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Geometric Correction of High Resolution Satellite Imagery Using Hybrid Non-parametric Model

Ahmed Habib, Zainab Weshahy, Mohamed El-Ghazaly, Ayman El-Shehaby.

Department of Geomatics, Faculty of Engineering, Cairo University, Egypt

Correspondence Author: Ahmed Habib, Department of Geomatics, Faculty of Engineering, Cairo University, Egypt.
E-mail: ahmed.habib.a@eng1.cu.edu.eg

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Abstract

Updating geographic information using high resolution satellite images has become a major competitor to the traditional photogrammetric works. This research presents a new technique to achieve geometric correction, starting with automatic satellite imagery matching with digital photogrammetric data, after outliers' exclusion. Matched points are ortho-corrected using DDTM. A downward Multi-layer perceptron neural networks technique will be used in the process of network training, instead of using the classic upward technique. In the new training process image coordinates were used as inputs and their corresponding ground coordinates were used as outputs. The trained network was used in predicting ground coordinates of a set of new regularized image points in the same space domain of the matched point dataset. Rational function model (RFM) will be implemented using regularized ortho-corrected points as GCPs in order to reach the final relationship parameters between satellite imagery and the 3D object coordinates. The new technique led to an improvement of the accuracy by damping down the error to 0.67 the error resulting from the conventional RFM model.

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

INTRODUCTION

Satellite data ortho-rectification is one of the basic operation for any remote sensing application. Most of commercial stereo pair satellite images are not delivered with detailed technical information about the platform and sensor used during data acquisition to be implemented with the rigorous model. One of the Non-parametric models used in Geometric correction is the 3D rational function model (RFM) (Grodecki, J. and G. Dial, 2003; Dowman, I., and V. Tao, 2002; Fraser, C.S., E. Baltsavias, and A. Gruen, 2002; Tao, C.V., Y. Hu, and W. Jiang, 2004; Toutin, T., 2004). It is considered the most commonly used algorithm in almost all commercial software packages of satellite data ortho-rectification (Dowman, I., and J. Dolloff, 2000). RFM coefficient are extracted using automatically generated GCP's from image matching between satellite images and aerial images (Gianinetto, M., *et al*., 2004). Technique of multi-layer perceptron neural network ware introduced (MLP) (Gianinetto, M., 2005). According to absence of technical information about the platform and sensor to be implemented in the rigorous model, rational polynomial function model is the most used non-parametric model in geometric correction. For the purpose of research, rational polynomial coefficient delivered by the satellite imagery vendor are omitted, in order to study the effect of each implemented technique under the same circumstances. Although linearized form of the RFM algorithm in an iterative least-squares solution is used in order to resolve the RFM parameters leading to good planimetric accuracy, it is affected by numeric instability due to the GCP number and distribution. The neural network approach leads to a lower geometrical accuracy, but it is characterized by a higher numerical stability (Gianinetto, M., *et al*., 2008). An approach of a combined procedure will be used to enhance the final geometric accuracy of the ortho-rectified satellite image.

Geometric Correction Models:

Although block adjustment algorithm is typically used in digital photogrammetry, non-parametric models are the most used in geometric correction of satellite imagery due to the lack of information about the sensor required for the rigorous model. Various models have been used to solve geometric correction of satellite data mathematically; most of the commercial software packages implement the Rational Function model (RFM). It has other synonyms as rational polynomial camera or rational polynomial coefficients (RPC) which are all expressing a 3D rational polynomial transformation. Neural networks technique has been also introduced lately as geometric correction model based on the multi-layer perceptron (MLP) procedure.

