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Adaptive Wallis Filter via Sparse Recognition for Automatic Control Points Extraction

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Abstract

With the rapid development of the remote sensing satellite, the size and the resolution of satellite images grow increasingly. The evaluation of remote sensing image quality requires precise information of control points extracted from unevaluated images and reference images. Therefore, we propose an adaptive Wallis filter method based on sparse recognition to increase the number of control points and improve the matching precision. Firstly, feature vectors of images are constructed by computing the image radiation-parameters. Secondly, the classification of sub-region terrain in the image can be determined using sparse recognition. Finally, according to specific type of sub-region terrain, we enhance the regions by the Wallis filter based on corresponding filter parameters and extract control points which would lead to the automatic evaluation for geometric precision. The experiments show that the proposed method can get better results especially in the detail on the images of Resourse-3 satellite, hence can increase the number and improve accuracy of control points.

Keywords: *sparse recognition, radiation-parameters, adaptive Wallis enhancement, extract control points*

1. Introduction

During remote sensing image processing, there is geometric deformation relative to actual targets due to the change of image projection pattern, the alteration of sensor exterior orientation, uneven sensor media and terrain, rotation and curvature of earth, and so on. Therefore, remote sensing image needs to be geometrically corrected before application. However, accuracy of geometric correction is often limited, which leads to existence of unpredicted residual deformation in the remote sensing image after systematic correction. In fact, it is necessary to carry out geometric accuracy evaluation for geometrically corrected image to guiding geometric precision correction [1, 2]. Geometric accuracy evaluation must depend on ground control points (GCPs) which are usually marked between remote sensing image and reference image by engineer. The accuracy of GCPs relies on engineer‘s knowledge and skill, so that GCPs collection is time-consuming and accuracy of GCPs is low. The traditional method seriously affects the efficiency of geometric accuracy evaluation [3]. Therefore, how to increase the number and to improve accuracy of GCPs is a key problem of remote sensing image evaluation.

In recent years, many researches of automatic extraction of GCPs had been done, which can be divided into two classes: pixel-based methods and feature-based methods. In the first method, they match GCPs through computing correlation based on the gray of pixels, which is easy to implement. But the first class needs large amount of calculation to get the matching result and is easily influenced by light and distortion of remote sensing image. In the second methods, they match GCPs through similarity measure based on feature points extracted from image, which operates simply and matches fast with high accuracy. Recently, the researches focus on Harris operator [4], Forstner operator [5], scale invariant features transform algorithm [6] and speeded up robust features (Surf) algorithm [7, 8]. When evaluating geometric accuracy, we should use multi-source reference image which is a mosaic image composed of different spectra, phase, resolution and sensor due to the map of remote sensing image growing [9]. Because there is a great difference of gray in multi-source reference image, it is impossible to extract and match GCPs using pixel-based method and it is difficulty to do that using feature-based method. Therefore, this paper presents a new method of two level matching strategy

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based on global optimization to extract and match GCPs from remote sensing image and multi-source reference image.

We usually carry out image processing before extracting GCPs in order to increase the number and to improve matching accuracy of GCPs. Recently the methods of image processing are divided into two classes. One is histogram-based enhancement algorithms. For example, in order to eliminate gray distortion, Xiaochun Liu takes histogram similarity transformation for remote sensing image and the reference image [10]. The other one is texture-based enhancement algorithms. For example, Li Zhang enhances textures of image using Wallis filter to increase the number and to improve matching accuracy of feature points [11]. With the rapid development of remote sensing satellite, the resolution of remote sensing image becomes more and more accurate. The resolution of CCD camera is 30 meters and resolution of hyper-spectral camera is 100 meters in Environment and Disaster Monitoring satellite (HJ) launched in 2008. Then the resolution of CCD camera is decreased to 2.1 meters and resolution of multi-spectral camera is reduced to 5 meters in Resourse-3 satellite (ZY-3) launched in 2012 [12]. We can conclude that the regional area is 14 times bigger in HJ than that in ZY-3 when the two images are in the same size. So there are various textures in HJ image and there are simple features in ZY-3 image. Traditional Wallis filter with global parameters is suitable for low resolution image such as HJ image. But when it is used for high resolution image, such as ZY-3 image, there will be many pixels with saturated gray. To solve this problem, this paper presents an adaptive Wallis filter based on sub-region: recognize sub-region using sparse recognition algorithm and enhance sub-region using Wallis filter with local parameters.

