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HIGH RESOLUTION SATELLITE IMAGERY GEOMTRIC CORRECTION USING DIFFERENT NEURAL NETWORKS TECHNIQUES

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ملخص البحث:

تعد الصور الفضائية عالية الدقة التحليلية من أهم مصادر المعلومات الجغرافية من حيث سهولة الحصول عليها وقلة تكلفتها نسبيا. تم إستخدام النماذج الرياضية المختلقة للشبكات العصبية لدراسة تحسين التصحيح الهندسي للصور الفضائية عالية الدقة التحليلية. تمت الدراسة بواسطة إجراء تطابق للصورة الفضائية لمنطقة الدراسة مع صورة جوية رقمية مقومة عموديا ومصححة لإستنتاج نقاط مرجعية أوتوماتيكيا ويتم تصحيح أرتفاعاتها بواسطة نموذج مجسم لسطح الأرض عالي الدقة مستنتج من التصوير الجوي. أستخدمت النقاط المستنتجة لتدريب نماذج مختلفة للشبكات العصبية لإستخدام هذه الشبكات بعد تدريبها في أستنتاج نقاط مرجعية موزعة علي شبكة متساوية المسافات ودراسة تأثيرها علي عملية التصحيح الهندسي. وجد أن إستخدام النموذج الرياضي للمعادلات السينية المنطقية في نقل الأشارة داخل الشبكة العصبية يؤدي إلي تحسين الدقة وتخفيض الأخطاء إلي 67% عنها عند أستخدام نماذج أخري.

Abstract

High resolution satellite images (HRSI) has become an easy and cheaper source of geographic information data. This paper presents a different neural networks techniques to improve geometric correction of the HRSI. In order to compare different neural networks techniques used, a satellite imagery matching with digital geometrically corrected ortho-photo using the automatic ground control extraction (AGE) technique. Matched points are ortho-corrected. Then, a downward Multi-layer perceptron neural networks technique is used with different transfer functions in the process of network training. The different trained networks was used in predicting ground coordinates of a set of previously observed ground check points. The study led to an improvement of the accuracy by reducing the error by 67% of the error generated when using logical sigmoid transfer function.

Keywords: Geometric Correction, Ortho-rectification, High Resolution Satellite Imagery, Artificial Neural Networks.

1_Introduction

Satellite imagery data ortho-rectification is a basic operation in any remote sensing application. Commercial satellite images are not delivered with detailed technical information about the satellite platform location and sensor orientation during data acquisition to be used as the rigorous model inputs. One of the Non-parametric models used in geometric correction of the satellite data is the 3D rational function model (RFM) [Dowman and Tao [1]]; [Grodecki and Dial [2]]; [Tao et al. [3]]; [Fraser et al. [4]]; [Toutin, [5]]. It is considered the most commonly used algorithm in almost all satellite image data commercial ortho-rectification software packages [Dawmen and

Tao [6]]. RFM coefficient are extracted using automatically generated GCP's from (AGE) Gianentto et al. [7] Although linearized form of the RFM algorithm leads to good planimetric accuracy, it is affected by numeric instability due to the GCP number and distribution. Recently, technique of multi-layer perceptron neural network were introduced (MLP) Gianennto [8]. The neural network approach leads to a lower geometrical accuracy, but it is characterized by a higher numerical stability Gianennto et al. [9]. Different neural networks transfer functions will be used to enhance the final geometric accuracy of the ortho-rectified satellite image.

2 Neural Networks Model

The Neural Networks is a mathematical non-parametric model in which we implement a group of mathematical methods as a cumulative flow of information in each unit of the network called neuron. The model is designed as a simulation of the cerebral biological activities. Neurons in the input layer are responsible for receiving input information, neurons in the output layer are responsible for returning output answers and the rest are distributed in hidden layers to be responsible of solving the network. The two different neural networks learning methodologies classification are Unsupervised and Supervised Learning techniques. In this paper we used supervised learning technique in which, input-output mapping processes deploying the theory of network synaptic weight modification. This can be achieved by training a set of samples in which, each sample has a unique input signal and a known corresponding output signal.

There are some famous supervised learning neural networks algorithms, and are used for a various kinds of applications. The algorithm selection and its functions are dependent on the application. Multi-Layer perceptron algorithm has been deployed in the field of geometric correction of satellite imagery [11] in a way that, input-output mapping between satellite image coordinates (u, v) and ground coordinates (X, Y, Z) are achieved through multi perceptron neural network of GCP's.