2.1 Rational Polynomial Coefficient Model:

The most non-parametric methods used in satellite images geometric correction commercial solution is the rational polynomial camera (RPC) (Aguilar, M.A., *et al*., 2007), or the rational function model (RFM) that defines the projection parameters between satellite image coordinates (u ,v) and ground coordinates (X, Y, Z) as in eq. (1).

$$u = \frac{p_a(X,Y,Z)}{p_b(X,Y,Z)} \;,\; v = \frac{p_c(X,Y,Z)}{p_d(X,Y,Z)} \quad (1)$$

The number of coefficients ($pa\ldots\ldots d,$) is dependent on polynomials' degree which in most cases is the third order and polynomial equations are expressed as in eq(2).

$$\text{Pa}\,(X, Y, Z) = a_0 + a_1X + a_2Y + a_3Z + a_4x^2 + a_5xy + a_6yz \ldots \ \ldots . + a_{18}yz^2 + a_{19}z^3 \quad (2.1)$$

$$\text{Pb}\,(X, Y, Z) = b0 + b1X + b2Y + b3Z + b4x2 + b5xy + \ldots . + b18yz2 + b19z3 \quad (2.2)$$

$$\text{Pc}\,(X, Y, Z) = c0 + c1X + c2Y + c3Z + c4x2 + c5xy + \ldots . + c18yz2 + c19z3 \quad (2.3)$$

Pd(X, Y, Z) = d0 + d1X + d2Y + d3Z + d4x2 + d5xy + … +d18yz2+ $d19z3$ (2.4)

The detection of transformation parameters (ai, bi, ci, di) can be achieved through an iterative least square adjustment process of the linearized form of the polynomial equations (1). Dealing with a large GCP number, in equation (2), the Tikhonov algorithm (Choi, H.G., *et al*., 2007) is mostly applied.

2.2 Neural Networks Model:

The Neural Networks is a non-parametric model which deploy a collaboration of a group of mathematical methods as a flow of information in a neuron which is considered as the unit of the network. The model is designed as a simulation of the cerebral biological dynamics, in which some neurons are responsible of receiving input information, some other neurons are responsible of returning output answers and the rest are distributed in hidden layers to be responsible of solving the network.

A popular methodology of learning called Supervised Learning technique with input-output mapping processes deploying the theory of synaptic weight modification of the network applied by training a set of samples in which, each sample has a unique input signal and a known corresponding output signal.

The supervised learning neural networks algorithms are various and are used for a various kind of applications. The selection of an algorithms and functions is dependent on the application. Multi-Layer perceptron algorithm has been deployed in the field of geometric correction of satellite imagery (Boccardo, P., *et al*., 2004) in a way that, satellite image coordinates (u, v) are mapped to the ground coordinates (X, Y, Z) on the basis of a GCP's trained multi perceptron neural network.

Each neuron responds with a signal through a transfer function according to the signals from the connected neurons through communication channels. This channel's function is to add weight to the signals according to their intensity. The response signal s of a neuron i can be expressed as in eq. (4).

$$s_i = f\left(\sum_{j=1}^{n} w_{ij}\ p_{ij} + b_i\right) \quad (4)$$

Where:

F is the transfer function which normally takes the shape of hyperbolic function eq. (5) or logical sigmoid function eq(6)

$$f(x) = \frac{1 - e^{-x}}{1 + e^{-x}} \quad (5)$$

$$f(x) = \frac{1}{1 + e^{-ax}} \quad (6)$$

Wij are the weights of the ith neuron. pij are the input at the ith neuron (N). bi are scalar additives, called bias, that are considered as weights of unitary additional input. Solution of the network is related to the determination of the network parameters which consists of the weights and the biases of the hidden and output neurons. Network parameters are solved during the training process. The training function is defined as the process which assumes weight values that minimize the performance function such as Error Back-Propagation function (7)

$$PF\big(w(t)\big) = \sum_{p=1}^{p}\sum_{k=1}^{k}\big(d_{kp} - f_{kp}\big)^2 = E(t)^T E(t) \quad (7)$$

Where, $W_{(t)} = [w_1, w_2, \ldots, w_N]T$ is the weight vector of the network at epoch t, t counts the epochs of the training process and it is fixed by the operator. d_{kp} is the expected value (target) of the kth output relative to the p^{th} training pattern. f_{kp} is the value of the kth output calculated by the network.