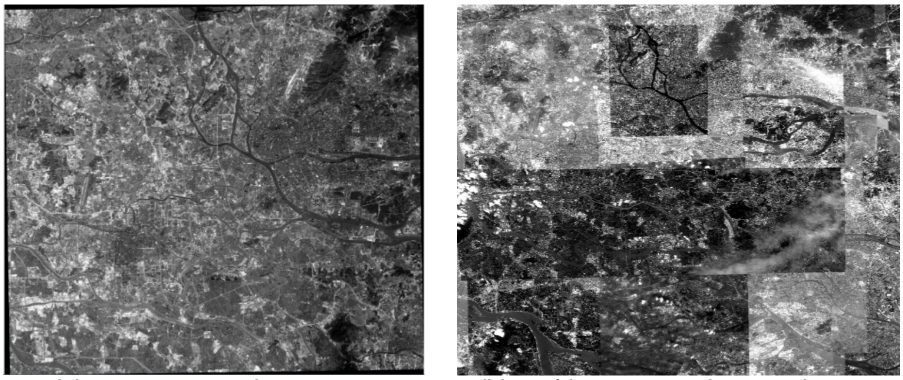
Recently, there are many traditional methods for remote sensing image classification, such as principal component analysis (PCA) [13] and independent components analysis (ICA) [14]. Recently some new measures were involved, such as artificial neural network [15], decision tree [16], support vector machine [17] and expert system [18], and so on. A lot of spatial information in high resolution remote sensing image will be wasted, if we use single traditional classification methods. That's because we do not make good use of context information, shape information and features of target, which can be got form spatial information of high resolution remote sensing image. Therefore, we construct recognition vector with radiation-parameters including statistical information of structure and gray, texture and gray in order to do better work for high resolution remote sensing image.

This paper use sparse recognition algorithm with better classification precision and robustness for high resolution remote sensing image. This algorithm is based on compressed sensing (CS) proposed by Allen Y. Yang and Yi Ma [19]. If each test sample can be represented by sparse polynomial, we can recognize sub-region terrain, which computes sparse representation of training sample according to test samples and classifies test samples. Assuming that all samples belong to the same low dimension space and the linear representation of each test sample can be got according to training samples which are in the same class with test sample, paper [21] computes sparse representation of training samples and recognizes those samples using sparse recognition algorithm. Allen Y. Yang and Yi Ma solve face recognition [21] and Fei Yin recognizes remote sensing image target [22] using sparse recognition algorithm. Therefore, we classify sub-region terrain of remote sensing image using sparse recognition algorithm to get better recognition rate.

This paper presents a new method to increase the number and to improve matching accuracy of GCPs for high resolution remote sensing image that there is simplex feature in sub-region. The algorithm is as follows: 1) Divide image into numbers of sub-regions which are in the same size; 2) Construct recognition vector with radiation-parameters computed from sub-region; 3) Recognize sub-region using sparse recognition algorithm; 4) Enhance sub-region using adaptive Wallis filter with local parameters. The experiments show that compared with existing feature extraction and recognition method, our method can get better results. Adaptive Wallis filter eliminates the number of pixels with saturated gray, which traditional Wallis filter cannot do for high resolution remote sensing images. In this way, we can effectively extract more and higher accurate GCPs to achieve the evaluation of geometric precision automatically and accurately.

2. Two Levels Matching Based on Wallis Enhancement

There are some problems about geometric accuracy evaluation with the map of remote sensing image growing. When evaluating geometric accuracy, we should use multi-source reference image, which is a mosaic image composed of different spectra, phase, resolution and sensor due to the map of remote sensing image growing. There is a great difference of gray in multi-source reference image, as shown in Figure 1(b), so it is difficult to extract and match GCPs from remote sensing image and multi-source reference image using existing methods.



(a) Remote Sensing Image (b) Multi-source Reference-image

Figure 1. Remote Sensing Image and Its Reference-image

Paper [9] presents two levels matching based on traditional Wallis enhancement to extract GCPs. The main algorithm is following:

(1) Take the first level matching: First, take down sampling for remote sensing image and multi-source reference image with the same parameters. Second, extract and match original GCPs using Surf algorithm, which has many advantages, such as scaling and rotation invariance, anti-illumination change and anti-viewpoint transformation, and so on. Third, get rid of wrong matching GCPs though estimation epipolar geometry constraint [19, 20] including M-Estimation algorithm [21-23] and random sample consensus algorithm (RANSAC) [24-27]. Surf algorithm includes four steps: extract feature points, determine their main direction, generate their description and match these points. When image contains a lot of similar structures, feature points extracted from these structures will easily mismatch due to similarly local neighborhood information contained in description of feature points.

(2) Compensate geometrical information of remote sensing image, which are generated from original GCPs extracted in the first level matching. We describe geometrical relation between remote sensing image and multi-resource reference image using first-order polynomial, as shown in Equation (1) and Equation (2):

