillesand, T.M., Kiefer, R.W., 1987; Janssen, L.L.F., Van Der Wel, F.J.M., 1994). The latter can be done with Artificial Neural Network (ANN) algorithms which are being applied to a number of image processing procedures recently.

The objective of this study was to investigate the effeciency of the artificial neural network algorithm designed for the rectification of the SPOT-P image of the Haliç region, □stanbul, and evaluate rectification accuracy by comparing with the results obtained from the conventional rectification algorithm and ground-based reference data.

2 APPLICATION

2.1 Study Area and Material Used

SPOT P image data collected on 22 July 1998, of the Haliç region, □stanbul (Figure 1), was used in the analysis. The image was obtained in the 10 m resolution "panchromatic" mode which has a spectral range of 0.51 to 0.73 µm using the SPOT (HRV) imaging system. The test site, also called the ‘historical peninsula’, covers mostly urban areas and a portion of the Haliç Bay. This area was selected because it contained lineer details such as buildings, land parcels, roads commercial/industrial services.

Figure 1. Study area.

2.2 Methods

Conventional rectification algorithm, depends upon establishing mathematical relationship between the locations of pixels in an image and the corresponding coordinates of those points on the ground (via a map) for "random distortions" and "residual unknown systematic distortions". To interrelate the geometrically correct (map) coordinates and the distorted image coordinates, a coordinate transformation is performed by applying a least-squares regression analysis to the set of ground control points (GCPs) and determining the coefficients of the transformation matrix for linear or non-linear transformations. After calculating the transformation coefficients, various resampling methods such as nearest neighbour, bilinear or cubic convolution can be used to determine the pixel values to fill into the corrected output image file from the original distorted image file.

Artificial neural networks can be seen as highly parallel dynamical systems consisting of multiple simple units that can perform transformations by means of their state response to their input information. How the transformation is carried out depends on the ANN model and its way of learning the transformation. There are many neural networks, such as Radial Basis Function (RBF), MultiLayer Perceptron (MLP) which are well suited to applications such as pattern discrimination and classification, pattern recognition, interpolation, prediction and forecasting, and process modelling. (Bischof, H., W. Schneider, W., Pinz, A.J., 1992; Foody, G.M., 1995; Heerman, P.D., Khazenie, N., 1992) Among them, the RBF network is a popular alternative to the MLP which although it is not as well suited to larger applications, can offer advantages such as easily being trained, over the MLP in some applications. The RBF network has a similar form to the MLP in that it is a multi-layer, feed-forward network. However, unlike the MLP, the hidden units in the RBF are different from the units in the input and output layers in a way that they contain the "Radial Basis Function", a statistical transformation based on a Gaussian distribution. As seen in the Figure 2 the basis function is a curve (typically a Gaussian function) which has a peak at zero distance and which falls to smaller values as the distance from the centre increases. As a result, the unit gives an output of one when the input is "centred" but which reduces as the input becomes more distant from the centre (NCTT, 1998).

In the hidden layer of an RBF, each hidden unit takes as its input all the outputs of the input layer **xi**. The hidden unit contains a "basis function" which has the parameters "centre" and "width". The centre of the basis function is a vector of numbers **ci** of the same size as the inputs to the unit and there is normally a different centre for each unit in the neural network. The first computation performed by the unit is to compute the "radial distance", **d**, between the input vector **xi** and the centre of the basis function, typically using Euclidean distance:

$$\mathbf{d = SQRT\ ((x^1 - c^1)^2 + (x^2 - c^2)^2 + \ldots\ (x^n - c^n)^2)} \quad (1)$$

The unit output **a** is then computed by applying the basis function **B** to this distance divided by the width **w**:

$$\mathbf{a = B(^d/_w)} \quad (2)$$

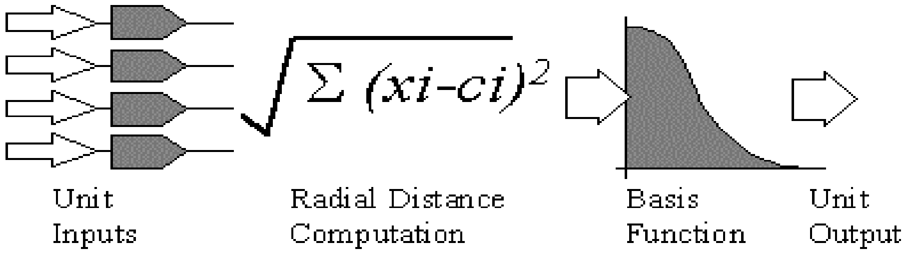

Figure 2. The RBF network sheme (NCTT, 1998).

The output layer of an RBF neural network is essentially the same as for the MLP. Normally it has a linear activation function, making it possible to calculate the weights for those units directly. However, if the output units have non-linear activation functions, then iterative training algorithms must be used.

The advantage of the radial basis function network is that it finds the input to output map using local approximators. Since linear combiners have few weights, these networks train extremely fast and require fewer training samples (NCTT, 1998).

3 APPLICATION AND RESULTS

In the conventional rectification process, the SPOT-P image of the test site was registered to the UTM (Universal Transverse Mercator) map projection system with 1: 25 000 topographical maps. As a first stage in the rectification process, 30 easily identifiable control points were selected and both their image and map coordinates were determined. The GCPs were chosen so as to represent the most uniform distribution possible (Figure 3). The second stage was to calculate the unknown coefficients for the first and second order polynomial equations. A least squares estimation was used to determine a affine transformation of best fit between the co-ordinates. The Root Mean Square (RMS) error for the image was selected in different levels (±1 and ±0.5 pixel) in the x and y direction and was reduced to an selected level by removing the GCPs with the highest RMS error (Table 1). Finally the resampling of the image using a cubic convolution technique was applied to image data.

