

# EXPERIMENTAL STUDY OF ARTIFICIAL NEURAL NETWORK FOR GEOMETRIC RECTIFICATION OF SATELLITE IMAGERY

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**KEY WORDS:** Geometric Rectification, BPNN, RBFNN, CEM, GA, Whiskbroom, Accuracy.

## ABSTRACT:

In this paper, series of experimental studies about the neural network model for whiskbroom remote sensing imagery geometry correction methods based on BPNN (Back-Propagation Neural Networks) and RBFNN (Radial Basis Functions Neural Networks) with detailed algorithm were raised initially, which were presented on the focus of the establishment of the neural network model for geometric correction and how to improve the performance of the NN. This study shows some experimental results obtained by autonomous procedures developed by the authors based on self-calibrating Collinearity Equation Model (CEM), BPNN, GA-improved BPNN and RBFNN. Comparison among the different methodologies has been conducted taking care of the geometric accuracy from the viewpoint of structure of ANN, GCP number, the resolve of parameters, and the applicability and so on.

## 1. INTRODUCTION

It is very necessary to correct remote sensing imagery before their utilities. At present the main geometric correction methods are establishing the model of imaging sensors on the basis of rigorous physical model or general non-parametric model, such as Collinearity Equation Model (short for CEM) (Deren Li, Zhaobao Zheng, 1992) and Rational Function Model (short for RFM) (Vincent C T, Yong H A., 2001). Both correction model are in the principle of mathematical correspondence equations through the establishment of the imaging space and the ground coordinates (TOUTIN T, 2004; KARSLIOGLU M O, FRIEDRICH J, 2005). For the first time, by Gerald Krell, ANN was used in the field of computer vision for the real-time image calibration. Piero Boccardo (2003), proposed MLPNN network model in hyperspectral remote sensing image geometry correction and had an analysis between MLPNN and RFM model. Since both the above two methods depend on model order bringing a direct impact on the quality of distortion correction, that is, the higher the order of the model, the calibration of complex distortion effects better. But because of the high-order mathematical model for computers, not only time-consuming but also in contradiction of the phenomenon with a numerical error, so the traditional technology has its limitations. Besides, there usually exist ill-conditioning problems (Susumu Hattori, Tetsu Ono, 2000; BelSly, D.A. 1991) when solving both the above model. As for neural network, because of the characteristics of self-learning, self-organizing, self-adaptability, fault-tolerance, its image mapping relationship of the distortion is the result of self-learning, so the above technical problems does not exist, and calibration results very stable. However, at present, ANN geometric correction for remote sensing imagery still lacks of systematic research, therefore, it has been chosen in this paper.

## 2. METHODOLOGY

### 2.1 Collinearity Equations Model

Rigorous models are based on time-dependent Collinearity Equations that is the most basic formula in photogrammetry. Liner array whisk-broom imageries are line-center projection imaging. That is to say points in the same scanning line are decided by the same orientation elements and different scanning line by different orientation elements. Suppose any point in the scanning line  $i$ , the relationship with the corresponding ground point can be described by the following formula:

$$\begin{cases} r_i = -f \frac{a_1(X-X_{si})+b_1(Y-Y_{si})+c_1(Z-Z_{si})}{a_3(X-X_{si})+b_3(Y-Y_{si})+c_3(Z-Z_{si})} \\ 0 = -f \frac{a_2(X-X_{si})+b_2(Y-Y_{si})+c_2(Z-Z_{si})}{a_3(X-X_{si})+b_3(Y-Y_{si})+c_3(Z-Z_{si})} \end{cases} \quad (1)$$

$(r_i, 0)$  is the imagery coordinate in the scanning line  $i$ ,  $(X, Y, Z)$  is the corresponding ground coordinate,  $(X_{si}, Y_{si}, Z_{si})$  is the camera focus coordinate belong to the scanning line  $i$ ,  $(a_i, b_i, c_i)$  is elements in rotate matrix array which is determined by exterior orientation elements. Specific process can be found in reference [1]. This paper will not talk a lot. Collinearity Equations is characterized by rigorous theory and high accury, however, there must be a prerequisite that is to obtain the track ephemeris parameters and sensor parameters. In

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practical application, these parameters are often not available. Instead, we can only use high precision control points obtained by hands or GPS to approximate orientation elements. So, at present there are some researches focused on the deteriorated condition of the coefficient matrix of normal equation in computing Collinearity Equations process and many approaches have been put forward such as adding virtual error-equations, generalized ridge estimation method, Stein estimation method, Tikhonov method and so on (Markiewicz, A. 1997; BelSly, D.A. 1991; Bertuzzi, A, Gandoli, 1991 ).