$$X = a_1 + a_2 x + a_3 y + a_4 xy \tag{1}$$

$$Y = b_1 + b_2 x + b_3 y + b_4 xy \tag{2}$$

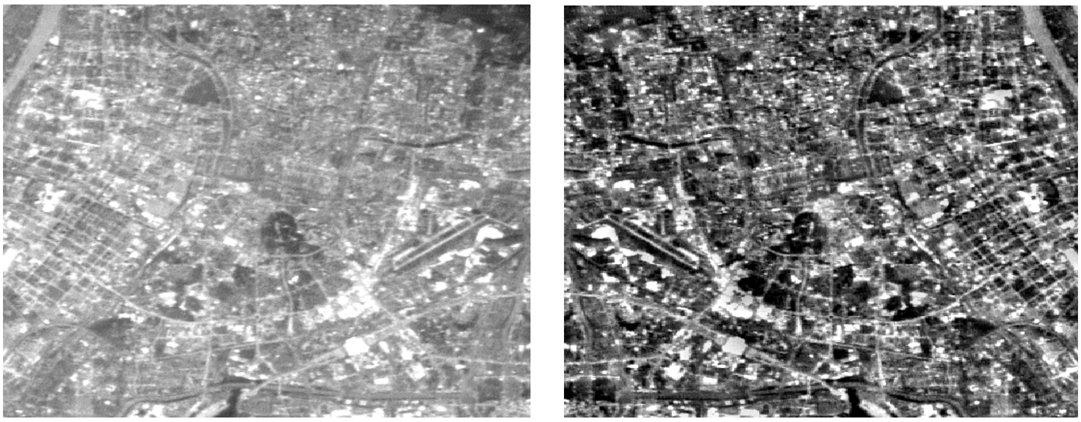
Where, *(x,y)* is the feature point of remote sensing image; *(X,Y)* is the feature point of multi-resource reference image.

(3) Enhance the textures of the above images by traditional Wallis filter.

(4) Take the second level matching: Extract and match GCPs using Surf algorithm and then get rid of wrong matching GCPs though estimation epipolar geometry constraint.

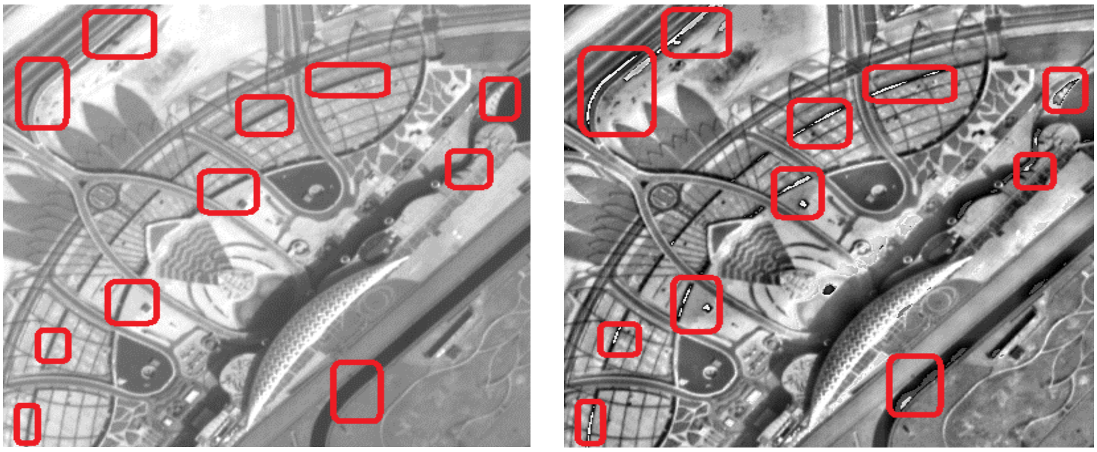
Take the sub-region image of HJ for example, which its size is 400×400 and its resolution is 30 meters. The sub-region covers 12km×12km area and contains abundant terrains and complicated textures. The experiments show that the sub-region of low precision can be well enhanced by traditional Wallis filter, as shown in Figure 2. With the same size, the area of sub-region took by image is 14 times bigger than that took by ZY-3, which covers

820m×820m area and the textures and terrains are simplex. The traditional Wallis filter cannot enhance textures of high resolution image well due to containing many pixels with saturated gray, as shown in Figure 3. Therefore, we propose a new method of two levels matching based on adaptive Wallis enhancement.



(a) HJ Image (b) Wallis Enhancement

Figure 2. Comparison of Wallis Enhancement on Low Pixel Image



(a) ZY-3 Image (b) Wallis Enhancement

Figure 3. Comparison of Wallis Enhancement on High Pixel Image

3. Adaptive Wallis Enhancement based on Radiation-parameters

When we enhance textures of high resolution remote sensing image using traditional Wallis filter, there are many pixels with saturated gray so that the number of GCPs is less and the accuracy of those is low. So we propose a new method of two levels matching based on adaptive Wallis enhancement to increase the number and to improve accuracy of GCPs, as shown in Figure 4. The main steps are following:

(1) Take the first level matching to extract and match original GCPs after down sampling of remote sensing image and multi-resource reference image. Then compensate geometrical information of remote sensing image, which are generated from original GCPs.

(2) Construct recognition vector of sub-region with radiation-parameters.

(3) Recognize sub-region using sparse recognition algorithm.

(4) Enhance sub-region image using adaptive Wallis filter with local parameters according to the class of sub-region.

(5) Take the second level matching to extract and match GCPs using Surf algorithm and then get rid of wrong matching GCPs though estimation epipolar geometry constraint.