Communication channels between neurons are responsible for signal transfer. Each neuron responds with a signal using a transfer function according to the signals from the connected neurons. Communication channels are responsible for adding weight to the signals according to their intensity. The response signal s of a neuron i can be expressed as in eq. (1).

$$s_i = f(\sum_{j=1}^{n} w_{ij}\ p_{ij} + b_i)\ \ldots (1)$$

Where:

f is the transfer function which in most cases hyperbolic function eq. (2) or logical sigmoid function eq. (3).

$$f(x) = \frac{1-e^{-x}}{1+e^{-x}} \quad (2)$$

$$f(x) = \frac{1}{1+e^{-ax}} \quad (3)$$

W_{ij} are the weights, pij are the input of the neurons (N) and bi are scalar additives, called bias. In order to solve the network is achieved through determination of the network parameters which consists of the weights and the biases of the hidden and output neurons. Network training function is defined as the process which assumes weight values that minimizes the performance function such as Error Back-Propagation function (4)

$$PF(w(t)) = \sum_{p=1}^{p}\sum_{k=1}^{k}(d_{kp} - f_{kp})^2 = E(t)^T E(t)$$

Where, W(t) = [w1, w2, … . . , wN]T is the weight vector of the network at epoch t, t expresses the epochs counts of the training process. Epoch's number is fixed by the operator. dkp is the expected value of the kth output relative to the pth training pattern. fkp is the value of the kth output calculated by the network.

$$E_{kp} = (d_{kp} - f_{kp}), \quad k = 1, \dots k \;, p = 1, \dots p$$

E_{kp} is the cumulative error of a batch training.

A neural networks iterative solution routine was written by the authors using MATLAB r2015 Neural Network toolbox. A designed down-ward projection of input-output Network mapping was implemented. Using satellite image coordinates (u, v) as an input, while the output has been expressed in terms of ground coordinates (X, Y, Z). A sub-routine was written Using MATLAB performance test calculator to obtain the optimum number of neurons that drive best network performance. Four hidden layers have been used and an output layer. Two different neurons' signal transfer functions were used by the training function of the network. The first transfer function used was hyperbolic tangent function (2), while logical sigmoid function (3) was used later. The number of parameters (Weights and Bias) to be solved by the network computed with respect to the training pattern number can be compared with the final number of neurons in the hidden layers [12] Progressive increment of the difference between residuals of photo control points and the residuals of check points can be used to monitor the over-fitting phenomena.

3. Application and Case study

A 132 square kilometers QuickBird satellite data for an area covering Fayed and Abu-Sultan on the Suez gulf was geometrically corrected using Multi-layer perceptron networks using two different transfer functions in a back-propagation technique described in the previous section and tested against previously observed 9 check points and the results is reported in the following section.

3-1 Dataset preparation

The experimental work took place in the area of Fayed and Abo-Sultan on the west coast of Suez gulf, where the following data were collected:

1) Distributed 45 ground GPS stations over the area of interest was divided into 39 control points and independent 9 checkpoints. The control and the checkpoints were collected with root mean square error in X, Y and Z of 0.037 meters, 0.040 and 0.052 meters respectively.
2) Aerial imagery with ground resolution 25 cm covering an area 12.5 X 14 km in the same area of interest was captured using Leica Ads80.
3) A bundle block adjustment of the captured aerial imagery was done using 36 gcp's and checked against 9 independent observed check points distributed as in (Fig : 1) with root mean square error in X,Y and Z of 0.261, 0.313 and 0.556 meter respectively (Table:1).

4) A 0.5 meter ground resolution orthophoto was produced.
5) A 0.5 meter ground resolution dense digital terrain model DDTM was produced.
6) The same area of the aerial imagery data was captured using QuickBird sensor of 0.62 meter ground resolution.