$E_{kp} = (d_{kp} - f_{kp})$, k=1,. K, p = 1, …. P, is the cumulative error of a batch training.

A MATLAB r2015 Neural Network toolbox was used to map an input-output network of a down-ward projection, in which the satellite image coordinates of the photo-control points (u, v) has been used as an input, while the output has been expressed by ground coordinates (X,Y,Z) of the points. Four hidden layers have been used and an output layer with two different techniques of training transfer function of the neurons' signal.

The first transfer function used was hyperbolic tangent function (5), then logical sigmoid function (6) was used. Obtaining the optimum number of neurons (of the hidden layer) that drive to best performance was achieved through the MATLAB developed routine based on repeated iterations using performance test calculator.

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 (Lawrence, S., *et al*., 1996) in order to achieve the significant number of neurons in the hidden layers as in eq. (8):

$$N_p = (3(XYZ).M_{PESIhidden}) + M_{BIAShidden} \quad (8)$$

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.

Application And Case Study:

An area of Quick Bird satellite data for about 132 square kilometers for the area of Fayed and Abu-Sultan on the Suez gulf was examined with the two different geometric correction methodologies of a 0.62-meter ground resolution.

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) 45 ground GPS stations distributed over the area of interest to be divided into 39 control points and independent 9 check points -which will be used as a check for aerial data and satellite data as well- with RMS of 0.037 meters, 0.040 and 0.052 meters in X, Y and Z respectively.
2) Aerial imagery covering an area 12.5 X 14 km data captured using Leica Ads80 camera with ground resolution 25 cm for Fayed and Abu-Sultan area (Fig :1).
3) A bundle block adjustment of the captured Ads80 imagery was done using 36 GCPs and checked against 9 independent observed check points distributed as in (Fig : 1) with RMS of 0.261, 0.313 and 0.556 meter in X,Y and Z respectively (Table:1).
4) A 0.5 meter ground resolution orthophoto was produced from the Ads80 imagery.
5) A 0.5 meter ground resolution dense digital terrain model DDTM covering the area of aerial photography.
6) The same area of the aerial imagery data was captured using Quick Bird sensor of 0.62 meter ground resolution.

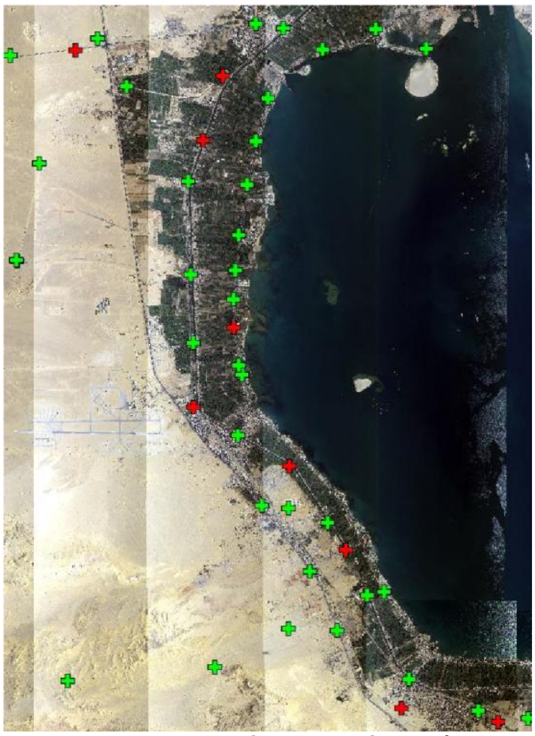

Fig. 1: Ortho-Photo of the study area deduced from LiecaADS80 Camera system showing Distribution of (36) ground control points and (9) check points.