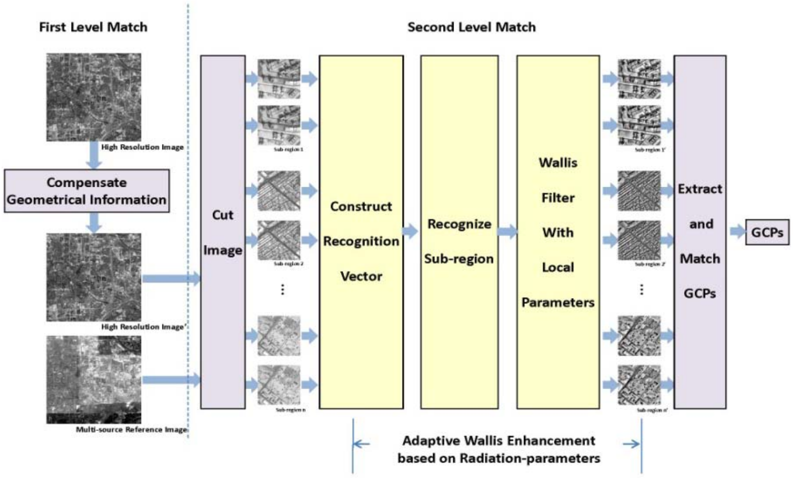
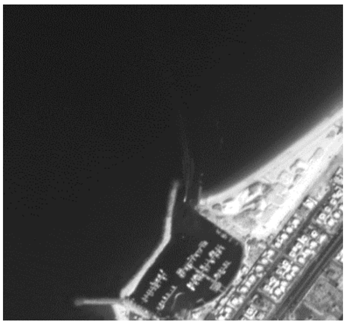
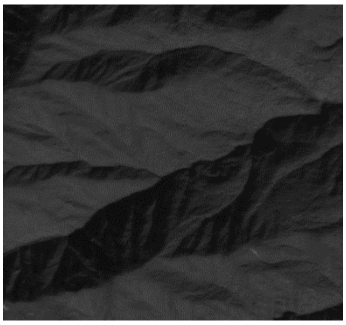
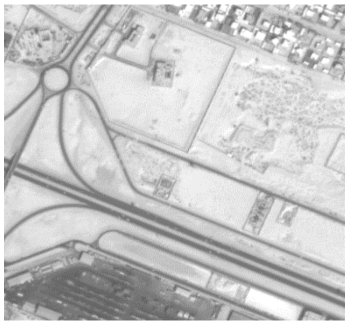


Figure 4. Two level Matching Based on Adaptive Wallis Enhancement

3.1. Construct Recognition Vector Based on Radiation-parameters


(a) Water


(b) Mountain


(c) Suburbs with minority buildings


(d) City with some buildings


(e) City with mass buildings

Figure 5. Remote Sensing Sub-region

Remote sensing sub-regions are classified into five sets: (1) Water set: Because most area of earth is water, we construct water set, as shown in Figure 5(a). (2) Mountain set: One third of land is mountain and its textures are particular, as shown in Figure 5(b). (3) Suburbs set with minority buildings: Sub-region contains few constructions and its textures are simple, as shown in Figure 5(c). (4) City set with some buildings: Sub-region contains some constructions, as shown in Figure 5(d). (5) City set with mass buildings: Sub-region contains mass constructions and its textures are complex, as shown in Figure 5(e). Then we construct recognition vector of remote sensing sub-region using twelve radiation-parameters. Training set and test set are constituted by those recognition vectors.

The main research of feature extraction for remote sensing image focuses on pixel-based method such as PCA and ICA and so on. For the past few years, many researchers made great efforts to improve classification precision. However, classification precision cannot be effectively improved due to the limitation of pixel-based methods. Because high resolution remote sensing image contains abundant of information and complex textures, this paper constructs recognition vector of remote sensing sub-region with twelve radiation-parameters, including column of signal to noise ratio, detail energy, gray mean, edge energy, generalized noise, gradient, angular second moment, gray variance, entropy, definition, contrast and signal to noise ratio (SNR). Reflecting complication and direction of texture, those twelve parameters describe details and edge features from both spatial domain and frequency domain. The recognition of remote sensing sub-regions mainly relies on statistical information of structures such as image texture and edge information. Due to both image texture and edge information belonging to high frequency information, the noise may be mistaken for image texture, if we only consider image texture. Therefore, in order to improve recognition accuracy, this paper selects SNR, generalized noise, column of signal to noise ratio and other radiation-parameters as recognition vector of remote sensing sub-regions.

3.2. Recognition of Sub-region Terrain via Sparse Recognition

Sparse recognition algorithm can get higher recognition rate and better robustness, compared with traditional recognition algorithms such as the nearest neighbor classifier. This method effectively avoids over-fitting and under-fitting, because linear representation of test sample can be got by some large weight training samples. The vector of linear representation is sparse, which reflects the difference of samples among classes, as shown in Equation (3):

$$\begin{aligned} &\hat{x}_0 = argmin\|x\|_0 \\ &\text{s.t. } x = X \cdot r \end{aligned} \tag{3}$$

Where, x is test sample; r is the vector of linear representation and recognition vector; $X = \left[x_{1,1}, \ldots, x_{1,n}, \ldots, x_{m,1}, \ldots, x_{m,n}\right] \in R^{12 \times mn}$, it is training samples matrix; $x_{i,j}$ is the j^{th} sample in the i^{th} class; m is the number of sample classes; n is the number of samples in per class.

