Geometry correction Algorithm for UAV Remote Sensing Image Based on Improved Neural Network

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Abstract. Aiming at the disadvantage of current geometry correction algorithm for UAV remote sensing image, a new algorithm is proposed. Adaptive genetic algorithm (AGA) and RBF neural network are introduced into this algorithm. And combined with the geometry correction principle for UAV remote sensing image, the algorithm and solving steps of AGA-RBF are presented in order to realize geometry correction for UAV remote sensing. The correction accuracy and operational efficiency is improved through optimizing the structure and connection weight of RBF neural network separately with AGA and LMS algorithm. Finally, experiments show that AGA-RBF algorithm has the advantages of high correction accuracy, high running rate and strong generalization ability.

1. Introduction
At present, unmanned aerial vehicle (UAV) with its flexibility and instantaneity causes the attention of people. Because of their low altitude remote sensing images of high resolution, strong pertinence, and with the advantages of fast and large area to get the data [1], the urban construction, land and resources exploration, environment monitoring, and other fields. UAV have been widely applied. But UAV has light weight, small volume and is easy to be influenced by wind or its jitter, which would make the image distorted. Moreover, most of the civilian UAVS using small digital cameras, then camera lens distortion and focal length changes will also cause image distortion. Therefore, geometry correction is necessary before the further application of UAV remote sensing image.

The key to the geometry correction of UAV remote sensing image is to establish geometry correction model, and the selection of geometry correction model will affect the accuracy of the calibration of remote sensing image. At present, many scholars have conducted extensive
and in-depth studies on the modeling of the geometry correction of UAV remote sensing image. Polynomial correction method is the traditional method for the geometry correction of UAV remote sensing image, but the correction precision of polynomial correction method can be influenced by correction scope and control point distribution and quantity. Many researchers have made many improvements on the shortcomings of polynomial correction. The papers [2][3] based on the polynomial correction method, make the deformations of the distorted images and geometry correction for each sub block, which solve the local problem of the data calculation well. The papers [4][5] using the method of local weighted fitting, specify the local correction area of the image, and the requirement of the density and uniformity of the control point is reduced by the polynomial correction method. The papers [6] is based on the rational polynomial correction model and Tikhonov regularization method is introduced into the calculation process of rational function model, which improves the correction precision of the rational function. In addition, the researchers propose other geometry correction methods for remote sensing image. The papers [7] [8] introduce vector machine into the geometry correction of remote sensing image, and establish the geometry correction model by supporting vector regression algorithm. The paper [9] proposes the geometry correction algorithm of remote sensing image based on RBF artificial neural network, which has the global optimum and the best approximation performance, and the principle is simple and easy to implement. On the basis of existing research, AGA is introduced into RBF neural network and we carry out the geometry correction of UAV remote sensing image, which improves the accuracy.

2. The geometry correction principle of UAV remote sensing image

Geometry correction of UAV remote sensing image is an essential step in the pretreatment of remote sensing image. Because there are a lot of factors causing UAV remote sensing image distortion, the imaging process is difficult to express mathematically accurately. Therefore, the geometric process of imaging should be avoided as much as possible, instead using the control points simulates the geometric distortion of remote sensing image mathematically, and consider that the overall distortion is caused by the basic transformation of translation, rotation, extrusion and distortion. Thus, an appropriate mathematical model can be used to represent the coordinates between the corresponding points before and after the image correction.

For UAV remote sensing image geometry correction, the process can be described as: input distorted image→choose ground control points→establish geometric model→correct the remote sensing image geometrically→resampling→output rectified images. The key steps are as follows:

1) Choose ground control points. The selection of ground control points is one of the important steps in geometry correction of remote sensing image [10]. Ground control points are the coordinate value corresponding to the same object on two images (reference drawing and distortion drawing). Its distribution, precision and quantity of the ground control points directly influence the accuracy of geometry correction of remote sensing image. In the selection of control points, we should choose the obvious and relatively stable position, and try to make it evenly distributed in the distortion region. In addition, the number of control points cannot be too small and should be greater than the minimum number required for the correction equation.
2) Establish geometric model. It’s the crucial step in geometry correction of remote sensing image. Establishing the geometry correction model is establishing the transformation formula between the distorted image space and the correction space, and the parameters of the transformation formula are solved by the control points. After establishing that model, transformation formula can be used to transform the distorted image space to correction space. The geometry correction model directly influences the effect and speed of the geometry correction of remote sensing image.

