A GENETIC-OPTIMIZED MULTI-ANGLE NORMALIZED CROSS CORRELATION SIFT FOR AUTOMATIC REMOTE SENSING REGISTRATION

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ABSTRACT

A new method of remote sensing image registration is proposed to reduce the adverse effects on the image registration caused by the rotation transform, based on genetic-optimized multi-angle normalized cross correlation (GMNCC) to get more matched scale invariant feature transform (SIFT) feature points. The GMNCC can detect the angle-offsets (AOs) of object images to reference image by determining the maximum of correlation coefficients between the two images with genetic algorithm, and complete the rotation offset correction. Then SIFT is used to extract the feature points and feature matching, which is subsequently refined by RANSAC to eliminate the false matched control points. Two Woldview-2 (WV2) images of Beijing Olympic Forest Park were used for testing the GMNCC-SIFT registration. GMNCC detects more accurate rotation angle-offsets than multi-angle normalized cross correlation (MANCC), reduces the detection process from 3000s to 2500s, and gives more matched points than simple SIFT to improve registration accuracy.

Index Terms— Remote sensing image registration, genetic algorithm optimized normalized cross correlation, SIFT, RANSAC

1. INTRODUCTION

Image registration (IR) is usually a process of space mapping through a space transformation to keep the spatial location consistent among the same target points. Registration is often necessary for integrating information taken from different sensors, finding changes in images taken at different times or under different conditions, inferring three-dimensional information from images and recognizing model-based objects [1]. Over the year, a broad range of techniques have been developed for the various types of data and problems. Gray-scale and featured based image registration techniques are more widely applied for those characteristics of small amount of calculation, fast and robust registration.

SIFT is capable of extracting distinctive invariant features from images, and it can be applied to preform reliable matching across a substantial range of affine distortion, change in 3-D viewpoint, addition of noise, and change in illumination [2]. Despite the attractive advantages of SIFT, there exist some problems when it is directly applied to remote sensing images, i.e., the number of the detected feature matches may be small, and their distribution may be uneven due to the complex content nature of remote sensing images [3]. This paper proposes a SIFT remote sensing image registration based on Genetic Algorithm (GA) optimized NCC. First, GA is used to optimize the normalized cross-correlation algorithm, determine the rotation angle (RA) of registration image, and complete the angle correction, then apply SIFT for feature points extraction and feature vectors matching, and then perform classical RANSAC to refine the registration point. An experiment with groups of 20 target images with random rotation offsets registered to a reference WV2 was performed to show the accuracy and performance of GMNCC.

2. ALGORITHM PRINCIPLES

2.1. Multi-angle normalized cross correlation

Normalized Cross Correlation (NCC) algorithm is a matching method based on gray feature. The basic principle can be attributed to using a similarity measure function and to comparing the gray matrix of reference image with the gray matrix of matching image to get the highest correlation coefficient to determine the matching position. When object image rotates, the NCC coefficients fluctuate with the changing of rotation angle, and the maximum indicates the best rotation angle-offset between the object image and reference image. Multi-angle NCC is developed to do angle correction before image registration.

The normalized cross-correlation method has the characteristics of good anti-noise property, high accuracy, strong adaptability, when small distortion (rotation, zoom, etc.). The literature [4] gives a fast normalized cross correlation method to overcome the shortcomings of high complexity and long computing time.

2.2. Genetic algorithm

Genetic algorithms are search and optimization algorithms based on natural selection and natural genetics. In general, GA aims to search for an optimal solution without trying out all possible cases. They operate on a set of solutions, a population, instead of just one solution. The members of this population, the individuals, receive a fitness value based on the coding of their genes. Fitter individuals will be preferred over others in a process called selection. A child population then serves as a new parent population. This cycle repeats until the user-chosen number of generations is reached. The fittest individual was kept as the optimal configuration of the pixel, during that iteration [5].

. In this paper, GA is used to calculate the accurate angle with the maximum NCC coefficients between object images to reference image in the shortest time of multi-angle NCC algorithm.

2.3. SIFT descriptor

A family of descriptors based on Gaussian derivatives can be computed up to a given order and normalized to be invariant to pixel intensity changes. Lowe [6] developed a SIFT descriptor based on the gradient distribution in the detected regions, which is invariant to image scaling and rotation, and partially invariant to change in illumination. There are four steps to implement the original SIFT descriptor algorithm:

Scale-space extrema detection: The first stage is to search over scale space using a Difference of Gaussian (DOG) function to identify potential interest points that are invariant to scale and orientation.