Equation (3) belongs to the NP-hard problem and cannot be solved in polynomial time. Fortunately, compressed sensing draws the conclusion as following [32]: if the optimal solution ($\hat{x}_0$) of Equation (3) is fully sparse, $\hat{x}_0$ can be solved which Equation (3) is transformed into minimal l_1 norm, as shown in Equation (4):

$$\begin{aligned} &\hat{x}_0 = argmin\|x\|_{l_1} \\ &\text{s.t. } x = X \cdot r \end{aligned} \tag{4}$$

There is an effective method for Equation (4), because it is a convex optimization problem. The l_1 norm can be solved using Basis Pursuit (BP) algorithm [33, 34], which is stable and well robust. Sparse representation can be transformed into linear programming problem though BP algorithm, because minimization of l_1 norm and linear programming can be defined as constrained optimization problems, as shown in Equation (5):

$$\begin{aligned} &\hat{x}_0 = argmin\|x\|_{l_1} \\ &\text{s.t. } x = \sum x_{i,j} \cdot \sum r_{i,j} \end{aligned} \tag{5}$$

3.3. Adaptive Wallis Enhancement

Wallis filter can map the mean and variance within windows to given values leading to approximate mean and variance in image. Therefore, it can strengthen contrast when the contrast is low and also can weaken contrast when the contrast is high, so that the tiny change of gray can be transformed into visual textures. In this way, Wallis filter can greatly enhance the texture and contrast of image while effectively suppressing noise. Although the image enhanced by Wallis filter is similar to noise image, we can match GCPs in lower uncertainties and in false probability to improve matching accuracy. The Wallis filter can be expressed as Equation (6):

$$g_c(x,y) = g(x,y)\cdot r_1 + r_0 \quad (6)$$

Where, $r_1 = c\cdot s_f \big/ (c\cdot s_g + s_f / c)$, it is multi-factor. $r_0 = b\cdot m_f + (1-b)\cdot m_g$, it is add-factor. m_g and s_g are the mean and variance within windows. m_f and s_f are the expected values of Wallis filter for image and they are parameters of Wallis filter. s_f should be a smaller value when the size of windows decreases. b is a constant which describes the brightness of image and c is also a constant which describes the contrast of image. The parameter of c should be a bigger value when the size of windows increases. The multi-factor of r_1 determines the performance of Wallis filter, and the relationship with other parameters can be described as Equation (7):

$$1/r_1 = 1/c^2 + s_g / s_f \quad (7)$$

We enhance different textures using dynamic size of windows with corresponding local parameters to make great use of Wallis filter, as shown in Table 1. We set small size of windows, s_f and c to enhance sub-region with complex textures, such as city area, and set big parameters to enhance sub-region with simple textures, such as lake, mountain and farm. The experiments show that adaptive Wallis filter with dynamic size of windows eliminates the number of pixels with saturated gray, which gets a better enhancement for huge remote sensing image containing various terrains. In this way, we can get more and high accuracy of control points.

Table 1. Parameters of Wallis Filter for Sub-region Terrains

Sub-region	size of windows	s_f	c
Water	33	139	0.9
Mountain	31	135	0.87
Suburbs with minority buildings	25	131	0.85
City with some buildings	21	127	0.83
City with mass buildings	17	121	0.8

4. Results and Analysis

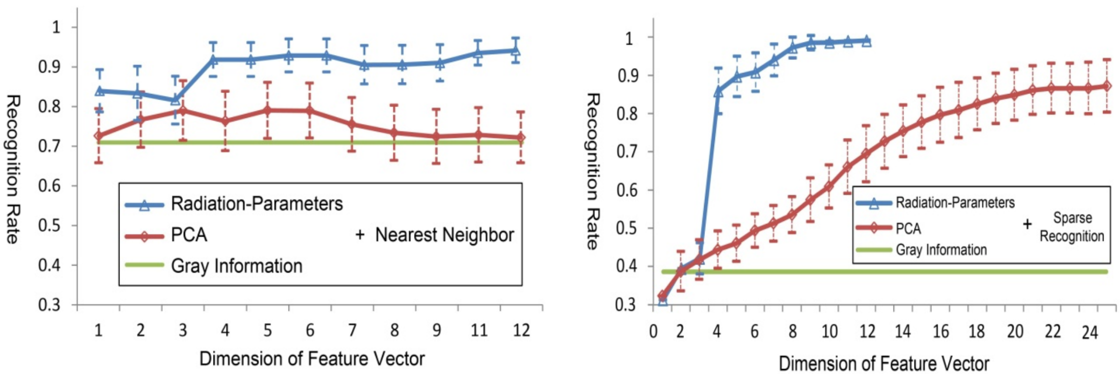
We construct recognition vector of high solution remote sensing sub-region with radiation-parameters and recognize sub-region using sparse recognition algorithm. In order to increase the number and to improve the accuracy of GCPs, this paper enhances different remote sensing sub-region terrains using adaptive Wallis filter with corresponding local parameters.