3) Resampling. When the distorted image space is transformed to correction space by geometric model, the pixel points uniformly distributed before transformation will present irregular distribution in the corrected image, so it’s necessary to resample the pixel value of the corrected image. In resampling, the nearest neighbor point method, bilinear interpolation method and cubic convolution method are the three most commonly used methods.

3. AGA-RBF neural network principle

Because the function of geometry correction for UAV remote sensing image is nonlinear and uncertain, it is difficult to describe it with an accurate mathematical model. RBF neural network can approximate any continuous function with arbitrary precision, and its network structure is simple, learning speed is fast, and has global optimum and best performance. Therefore, in this paper, the RBF neural network which used for the geometry correction of UAV remote sensing image is trained with the selected ground control points, so as to maximize the approximation of the geometry correction function of UAV remote sensing image and realize the correction of remote sensing image.

RBF neural network is a forward neural network including input layer, hidden layer and output layer. The structure of RBF neural network with m input layer nodes, h hidden layer nodes and n output layer nodes is displayed in Fig.1. The basic idea of RBF neural network is: the RBF function is used as the "base" of the hidden unit, then its hidden layer space is formed, the input signal from the input layer map to hidden layer in nonlinear manner, and then the hidden layer map to output layer through the linear weighted method.

![Figure1. RBF neural network structure](image)

This neural network generally use Gaussian function as the activation of hidden layer units, expressed as

$$\alpha_i(x) = \exp\left(\frac{1}{2\delta_i^2} \| x - c_i \| \right), i=1,2,\ldots,h$$  \hspace{1cm} (1)

Where, \(x=(x_1, \ldots, x_m)\) is an input vector of RBF neural network, \(\alpha_i(x)\) is the output of the \(i\) node in the hidden layer, \(c_i\) is the central value of the Gaussian function, \(\delta_i\) is the variance of the Gaussian function, \(h\) is the unit number of the hidden layer.

The output of the output layer is:

$$y_j = \sum_{i=1}^{h} \omega_{ij} \alpha_i(x), j=1,2,\ldots,n$$  \hspace{1cm} (2)
Where, $y_j$ is the output of the j node, $\omega_{ij}$ is the connection weight between the i node and the j node, n is the unit number in output layer.

Thus, when designing RBF neural network, its main task is to find the optimal basis function center $c_i$, the variance $\delta_i$ and the connection weight $\omega_{ij}$ from hidden layer to output layer. In addition, $c_i$ and $\delta_i$ are important parameters of RBF neural network learning and generalization ability. If not selected properly, it will cause serious impact on network performance. This paper adopts the AGA to optimize of $c$ and $j$, compared with the traditional algorithm, adaptive genetic algorithm without prior knowledge is not sensitive to initial parameters, and has extra characteristics of fast convergence speed and not easy to be trapped in local minimum etc. Finally the LMS algorithm is used to optimize $\omega_{ij}$ to achieve the optimization of the entire RBF neural network. The following will introduce the principle of the algorithm in detail:

1) Chromosome coding

Suppose that the maximum value of $c_i$ in the RBF neural network is 1, then constructing the chromosome coding as:

$$c_1c_2c_3...c_l\delta_1\delta_2...\delta_l$$

(3)

The neurons are encoded in binary mode represent by signal $c_i$ with 0 and 1. When the signal is 1, it's said that the neurons exist and 1 is used to represent the upper limit of the number neurons, otherwise 0. The variance is coded in real number represented by $\delta_i$. A chromosome constructed in this way represents a structure of the RBF neural network, and the number of neurons is uncertain.

2) Construction of genetic operators

The most basic genetic operators include three kinds: the selection operator, crossover operator and mutation operator.