Feature point localization: The location and the scale of each candidate point are determined and the feature points are selected based on measures of stability.

Orientation assignment: One or more orientations are assigned to each feature point location based on local image gradient directions.

Feature point descriptor: A feature descriptor is created by computing the gradient magnitude and orientation at each image sample point in a region around the feature point location. These samples are then accumulated into orientation histograms summarizing the contents over 4×4 regions with 8 orientation bins. So each feature point has a 128-element feature.

2.4. RANSAC

The basic assumption of RANSAC algorithm is that in the sample contains the correct data (inliers, can be described by the model data), also contains abnormal data (outliers, far from the normal range, unable to adapt to the mathematical model of the data), namely that the dataset contains noise. At the same time, RANSAC also assumes that given a set of correct data, there can be calculated out of these data to the model parameters [7]. Using RANSAC algorithm to eliminate false matching points, you need to select a suitable model of geometric constraint, the commonly used linear geometric constraint model is the epipolar and homography matrix

RANSAC is applied to the matched SIFT points to refine the registration control points, which takes advantage of almost all possible matching points and has good robustness to image noise.

3. EXPERIMENTAL RESULTS

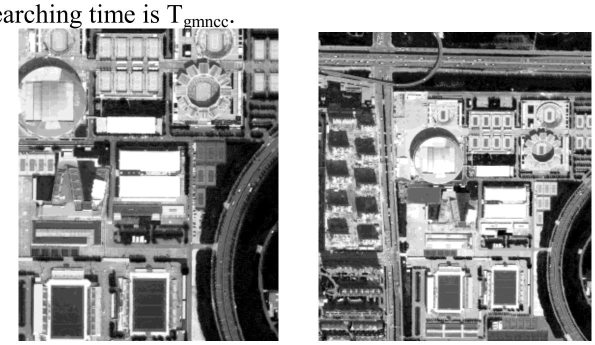
3.1. Experimental Design and Data

Two WV2 remote sensing images in the Beijing Olympic Forest Park with different phases are used as reference and object image showing in Fig.1 (a) and (b).They were acquired in September, 2013 and September, 2012 respectively. 20 sets of angles selected randomly between 0~360° (positive when rotate clockwise, and negative when anti-clockwise) are applied to the object image to generate a group of remote sensing images rotated (RSIR) with different angles (shown in Table 1), which will be registered to the reference image with the novel method.

Two experimental schemes are designed in order to evaluate the algorithm designed in this paper:

(1)Use simple SIFT to register 20 object images (I_1 ~ I_{20}) to the reference image. The number of matched SIFT points is N_{masift}, and the number of RANSAC refined matched points is $N_{gmsiftransac}$.

(2)Use multi-angle NCC to detect the angles of the 20 images and complete angle correction. Then the number of matched SIFT points is $N_{manccsift}$, the number of RANSAC refined matched points is $N_{gmnccsiftransac}$. The detected angle of 20 object images is A_{mancc} and the searching time is T_{mancc}. Whereas, the GMNCC is also applied to the registration of 20 object images, with detected angle as A_{gmncc} and searching time is T_{gmncc}.

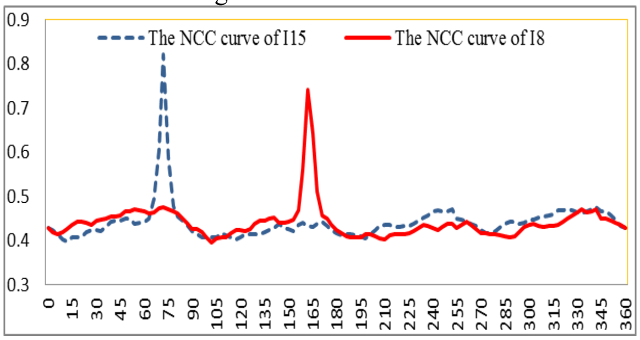


(a) (b)

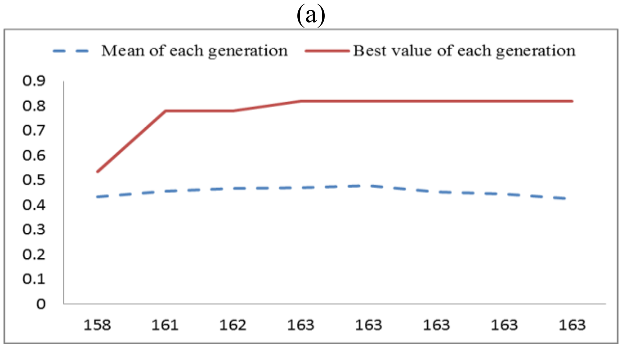
Fig.1. Two WV2 images of the Olympic Forest Park: (a) Reference image; (b) Object image

3.2. Experimental result

The NCC coefficients between the object image with a random angle-rotation-offset and reference image are changing with the rotation of object image to reference one, and get the maximum value when the angle offset is zero between the two images.