## 2.2 Principle of Neural Network for Geo-correction

Compared with the symbolism, the Artificial Neural Networks (acronym for ANN) structure is composed of large number of simple interconnected processing neurons, which forms complex parallel network architecture, although neurons only complete a simple calculation function, the whole network is a highly complex non-linear powerful system (C.Lau,1992). ANN has been successfully applied to combinatorial optimization, classification and pattern recognition, knowledge management, signal processing, and other areas (B.Michaelis,G.Krell, 1993; B.Michaelis;G.Krell. 1992; Lilienblum,T.etl,1996).

According to neural network theory, ANN technology is able to approximate non-linear, uncertain complex issues along with random accuracy. Indeed, remote sensing imaging model itself is a complex nonlinear model. Therefore, we proposed BPNN and RBFNN with excellent performance at function approximation. In essence, geometric correction process on the basis of the imaging model aimed to establish mapping relation between coordinates of the pixel image (column and row values as the coordinate) and the geographical coordinates given the projection and datum. In the BPNN and RBFNN models we put forwarded, the realization of such a mapping relationship is represented by weights, parameters of the model, which have to be estimated on the basis of the GCP as training samples through an iterative learning process.

Essential idea is to substitute the upward projecting model relating image( $r, c$ ) and ground( $X, Y, Z$ ) coordinate with a well designed and trained BPNN or RBFNN. These two types of NN have been chosen for their function approximation and estimation features. They show their high suitability especially for non linear functions as considered relations are and own simple structure but easy to control. Put these two neural networks together for comparison, we can get better model for geometric rectification.

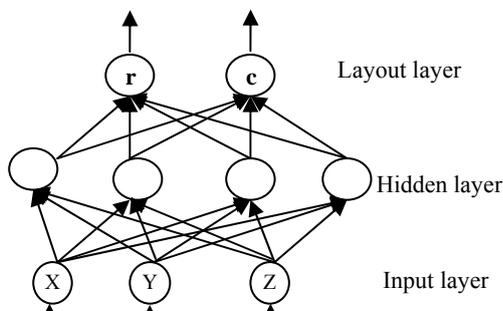


Figure 1. Neural Network Structure with 3 layers

In neural network theory, the neural network model structure is a very important but very complex issue which directly

determines the accuracy of the network model. However, the current study on how to determine the optimum parameters have not set a definitive answer. Considering the characteristics of imaging geometric model, our ANN geometric correction models constituted of the structure with the following designed optimization. (1) For RBFNN and BPNN, any continuous function within a closed interval can be approximated by a network with single hidden layer, which means that a three-layer network can complete n-dimensional to the m-dimensional mapping. As for geometric correction, the control point amount, as training data, not comparatively large, single hidden layer data-processing is efficient and stable.(2) The most appropriate number of neurons has to be defined time to time according to the number of GCPs and image type. We first set the number of hidden layer nodes variable from 0 neurons to start being trained, and then repeat to increases neurons continuously by checking output errors until achieve the error requirements or the greatest number of hidden neurons. Of course, it's at the cost of time efficiency. (3) For BPNN, the initial cumulative input weights should ensure the state of each neuron close to zero value. Moreover, weight values at random should be relatively small. GCPs data as the training samples should be processed to be normalization to enhance the generalization capability in order to restrain the impact result from the distribution of GCPs. The most important we must pay attention to is BPNN owns two shortcomings that is, a. BPNN is based on error function gradient descent direction which in fact is efficient in local searching but deficient in global searching space; b. BPNN's initialized parameters are given in random which may be resulting in local minimum value if the initializations was not proper. Therefore, in this paper, we introduced genetic algorithm to BPNN in order to improve it.

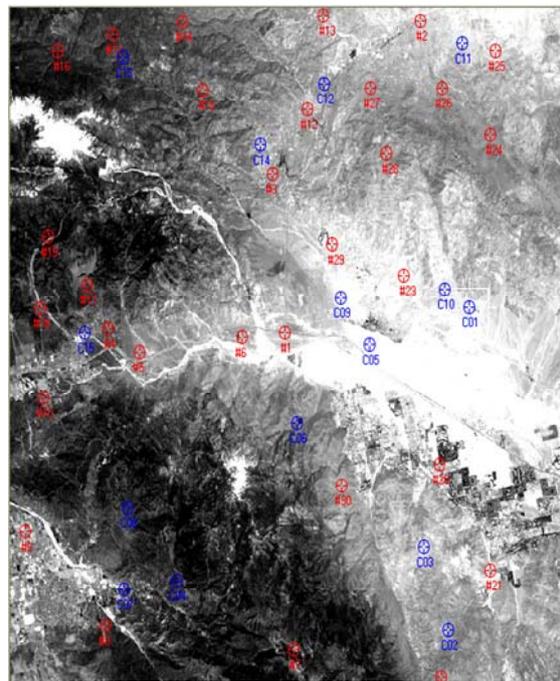


Figure 2. Distributions of CPs and CKs.