The selection operator uses roulette selection method, that is, the higher the fitness is, the more easily the individual is selected, and the individuals with low fitness may also be selected, but the probability of being selected is smaller. This keeps the diversity of the population at the same time as the "survival of the fittest".

The crossover operator uses a approach similar to two-point crossover but the location of the two points is not randomly generated, which one of the two is left in the neuron coding area, the other is in the variance coding region.

The mutation operator uses two point mutation, and the gene in the coding region of the neuron is calculated by negation operation, that is, changing 1 to 0 in mutation gene, or 0 to 1. The gene in the covariance coding region adopts Gaussian variation, which adds a Gauss random number to real number in mutation gene.

Both crossover probability $P_c$ and mutation probability adopt adaptive probability, we have:

$$P_c = \begin{cases} P_{c1} - \frac{(P_{c1} - P_{c2})(f' - f_{avg})}{f_{max} - f_{avg}}, & f' \geq f_{avg} \\ P_{c1}, & f' < f_{avg} \end{cases}$$

(4)

$$P_m = \begin{cases} P_{m1} - \frac{(P_{m1} - P_{m2})(f'' - f_{avg})}{f_{max} - f_{avg}}, & f'' \geq f_{avg} \\ P_{m1}, & f'' < f_{avg} \end{cases}$$

(5)

Where, $P_{c1}$, $P_{c2}$ are the highest and lowest values for the crossover probability and
$P_{m1}$, $P_{m2}$ are the highest and lowest values for the mutation probability. $f_{\text{max}}$ is the highest fitness value in the population of this generation and $f_{\text{avg}}$ is the average fitness value. $f'$ is the two individuals' greater fitness value which are to cross and $f''$ is the individual's fitness value which is to mutate.

3) The calculation of fitness value

The fitness function of each individual is set as the reciprocal of the sum of the absolute value of the difference between the desired output and the actual output of the RBF neural network. For the $n$th chromosome, the fitness value can be expressed as:

$$f(q) = 1/E(q) = 1/\sum_{k=1}^{1} \sum_{j=1}^{n} |y_{kj} - y_{kj}|$$

The fitness function selected by this method can reflect the performance of each chromosome.

4) Solve $\delta_i$

If there are $h$ centers in the hidden layer and the maximum distance between the centers is $c_{\text{max}}$, the width of the Gauss basis function is:

$$\delta_i = \frac{c_{\text{max}}}{\sqrt{2h}}, i=1,2,...,h$$

4. The geometry correction algorithm of UAV remote sensing image based on AGA-RBF neural network

When the RBF neural network is used to calibrate the UAV remote sensing image, we use AGA to optimize the basis function center $c_i$ and LMS algorithm to optimize $\omega_{ij}$. Then, the selected control points are used as training samples to train the RBF neural network, so that the parameters of the network are all optimized. Finally, the trained network is used to do approximately geometry correction for original input image, then the picture of the geometric distortion is obtained.

Based on the above network structure and training thought, the general steps of AGA-RBF algorithm can be summarized as follows:

Step 0: Normalize the ground control points coordinates in distorted images and reference images to [-1,1] according to the equation (8),

$$v_{i\text{-new}} = -1 + 2 \frac{v_i - \text{min}(v)}{\text{max}(v) - \text{min}(v)}$$

Where, $v_i$ represents the control points' coordinate value in one dimension, $\text{max}(v)$ and $\text{min}(v)$ are the maximum value and the minimum value of the dimensional coordinates in all control points;

Step 1: Set the parameters of adaptive genetic algorithm. Population size is $P_s$, cross probability upper and lower bounds are $P_{c1}$ and $P_{c2}$, variation probability upper and lower limit are $P_{m1}$ and $P_{m2}$ and the maximum iteration number is $\text{MAXT}$;

Step 2: Initialize the population. Set the number of iterations $t$ as 0, there will be $P_s$ random natural numbers in the interval [1,h]. Then choose each random natural numbers as clustering number and use the K - means clustering algorithm to do clustering with the selected control points, so $P_s$ groups of basis functions centers will be obtained. Finally, formulas (7) is used to calculate the width of the basis function centers of each group, and the encoding is made according to formula (3);

Step 3: According to the network structure corresponding to each chromosome, use the selected control point and LMS algorithm to optimize the weights $\omega_{ij}$, get the initial
complete network, and calculate the fitness f(q) of each chromosome, q=1,2,...,1;

Step 4: Based on the genetic operators to select, crossover and mutate, the new population will be generated.