4.1. Discuss Recognition Precision of Remote Sensing Sub-region Terrain

We construct train sample set and test sample set with feature vectors composed from radiation-parameters of remote sensing sub-region terrains: water, mountain, suburbs with minority buildings, city with some buildings, and city with mass buildings. In fact, 30 samples belong to train sample set which are randomly selected from each class including 40 samples, and others of each class belong to test sample set. Take mean and standard deviation of recognition rate as measure of each algorithm, which are computed from 1000 times recognitions. In order to prove the effectiveness of our method, we design three experiments as follows:

(1) Discuss recognition rate of remote sensing sub-region terrain under different feature vectors and that under different classification strategies. According to the mean and standard deviation of recognition rate, we choose the most suitable feature vector and classification strategy so that we can get the highest recognition precision. The feature representations include gray information, feature vector based on PCA and radiation-parameters. And the recognition algorithms contain the nearest neighbor classifier and the sparse recognition algorithm.

We can see the difference of recognition rate between the nearest neighbor classifier and the sparse recognition algorithm under three feature vectors in Figure 6: Under different dimension of feature vector, the change of recognition average is described by the solid line; under the given dimension of feature vector, the change of standard deviation is described by the dashed line, which reflects stability of algorithm. The experiments show that the recognition rate is between 70% and 80%, as described by green line and red line in Figure 6(a), when we extract feature vector based on gray information and PCA using the nearest neighbor classifier; then the recognition rate is always more than 80%, the highest being 95%, as described by blue line in Figure 6(a), when we compute radiation-parameters as recognition vector. Thus as described by green line in Figure 6(b), the recognition rate of feature vector based on gray information is approximate 37% using sparse recognition algorithm. From the red line in Figure 6(b), we can see that higher recognition rate can be got with the dimension of feature vector based on PCA increasing. The recognition rate is about 86%, when the dimension of feature vector is over 20. This paper can get the best recognition rate which the highest is 99.64% using radiation-parameters, as described by blue line in Figure 6(b). It can be concluded that we should compute radiation-parameters as recognition vector using sparse recognition algorithm to get the best result.



(a) Recognition Rate of the Nearest Neighbor Classifier

(b) Recognition Rate of Sparse Recognition algorithm

Figure 6. Recognition Rate for Various Feature Transformations and Classifiers

(2) Discuss the importance of radiation-parameters. Removing radiation-parameter one by one from recognition vector, we compute recognition rate based on sparse recognition algorithm. Then this paper sorts twelve radiation-parameters (RP) according to those recognition rates. The higher the sparse misrecognition rate is, the more important the radiation-parameter is. For example, the sparse recognition rate of feature vector excluding column of signal to noise ratio is 98.64% and sparse misrecognition rate is 1.36%, which is the highest sparse misrecognition rate among twelve radiation-parameters. It can be concluded that column of signal to noise ratio great influent sparse recognition and it is the most important radiation-parameter. As shown in Figure 7, the experiments show that the importance of radiation-parameters is following: column of signal to noise ratio (RP_{-A}), detail energy (RP_{-B}), gray mean (RP_{-C}), edge energy (RP_{-D}), generalized noise (RP_{-E}), gradient (RP_{-F}), angular second moment (RP_{-G}), gray variance (RP_{-H}), entropy (RP_{-I}), definition (RP_{-J}), contrast (RP_{-K}) and signal to noise ratio (RP_{-L}).

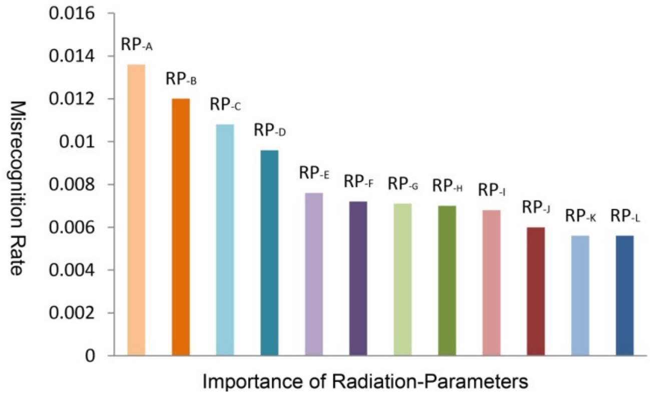


Figure 7. Importance of Radiation-Features

(3) Discuss the effectiveness and robustness of different classification strategies including the nearest neighbor classifier and the sparse recognition algorithm based on radiation-parameters. The experiments show that the sparse recognition rate of these two recognition algorithms are improved with the increase of training samples, which is robust, as shown in Figure 8. When the number of training samples is between 20 and 30, the recognition rate of sparse recognition algorithm increases steadily and that of nearest neighbor classifier increases after slightly decreasing. The mean of recognition rate is higher and the standard deviation of that is smaller based on sparse recognition algorithm than those of the nearest neighbor classifier. So, the sparse recognition algorithm can get higher recognition precision and better robustness than those of other traditional methods.