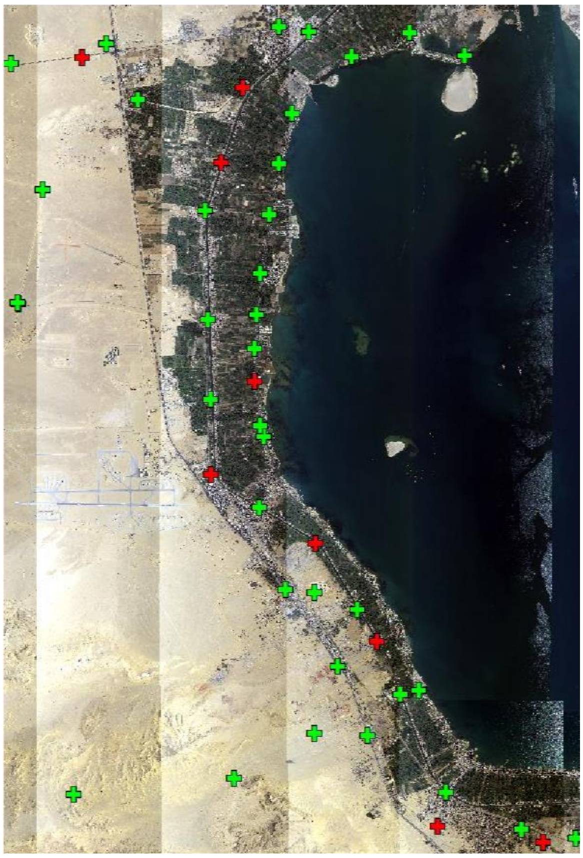

Figure 1. Ortho-Photo of the study area deduced from LiecaADS80 Camera system showing Distribution of (36) ground control points and (9) check points.

Table 1. Accuracy assessment of Block adjustment check points errors and root mean square errors.

PointID	Err_X Meters	Err_Y Meters	Err_Z Meters
14	0.013	-0.086	-0.634
16	-0.752	-0.160	-0.951
18	-0.034	0.012	-0.807
20	0.153	-0.618	0.623
22	-0.347	-0.180	-0.200
32	-0.392	0.270	-0.548
34	-0.330	-0.741	-0.326
36	-0.460	-0.471	-1.179
39	-0.358	-0.544	-1.342
Mean	-0.279	-0.280	-0.596
RMS	0.261	0.313	0.556

3-2 Methodology and Applications

RFM model has an acceptable planimetric accuracy but, it is affected by the distribution of GCP's [13]. Irregular distribution of GCP's can only compensate errors locally and leads to improper distributed distortion over the whole output ortho-rectified satellite data, [14]. In order to achieve a proper distribution of GCP's, a methodology has been adopted to replace the ground observed GCP's in which an automatic ground control extraction model (AGE) [15] is used to identify photo control points from the satellite data by matching with the preset ortho-photo. Extracting elevation of the control points from the DDTM, produces non-regularized full control points. The non-regularized control points are then used as an input of the neural networks model to extract regularized full control points. Applying neural networks different transfer functions. Conventional RFM model and neural networks model were implemented to achieve final geometric correction. The process took place on a 0.62m ground resolution QuickBird satellite scene according to the applied workflow in (fig: 2). The aerial ortho-photo was used in the (AGE) with a criteria of correlation acceptance (L> 90%) resulting in an automatic detection of 572 photo control point and a DDTM to add elevation data of the chosen points. The ortho-corrected points has been used to detect Geometric correction parameters of the conventional (RFM). The same set of points were used to solve the designed neural networks parameters. The results of two methods of geometric correction have been checked against the same 9 independent checkpoints that were used to check the aerial block adjustment, and the results have been reported.

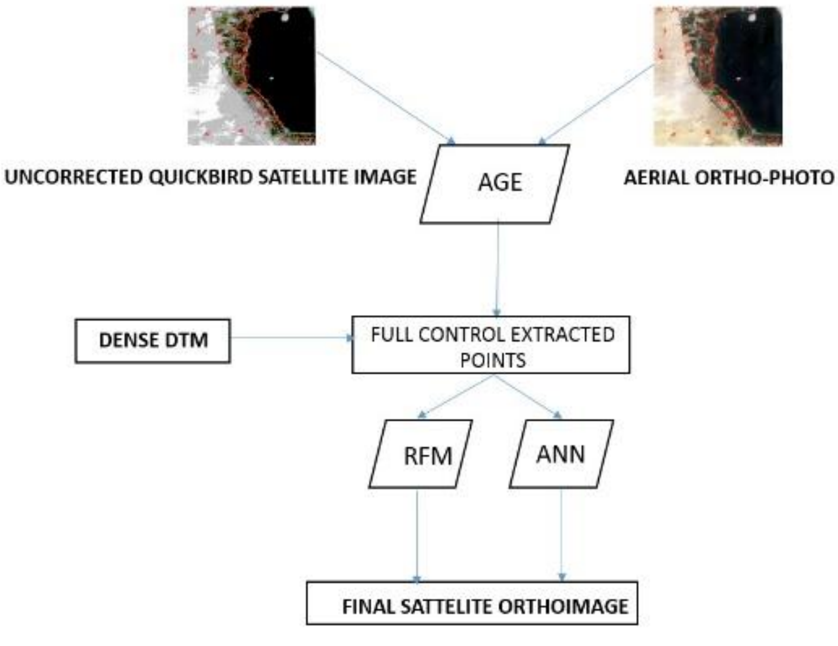

Figure2. Workflow of the geometric correction procedure of the quickbird satellite data of the area of Fayed and Abu-soltan

4. Satellite Data Ortho-rectification

Ortho-rectification has been processed by two different procedures. First one was conventional, RFM model in ERDAS IMAGINE 2011 software using ground control points deduced from the AGE process. The Second procedure was non-conventional procedure through a developed software by the authors using the same ground control points to train a Multi-Layer Perceptron Neural Networks (MLP-NN) in order to solve network parameters. Different training and transfer functions were used. A designed function based on the aimed number of parameters was applied to prevent over-training of the network.