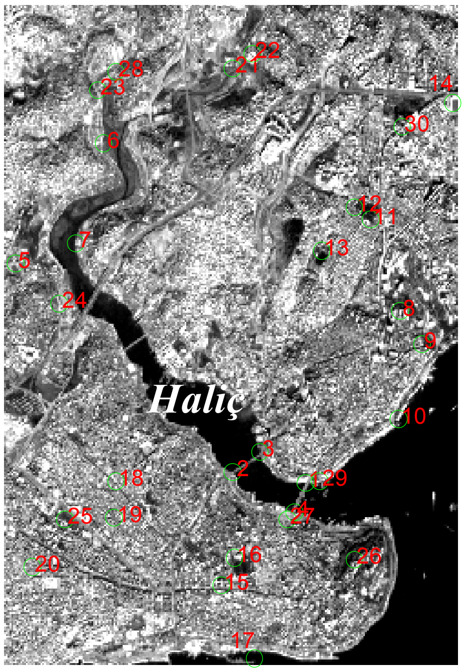

Figure 3. The GCPs used in the study area.

	RMS error	
	0.5 pixel	**1 pixel**
1st degree	8	19
2nd degree	11	21

Table 1. Number of GCPs used in the transformations.

In the ANN rectification process, image file coordinate system was converted to UTM system with Radial Basis Function. Then, bicubic interpolation algorithm was selected as an resampling techniques. In this step, 16 pixel values surrounding each target pixels calculated with inverse function, were determined with a two dimensional 3rd degree function. The brightness value obtained for each target pixel from surrounding 16 pixels using bicubic interpolation was calculated using with neigbouring 4 pixels of the target pixel by MLP backpropagation network structure. The network architecture used consists of 6 input units, 18 first hidden units, 9 second hidden units, and 1 output units. Input layers was formed with neigbouring 4 pixel values and coordinate offset values of target point. Output layer consists of brightness values obtained bicubic interpolation. The result is given in Figure 4.

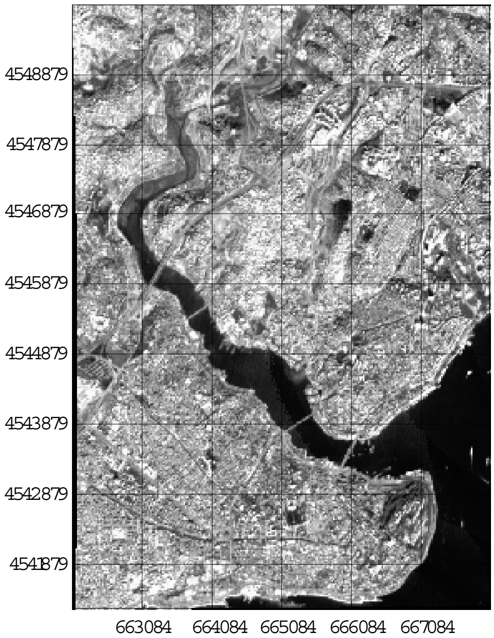

Figure 4. Rectified image of the study area by using ANN.

As rectification process creates reference to real world features and points, this allows user for an accurate representation of the features portrayed and the calculation of measurements, such as distance, or surface area. For comparisons of the results, length of the one of the bridges in the area, the Unkapan□ Bridge, was taken as an reference data (Figure 5).

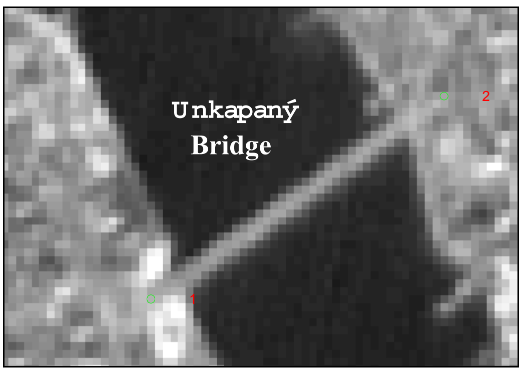

Figure 5. Reference data used.

Table 2 gives the calculated lengths of the Unkapan□ bridge from different methods used. As it can be seen from the table that some errors are predictable due to being dependent upon several factors, i.e. analyst precision (homogeneity of selected GCPs, pointing precision of GCPs, etc.) and hard copy map quality (scale, projection type, etc.) (Sunar, F., Kaya, □., 1997). In general, the use of second order polynomial equations are found to provide a more accurate transformation than first order equations. However as may seen in this study, the errors were quite harmonies in all methods and it was thought that they were also reasonable good (less than 1 pixel).

Reference bridge length : 454 m				
	with RMS **±1** piksel	**Error (m)**	with RMS **±0.5** piksel	**Error (m)**
Conventional 1st degree	461.255	-7.255	461.489	-7.489
Conventional 2nd degree	461.630	-7.630	462.694	-8.694
ANN	461.258	-7.258	462.697	-8.697

Table 2. The calculated lengths and associated errors.

4 CONCLUSION

Conventional rectification of remote sensing imagery is commonly based on polynomial functions. In this study the ANN techniques with different topological design strategies were examined for simulating the geometric rectification process. The rectification results were compared with one reference data, and each of the methods merits and weakness were addressed. It was seen that result from NN rectification process was quite harmonious with that calculated through conventional remote sensing method.

Future improvements will include the use of any additional network or GPS coordinates in the registration step to compare and assess their effects on accuracy.

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