**2.3 Analysis**

At last, a necessary statistic  $\chi^2$  test on the GCPs residuals for the tests elaborated with CEM and NN methods at the situation of 30 CPs has been carried out. This has permitted to verify their adaptation to the  $\chi^2$  expected normal distribution. The test consists in calculating the  $\chi^2$  parameter for the residuals and comparing the obtained value with the theoretical one derived from the defined tables according to the correct degree of freedom and to the chosen level of confidence. If the obtained  $\chi^2$  is smaller than the theoretical one the test is positive, therefore the residuals distribution can be considered to be a normal one. If not it is possible to hypothesize the presence of some systematic phenomena.

**3. EXPERIMENT**

Based on the above network architecture design, SPOT panchromatic image with 10 m resolution, multi-spectral imaging with 20 m resolution and DEM with 20m plane resolution have been selected as experimental data, from which 50 control points(CPs) and 10 check points(CKs) have been extracted respectively, for Comparative Analysis among Collinearity Equation Model, BPANN and RBFANN model. The distribution of these points can be seen from figure 2, in which the red points stands for CPs and the blue points stands for CKs.

Three experiments were designed for the following objectives:

1. Design two kinds of ANN model for geometric rectification and compared with the Collinearity Equation Model through precision and stability.
2. Explore geometric correction accuracy result ground control points for the neural network model in different quantity and different precision condition.

3. Optimize the BPNN to overcome its shortcoming of gradient descent algorithm for training connection weight. At present, we tried adaptive genetic algorithm.

**3.1 Experiment a**

Under the condition of the existing CPs and CKs, by VC++ and Matlab tools, we have developed to solve CEM by ridge estimation method and select Condition Number [8] as ill-condition diagnostic index for the coefficient matrix of CEM; More over, we trained the BPNN and RBFNN by the 30 CPs. The table 1 shows the result from the experiment. Besides, the CPs precision can be found in table 2. In BPNN model, logarithmic function was selected as transfer function between the first layer and the second layer, and liner function between the second layer and the third layer. As standard BP learning algorithm is based on gradient descent method that will make learning process occur concussion when amending its weight parameters and the convergence speed slow, this paper used Levenberg-Marquardt learning algorithm characterized by fast iterative process and stability. In RBFNN, Gauss function was used as radial basis function.

As a result, the neural network model calibration accuracy got even higher result than CEM, which reached sub-pixel level accuracy; besides, RBFNN showed better performance than BPNN, which reflected that function approximation of RBFNN in the capacity and speed is better than BPNN[9]; it is necessary to specify that Condition Number reached 1.42E+11 in the test, proving the existence of deterioration in the condition of the coefficient matrix of CEM's normal equation (specific in reference [8]), leading to a larger checkpoints residuals; The factors in the neural network model do not exist, showing a relatively high accuracy.

algorithm	CEM		BPNN		RBFNN	
	X direction	Y direction	X direction	Y direction	X direction	Y direction
RMSE	0.8767	0.5027	0.4578	0.6902	0.4001	0.651
	1.0106		0.8282		0.7641	

Table 1. RMSE and residue result from different models (unit: pixel)