The two methods were tested using chosen fixed 9 checkpoints.

5. Analysis and Results

Geometric correction achieved of the QuickBird satellite data of the test area using RFM and neural networks methods was analyzed. Former research discussed number and distribution of control points using conventional and non-conventional methods stated that best geometric correction of a single QuickBird scene using different models occurred when using more than 18 will-distributed GCPs [10]. RFM and Multi-layer perceptron neural network was used to solve the geometric correction parameters. Results of conventional RFM model have been checked against 9 check points giving a total RMSE of 1.55 meters (2.5 pixels). A non-conventional process was delivered by training a neural network designed by the authors, composed of 32 neurons distributed on 4 hidden layers designed by the authors (fig: 3). Results indicated an improvement of the total RMSE measured from the 9 check points reaching 1.287 meters (2.1 pixel). (Table 2).

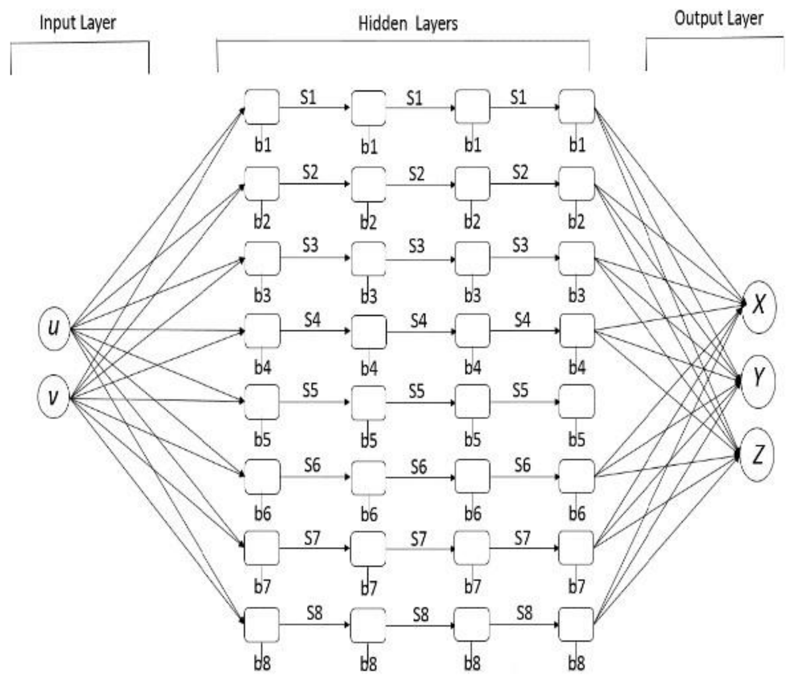

Figure3. Design of 4 hidden layers' Neural network.

Table 2. Accuracy assessment of check points errors of conventional RFM and non-conventional ANN models

Point ID	Conventional RFM		ANN (mlp)	
	Err_x	Err_y	Err_x	Err_y
14	1.678	-0.061	0.751	1.085
16	-0.733	0.251	-0.506	-0.148
18	-0.928	2.150	-0.901	-1.733
20	-0.348	0.865	-0.374	-0.611
22	0.981	0.139	0.547	0.127
32	0.705	0.442	0.604	-0.272
34	-1.998	-0.155	-1.690	-0.088
36	-1.600	-1.607	-1.418	1.496
39	1.125	0.890	0.881	-0.601
Mean	-0.124	0.324	-0.234	-0.083
RMS	1.223	0.949	0.924	0.896

6. Conclusion

The assessment of conventional techniques versus a new technique developed by the authors has been carried out in this research. Satellite ortho-image was developed by a sequence of steps beginning with GCP's extraction using automatic GCP's extraction (AGE) process, resulting in a randomly distributed GCP's which were used to train a multi-layer perceptron (MLP) neural network. Although conventional rational function model (RFM) leads to a good geometric correction, it is always affected by the number and distribution of GCP's which is characterized by numeric instability. Non-parametric neural network model –which is characterized by its numeric stability- was trained by the extracted GCP's. Results of both procedures were assessed leading to an improvement of accuracy using non-conventional geometric correction process developed by the authors form 2.5 pixels to 2.1 pixels.

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