Step 5: For each chromosome in the new population, use the selected control point and LMS algorithm to optimize the weights $\omega_{ij}$, then the complete network will be obtained.

Step 6: Calculate the fitness value f(q), q=1,2,...,1. Set t=1, then determine whether t<MAXT, if it is, turn to step 4, otherwise step 7.

Step 7: Obtain the optimal network structure. After the distorted image is approximately geometrically corrected and resampled, the corrected image will be obtained.

5. Analyze experiment

With the purpose of verifying the feasibility of the algorithm, this paper uses the simulated checkerboard diagram to test it, and the simulation data is shown in Fig.2. Among them, (a) is a reference image without distortion, whose size is 450 pixel x 450 pixel, (b) is the distorted image transformed from image (a) after simulating geometric distortion, and (c) is the corrected image.

![Figure 2. Experimental simulation diagram](image)

Before applying the method to geometry correction of the distorted image, the control points should be extracted from the image firstly, and the number and distribution of the control points have a great influence on the correction accuracy of the image. This paper extracted 64 control points from the image, and chosen the image distortion of pixel coordinates of control points as the neural network's input, the pixel coordinates of the corresponding reference image control points as the outputs of the network to train the network, and the trained AGA-RBF neural network was used to do geometry correction test on the distorted image. The effect of the calibration is presented in Fig.2(c). With the purpose of objectively explaining the effect of this algorithm, 8 points were randomly selected from the corrected images to check out the network performance, and the final results are given in Table 1.

| Point number | Reference image | Distorted image | Corrected image | Root-mean-square error |
|--------------|----------------|----------------|-----------------|-----------------------|
| 1            | (114.00,58.25) | (128.00,65.00) | (115.00,58.00)  | 0.7289                |
| 2            | (225.00,50.25) | (232.00,57.75) | (227.00,50.00)  | 1.4252                |
| 3            | (282.00,113.00)| (283.00,122.00)| (283.00,113.15) | 0.7150                |
| 4            | (170.00,169.30)| (176.00,175.00)| (170.50,169.00) | 0.4123                |
| 5            | (226.00,225.00)| (227.00,226.00)| (226.00,224.50) | 0.3536                |
| 6            | (57.00,282.00) | (67.00,275.00) | (58.00,280.75)  | 1.1319                |
| 7            | (338.00,338.00)| (328.50,335.75)| (336.50,338.75) | 1.1859                |
| 8            | (169.00,348.00)| (170.00,340.00)| (170.00,347.50) | 0.7906                |
In order to further verify the effect of the algorithm on the geometry correction of UAV remote sensing image, this paper used the actual UAV remote sensing image to carry out the experiment, as shown in Fig.3(a). The image was taken from the author's unit located in Tianjin city. Based on the selected ground control points, this paper uses AGA-RBF network of UAV remote sensing image to carry on geometry correction, and uses bilinear interpolation method to resample the final corrected image, as described in Fig.3 (b). It can be seen from the figure that the geometry correction of UAV remote sensing image has achieved good effect, which further illustrates the effectiveness of the algorithm.

(a) The original image  (b) The corrected image

Figure 3. Comparison of UAV remote sensing image before and after geometry correction

6. Conclusion

This paper has analyzed the current research situation of the UAV remote sensing image geometry correction, introduced the adaptive genetic algorithm and RBF neural network, and proposed UAV remote sensing image geometry correction algorithm and implementation steps based on adaptive genetic algorithm to optimize RBF neural network which combined with the UAV remote sensing image geometry correction idea. The experimental results show that this method has high correction precision and strong generalization ability, which can satisfy the needs of actual work. But about the control points selected in the algorithm, further study is needed.

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