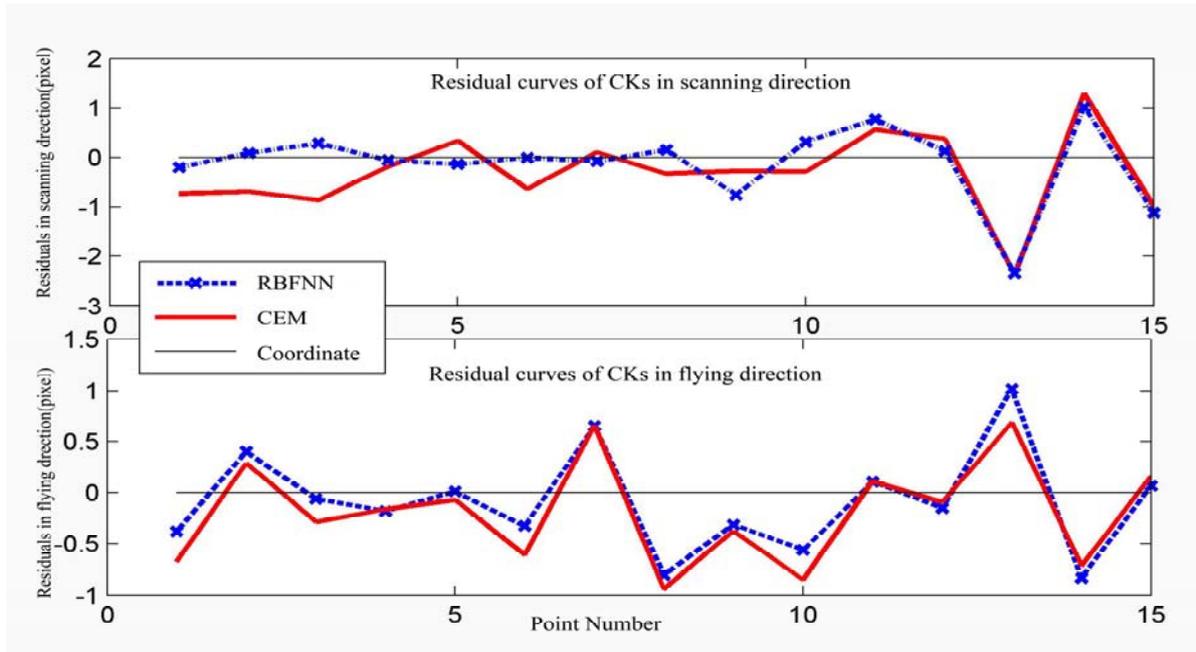


Figure 3. Residuals curves of CKs

In addition, in order to compare the performance of RBFNN with CEM, we have proceeded to inspect the residual distribution of the CKs in table 1 that result from the tree models. Figure 3 shows the distribution curves obtained. From the map it is clear that:

Corrected results from RBFNN were almost the same as CEM, particularly in the flight direction exactly the same, which indicates this neural network model that established by RBFNN correctly describes the imaging space geometric relations with grounds. Moreover, if we pay attention to the RMSE in X direction, we will find that the two neural network algorithms both got higher accuracy than CEM, which is very important. Since terrain changes in the geometric impact in the scanning X direction are more serious, however, the neural network algorithms would improve the accuracy. Nevertheless, in the Y direction, the two neural network model got slightly larger residuals than CEM, as in the line CCD sensor of the strict CEM[1], each of the scanning lines, the plane coordinates

Y value in imagery is zero, which means CEM has taken into account of the satellite attitude angle (linear change with the passage of time, orientation elements) at each scanning line. Furthermore, topographic changes also affect relatively slighter in the Y direction, so the error in the Y direction is relatively small. The neural network model is a whole global optimization approach, bringing about corrected errors to be relatively uniform.

### 3.2 Experiment b

In order to test the impact of CPs, we used a different number of CPs respectively in correct experiments, ensuring that the selected control point to be a relatively uniform distribution. Furthermore, in 30 CPs experiment, we selected # 1 and # 7 (Shown in figure 2) points in the middle and bottom of image and added its image coordinates by 3 pixel error to identify the impact result in the gross error. The experimental results have been shown in table 2.

algorithm	Different number of CPs	CPs RMSE	CKs RMSE
RBFNN	10	0.00001981	3.5348
	20	0.39477	1.5152
	Normal 30	0.5588	0.7641
	30 with gross error	0.6704	0.8586
BPNN	10	0.5189	1.7705
	20	0.4023	1.6949
	Normal 30	0.4771	0.8282
	30 with gross error	0.4675	1.0368
CEM	10	0.4716	1.5966
	20	0.5955	1.2380
	Normal 30	0.6747	1.0106
	30 with gross error	1.5463	1.3351

Table 2. RMSE result in different control points condition (Unit: pixel)

- Clearly, as for the control points for the algorithm based on the geometric model correct, the number of CPs takes a greater impact on the final results. For neural network model, the more control points the better training results, the higher the accuracy when the number of control points reaches to 30 when the neural network model accuracy higher than CEM. However, when the number of control points less than 30, BPNN and RBFNN got lower precision than CEM; In particular it is worth noting that in only 10 control points cases, although the RBFNN got much smaller RMSE, but the checkpoints were far greater than the CEM RMSE. As far as BPNN and RBFNN is a division of this type of neural network learning, the number of training samples, to a great extent, affects the quality of model [11]. Therefore, if in application of neural network geometric correction, we must ensure that there are a large number of control points.