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:

Although, geometric correction of satellite data using RFM model has an acceptable planimetric accuracy, it is affected by the distribution of GCPs (Toutin, T., 2004). Irregular distribution of GCP's leads to improper distributed distortion over the whole output ortho-rectified satellite data, because it can only compensate errors locally (Strakhov, P., *et al*., 2016). In order to achieve an proper distribution of GCP's, a methodology has been adopted to replace the traditional GCP's acquisition in which an automatic ground control extraction model (AGE) (Scaioni, M. and M. Gianinneto, 2008) is used to identify matched control points from the satellite data with the preset aerial ortho-photo of the area of interest and extracting elevation of the control points from the DDTM as well, resulting in non-regularized full control points. The non-regularized control points is then used as an input of the neural networks model to extract regularized full control points to be used as an input of the geometric correction using RFM model. The former two models were implemented to achieve final geometric correction using the same set of ground control points. The process took place on a 0.62m ground resolution QuickBird satellite scene according to the applied workflow in (fig: 2). The aerial orthophoto 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 results of two methods of geometric correction have been checked against the same 9 independent check points that were used to check the aerial block adjustment, and the results have been reported.

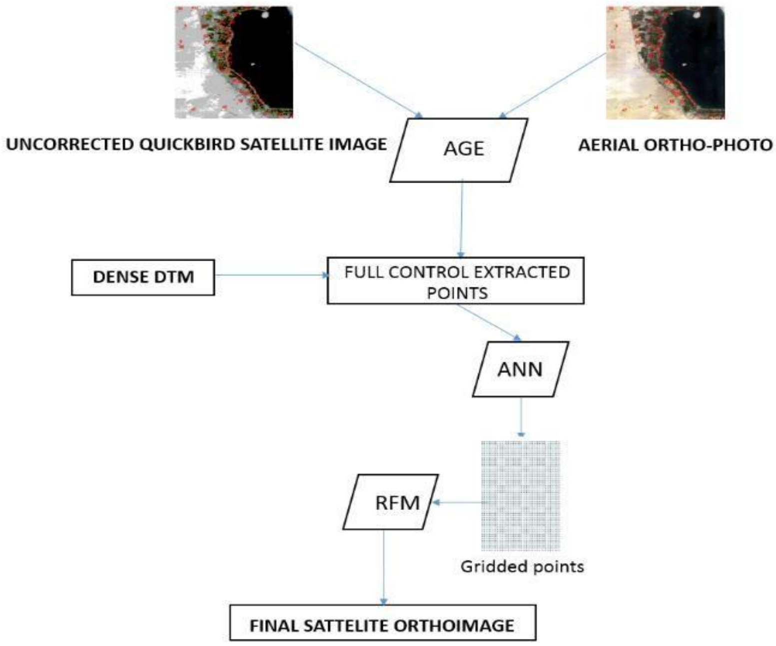

Fig. 2: Workflow of the geometric correction procedure of the quickbird satellite data of the area of Fayed and Abu-soltan

Satellite Data Ortho-Rectification:

Orthorectification procedure has been developed by two different procedures. First one was conventional, using homologies ground control points deduced from the AGE process directly by a commercial off the-shelf software. Implementing the RFM model in ERDAS IMAGINE 2011 software. The Second was non-conventional procedure through a developed software by the authors using the deduced ground control points to train a Multi-Layer Perceptron Neural Networks (MLP-NN) in order to generate an equally spaced ground control points. Different training and transfer functions where used. A designed function based on the aimed number of parameters was applied to prevent over-training of the network. Equally spaced gridded control points were developed and used in the non-conventional RFM process. The two methods were tested using chosen fixed 9 check points.