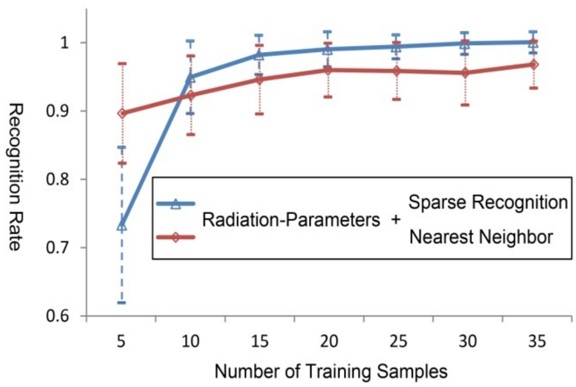


Figure 8. Recognition Rate based on Radiate-Parameter

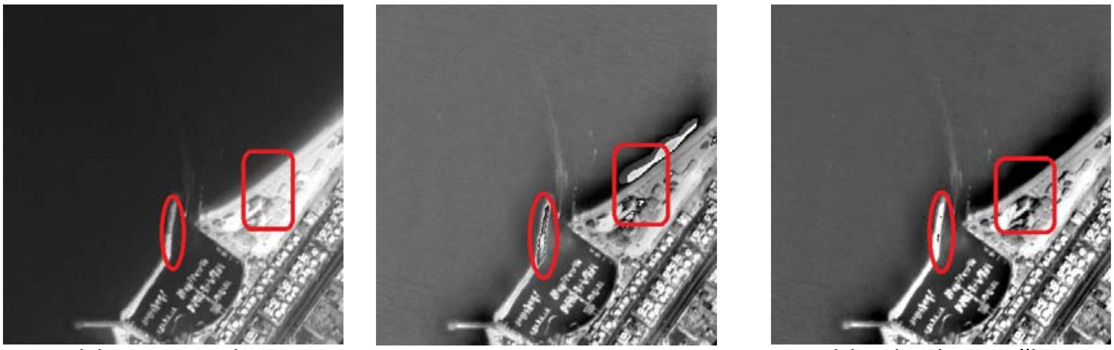
Therefore, this paper computes radiation-parameters as feature vector and recognize remote sensing sub-region terrain using sparse recognition algorithm to get higher recognition precision and better robustness.

4.2. Discuss Adaptive Wallis Enhancement

We enhance textures of high solution remote sensing image using traditional Wallis filter and adaptive Wallis filter. In order to prove the effectiveness of adaptive Wallis enhancement, we design two experiments as follows:

(1) Discuss the enhancement of traditional Wallis filter and adaptive Wallis filter for high solution remote sensing sub-region terrain.

Figure 9 and Figure 10 show the difference of enhancement between traditional Wallis filter and adaptive Wallis filter for water-region and middle-density region. The experiments show that there are many pixels with saturated gray when we enhance remote sensing sub-region terrain with simple textures using Wallis filter with small window, s_f and c, as shown in Figure 9(b). There are very few pixels with saturated gray using adaptive Wallis filter, when we enhance water-region and mountain-region with simple textures. That is because the gray and dynamic range image (gray range of image) of remote sensing sub-region terrain is small. However, our method great reduces the number of pixels with saturated gray, compared with traditional Wallis filter, as shown in Figure 9(c). Thus the experiments show that a lot of pixels with saturated gray also exist when we enhance remote sensing sub-region terrain with complex textures using Wallis filter with big window, s_f and c, as shown in Figure 10(b). Our method also great reduces the number of pixels with saturated gray, when we enhance city-region, which contains various textures with big dynamic range image, as shown in Figure 10(c). Therefore, we should enhance different remote sensing sub-region terrains using adaptive Wallis filter with different size of window and other parameters so that we can effectively avoid the existence of pixels with saturated gray. In this way, remote sensing sub-region terrains can be better enhanced, so that the number of GCPs can be increased and the accuracy of that can be improved.