(a)



(b)

Fig.2. (a)The curve of NCC coefficients with rotation angles (x axis: rotation angles,y axis: NCC coefficients); (b) The maximum value extracted process of GMNCC (x axis: detection angles,y axis: NCC coefficients)

The multi-angle NCC coefficients curve of RSIR image I_8 is shown in Fig.2 (a). When the rotated angel reaches 197°, the NCC curve get the global maximum value and shows the best calibration angle. The correction angle of RSIR image I_{15} can also be calculated the global maximum value of the blue doted curve in Fig.2 (a).

Fig.2 (b) shows the process of GMNCC exploring the best correction angel of RSIR image of I_8, with 8 iterations and 30 samples in each generation. The blue dotted line expresses the mean value of each generation and the red solid line shows the changing process of best fitness with the evolution. Obviously, the algorithm has detected the rotate angle 163° (that is -197°) after fourth generations. The GMNCC is faster and more intelligent than multi-angle NCC.

GMNCC and traditional multi-angle NCC are applied to the 20 images to detect their rotated angles for correction respectively. The smaller searching interval of RA for images registration can lead to more accurate detected correction angles, but also result in a more time-consuming exploring process. The searching interval of RA of GMNCC is set to 1° or 0.1°, while that of MANCC is 3° to reduce its searching time. The detected angles of 20 images are shown in Table1. It shows that GMNCC detects more accurate correction angles than multi-angle NCC. The operating time of the searching process on I_8 is reduced from MANCC's 3000s to GMNCC.s 2500s, as shown in Table 2. The algorithm of GMNCC can get a more accurate angle-offset in less time, and the registration results are obviously improved.

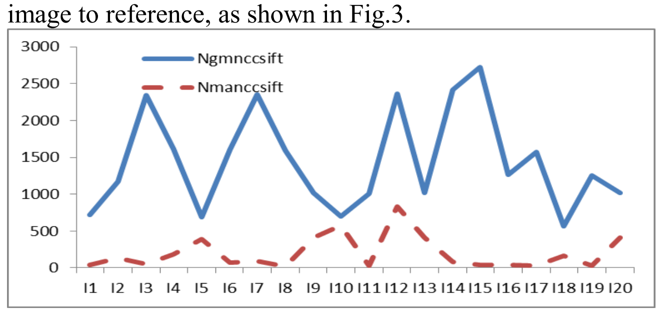
Table1. The comparison of corrected angles of multi-angle MANCC and GMNCC

object images	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8	I_9	I_{10}
Rotation angle of RSIR (°)	293	326	46	329	228	35	100	197	345	347
A_{mancc}	−291	−324	−45	−330	−225	−36	−99	−198	−342	−345
A_{gmncc}	−292	−327	−46	−329	−228	−35	−101	−197	−346	−346
object images	I_{11}	I_{12}	I_{13}	I_{14}	I_{15}	I_{16}	I_{17}	I_{18}	I_{19}	I_{20}
Rotation angle of RSIR (°)	57	349	345	175	288	51	152	330	285	345
A_{mancc}	−54	−348	−342	−174	−288	−54	−153	−324	−288	−345
A_{gmncc}	−57	−349	−344	−175	−288	−52	−152	−329	−285	−345

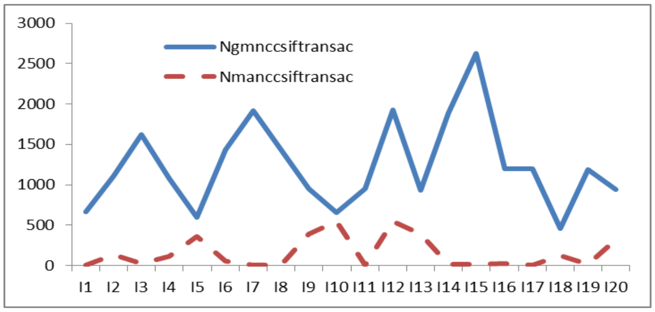
Table 2. Searching time of MANCC and GMNCC of I_8

Algorithm	**Rotated angle**	**Correction angle**	**Time (s)**
MANCC	197°	-198°	3000
GMNCC	197°	-197°	2500

The SIFT descriptor are appied on twenty images to extract correspondence points (CPs) before and after the accurate rotation-angle–offset correction. The number of matched points of the combination of GMNCC and SIFT is about 167.3 time to that of simple SIFT. The more control points obtained by RANSAC, the more accurate the registration results will be. $N_{manccsift}$ and $N_{gmnccsiftransac}$ are more than ten times to the corresponding N_{masift} and $N_{gmsiftransac}$, leading to a more accurate registration of object image to reference, as shown in Fig.3.