Analysis And Results:

Geometric correction achieved of the QuickBird satellite data of the test area using conventional and nonconventional 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 (Aguilar, M.A., *et al*., 2007). Multi-layer perceptron neural network was used to regularize the (AGE) extracted image control points as an intermediate process in the approach of ortho-image generation of EROS-A data; the residual error on GCPs of 1.06 pixel and residual errors on independent control points derived from 1:2,000 map of 5.42 pixel (Gianinetto, M., *et al*., 2008). It has been stated that image ortho-rectification implementing Neural network GCPs regularization has been tested for the SPOT-5/HRG data, showed the capability of full image exploitation, in order to obtain precise planimetric geo-positioning in a fully automated way, even better than those obtained with rigorous sensor models (Scaioni, M. and M. Gianinneto, 2008). Optimizing RFM Using AI techniques such as ANN produce better accuracy than conventional 2D & 3D and RFM, regardless the difference in accuracy gained from a conventional way to another (Bagheri, H. and S. Sadeghian, 2013; Bagheri H and S. Sadeghian, 2014). In this research The number of GCP's extracted by the (AGE) process reached 572 points using the aerial ortho-photo as a source of ground coordinates for the uncorrected satellite data. The extracted points have been used in the conventional RFM process. Results have been checked against 9 check points giving a total RMSE of 1.55 meters (2.5 pixels).The non-conventional process delivered by regularizing ground control points using the (AGE) extracted points to train a neural network designed by the authors, composed of 32 neurons distributed on 4 hidden layers designed by the authors (fig: 3), generating 756 gridded GCPs to be used in a developed RFM module designed by the authors. Resulting in an improvement of the total RMSE measured from the 9 check points reaching 1.09 meters (1.76 pixel). (Table 2).

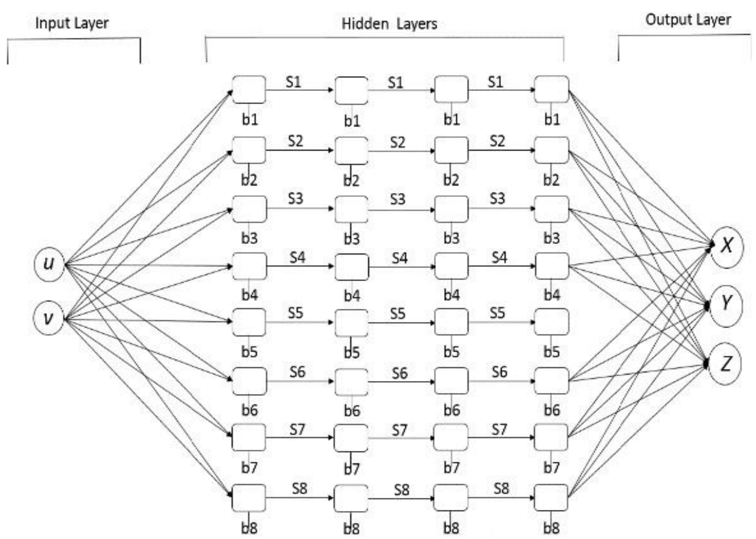

Fig. 3: Design of 4 hidden layers neural network for regularizing ground control points.

Table 2: Accuracy assessment of check points errors using conventional and hybrid mathematical models

Point ID	Conventional RFM		Hybrid ANN +RFM	
	Err_*x*	Err_*y*	Err_*x*	Err_*y*
14	1.678	-0.061	0.205	-0.261
16	-0.733	0.251	0.264	-0.622
18	-0.928	2.150	0.235	-0.470
20	-0.348	0.865	-1.610	-0.839
22	0.981	0.139	-1.392	-0.578
32	0.705	0.442	0.503	1.616
34	-1.998	-0.155	1.167	-0.079
36	-1.600	-1.607	-0.306	-0.398
39	1.125	0.890	-0.622	-0.489
Mean	-0.124	0.324	-0.173	-0.236
RMS	1.223	0.949	0.851	0.685

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. A set of gridded image points was introduced to the trained network in order to produce a set of gridded GCP's. Although processing random GCP's using conventional rational function model (RFM) leads to a good geometric correction, it is always affected by the number and distribution of GCP's which lead to numeric instability. Non-parametric neural network model is characterized by its numeric stability, it was trained by the random GCP's and used in producing gridded 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 1.76 pixels.

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