- As for the control points including the gross error we had designed, RBFNN take advantage of its adaptability, and self-organization of inhibitory effect against impacts of these CPs. As a result, the final checkpoints precision has reached one pixel within. However, CEM precision results are poor. Whereas, this fault-tolerance capability, if in the more control points conditions with gross error, would become a drawback. At last, statistic  $X^2$  test for the CPs residuals on the experiments with 30 normal CPs were completed. The test has been positive for the residuals obtained from BPNN, RBFNN and CEM.

### 3.3 Experiment c.

Genetic algorithm neural network is a method that uses genetic algorithms to optimize connection right value to replace gradient decrease method. Joining the genetic algorithm in the process of the neural networks makes it have the global optimum and local search capability. At the same time, it can not only enhance the rate and efficiency of algorithmic constringency, but also effectively avoid appearing precocity and plunging into local optimum. The method can completely satisfy the accuracy and speed requirements of the real-time system.

In this paper, we raised a technique process specified below:

1. Build 40 BPNN with 3 layers through initializing them in random and train them after 500 epochs by the same 30 CPs.
2. Recode the weights of the 40 BPNN in float array as the first population and perform GA algorithm by Selection operation and Mutation operation without Crossover operation until reach the max iteration limitation so as to get one optimum individual.
3. Replicate 40 individuals produced in step 2 to form a new population and mutate the new population in a

small limited extension inferred from the first population in step 2.

4. Carry out Adaptive Genetic algorithm on the new population produced from step until GA reaches the max iteration. As a result, we can get the individual containing the best fitness indicating that the BPNN's relative optimum weights.
5. Build a BPNN with the parameters by decoding the individual produced in step 4 and train it by the 30 CPs.
6. Use the BPNN produced in step 5 to simulating the geo-correction process.

In the steps above, detailed knowledge about Adaptive Genetic algorithm can be found in reference [14]. And we adapted the following fitness function,

$$\begin{cases} J(x) = \frac{1}{N \times M} \sum_{k=1}^N \sum_{j=1}^M (y_j(k) - \hat{y}_j(k))^2 \\ f(x) = \frac{1}{1 + J(x)} \end{cases} \quad (2)$$

Where,  $f(x)$  represents fitness function,  $N$  is input sample's number,  $M$  is output layer neurons number of BPNN,  $y_j(k)$  is the  $j_{th}$  neuron's output value at input sample  $k$ , and  $\hat{y}_j(k)$  is the  $j_{th}$  neuron's expected output value at input sample  $k$ . Hence, we adapted reciprocal of  $(1 + J(x))$  to transform the minimum question to maximum question.

Based on the experiment result, the following findings can be obtained:

- GA-BPNN can get better result at the cost of more time-consuming. It is interesting, from table 3, the GA-BPNN and BPNN got higher accuracy at CPs but lower accuracy at CKs than RBFNN. We think it is due to the BPNN's shortcomings of local optimum.
- GA-BPNN is, in this experiment, only a little better than BPNN and a little worse than RBFNN which indicates that adequate experiments should be perform in the future.

algorithm	CEM	BPNN	GA-BPNN	RBFNN
RMSE of CPs	0.6747	0.4771	0.3611	0.5588
RMSE of CKs	1.0106	0.8282	0.7982	0.7641

Table 3. RMSE from different models(unit: pixel)

#### 4. CONCLUSION:

The obtained results from the performed experiments allow concluding that:

- i. Given a sufficient number of control points as a training sample conditions, BPNN and RBFNN model performance higher accuracy than Collinearity Equation Model, especially in the scanning direction, and total checkpoints RMSE reach to a sub-pixel level;
- ii. The sick issue of equation does not exist in ANN model that results in high precision;
- iii. As for efficiency and precision, the RBFNN shows better than BPNN;
- iv. ANN model for the geometric correction completely dependent on the accuracy of the number of control points, as the increasing control point number significantly improved accuracy;
- v. ANN model has strong error-tolerant capability, which can automatically inhibit the impact of the control point with large error so that it can improve efficiency in practical geometry correct application.

VI. GA-NPNN is a relative better method to optimize the BPNN's initial weights if time-consuming is less important than accuracy.

In addition, deficiency of using neural network for imagery correction is the longer time-consuming. If we had to meet the requirements of real-time detection, use of parallel processors is required, or through the entire hardware to achieve neural network.

#### ACKNOWLEDGMENTS

This work is supported by Natural Science Foundation of China (No.40671127) and 111 Project (B06004).

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