(a)



(b)

Fig.3. (a) Comparison of $N_{gmnccsift}$ and $N_{manccsift}$ (x axis: code of object images, y axis:number of matched points); (b) Comparison of $N_{gmnccsiftransac}$ and $N_{manccsiftransac}$ (x axis: code of object images, y axis:number of matched points)

Finally, these correspondence points got by the combination of GMNCC, SIFT and RANSAC are applied to do registration of the twenty object images with linear polynomial projection. The registration process of I8, shown in Fig.4, shows more accurate correspondence between the result images to the reference image and improve the performance of normal SIFT matching.

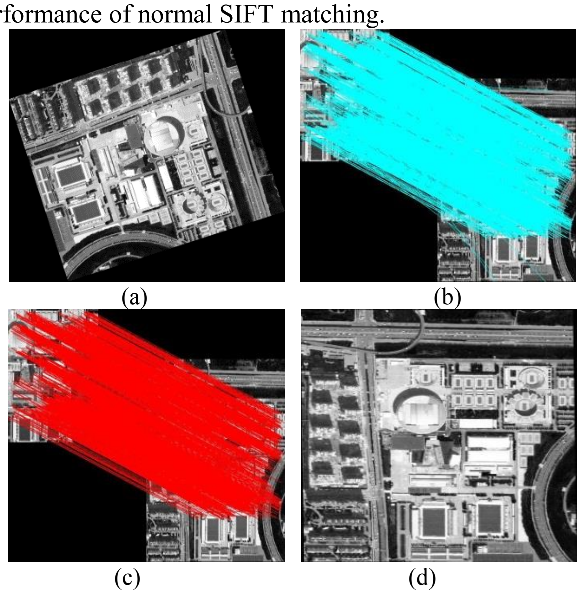


Fig.4. the registration process of I_8: (a) the test image of I_{15}; (b) CP matching of SIFT after GMNCC; (c) refined CP matching by RANSAC after GMNCC and SIFT; (d) registration of I_8.

4. CONCLUSIONS

A genetic-optimized multi-angle normalized cross correlation (GMNCC) algorithm was given in this paper to get more the matched SIFT feature points and improve the registration accuracy. Experiments have been performed to register group of remote sensing images with different angle-offsets to a reference image, detecting more accurate rotation angles and presents more matched control points. Besides, the algorithm can also be extended to the registration remote sensing images of unmanned aerial vehicles (UAV).

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5. REFERENCES

[1] Medha V. Wyawahare, Dr. Pradeep M. Patil, and Hemant K. Abhyankar, "Image Registration Techniques: An overview," *International Journal of Signal Processing, Image Processing and Pattern Recognition*, vol. 2, no.3, pp.11-28, Sept. 2009.

[2] Maoguo Gong, Shengmeng Zhao, Licheng Jiao, Dayong Tian, and Shuang Wang, "A Novel Coarse-to-Fine Scheme for Automatic Image Registration Based on SIFT and Mutual Information," *IEEE Trans. Geosci. Remote Sens.* vol. 52, no.7, pp.4328-4338, Jul. 2014.

[3] A.Sedaghat, M.Mokhtarzade,and H. Ebadi, "Uniform robust scaleinvariant feature matching for optical remote sensing images," *IEEE Trans. Geosci. Remote Sens.*, vol. 49, no. 11, pp. 4516–4527, Nov. 2011.

[4] Jae-Chern Yoo, Tae Hee Han. "Fast Normalized Cross-Correlation," *Circuits, Systems and Signal Processing*, pp. 819-843, 2009.

[5] H.P.Schwefel."Numerical Optimization of Computer Models." *John Wiley, Chichester,U.K*, PP.12-16, 1981.

[6] David G. Lowe. "Distinctive Image Features from Scale-Invariant Keypoints,"*International Journal of Computer Vision*, pp.91-110, 2004.

[7]M. Fischler, R. Bolles. "Random sample consensus:A paradigm for model fitting with applications to image analysis and automated cartography," *CACM*, pp.381-395, 1981.