(a) Water-region (b) Wallis enhancement (c) Adaptive Wallis enhancement

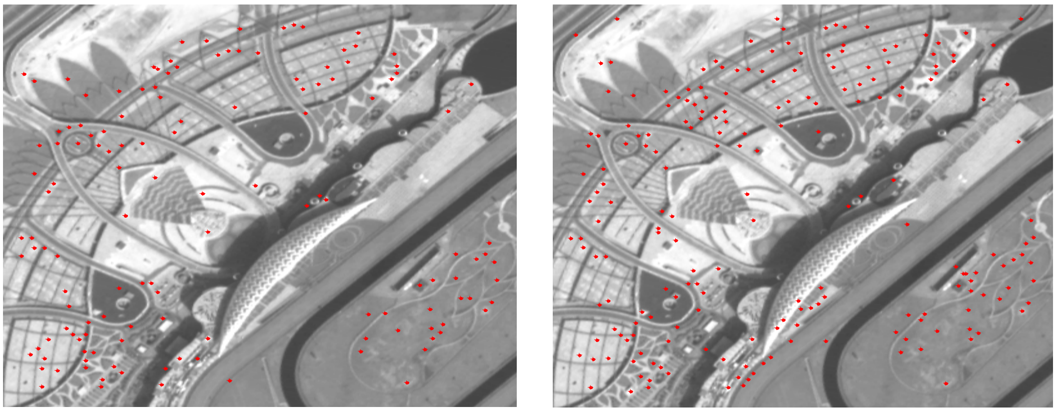
Figure 9. Comparison of Enhancement

(a) Middle-density region (b) Wallis enhancement (c) Adaptive Wallis enhancement

Figure 10. Comparison of Enhancement

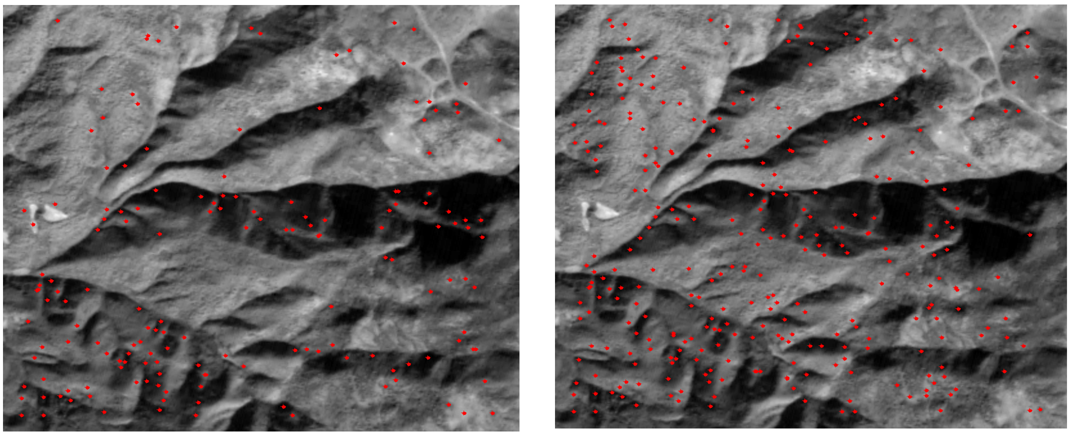
(2) Discuss the performance of adaptive Wallis enhancement for high solution remote sensing sub-region terrain. Enhance textures of remote sensing sub-region terrains of ZY-3 whose size is 400×400 using traditional Wallis filter and adaptive Wallis filter. Then extract the GCPs from enhanced remote sensing sub-region terrains using two levels matching method described in chapter 3. We compare the number and the accuracy of GCPs using different filters to prove the performance of adaptive Wallis enhancement.

Figure 11 and Figure 12 show the performance of GCPs extraction and match between mountain-region and city with some buildings region. The experiments show that 136 GCPs can be extracted and matched from city with some buildings region and 162 GCPs can be extracted and matched from mountain-region using traditional Wallis filter, as shown in Figure 11(a) and in Figure 12(a). Thus in the same remote sensing sub-region terrains, we can extract and match 202 GCPs and 310 GCPs using adaptive Wallis filter, as shown in Figure 11(b) and in Figure 12(b). Our method can extract and match more 48% and 91% GCPs than traditional Wallis enhancement for those two remote sensing sub-region terrains, as shown in Table 2. So our method can extracts and matches more GCPs from enhanced remote sensing sub-region terrains, compared with traditional Wallis filter.



(a) Wallis enhancement (b) Adaptive Wallis enhancement

Figure 11. Comparison of Control Points Extraction and Match for Middle-density Region



(a) Wallis enhancement (b) Adaptive Wallis enhancement

Figure 12. Comparison of Control Points Extraction and Match for Mountain Region

The right GCPs are judged by experts (experts who evaluate geometric accuracy of remote sensing image check GCPs one by one between remote sensing image and its multi-source reference-image), because experimental data is real remote sensing image (ZY-3 image). The experiments show that the correct rate of city with some buildings region is 91.91% and that of mountain-region is 91.36% using traditional Wallis enhancement. Thus the correct rates of those two remote sensing sub-region terrains are 98.02% and 97.42% using adaptive Wallis enhancement, as shown in Table 2. Therefore, the correct rate of GCPs which are extracted using our method is more 6% than that of using traditional Wallis enhancement. In this way, we can get more and high accuracy GCPs.

Table 2. Comparison of Control Points Extraction and Match

Enhancement Algorithm	Number of All GCPs		Number of Right GCPs		Rate of Right GCPs	
	city with some buildings	mountain	city with some buildings	mountain	city with some buildings	mountain
Traditional Wallis filter	136	162	125	148	91.91%	91.36%
Adaptive Wallis filter	202	310	198	302	98.02%	97.42%

The experiments show that our method can great reduce the number of pixels with saturated gray and effectively enhance textures of remote sensing image. Therefore, the number of GCPs is increasesd and the accuracy of GCPs is effectively improved using adaptive Wallis enhancement.

5. Conclusion

Automatic extraction of GCPs includes two key procedures: image processing and extraction of GCPs. It is a key technology of geometric accuracy evaluation, which its precision is determined by the accuracy of GCPs and its robustness is determined by both the number and uniformity of GCPs. In order to increase the number and to improve the matching precision of GCPs, this paper constructs recognition vector with sub-region radiation-parameters and recognize remote sensing sub-region terrain using sparse recognition algorithm. Then we enhance remote sensing sub-region terrain using adaptive Wallis filter with local parameters. The experiments show that compared with existing feature extraction and recognition methods, our method gets better results for high resolution image like ZY-3 image. With more and higher accurate GCPs, the precision and robustness of geometric accuracy evaluation are improved effectively. Finally we should note that the parameters of adaptive Wallis filter are empirical values which are got though many experiments. We can extract more and higher accurate GCPs using SURF algorithm from image enhanced by adaptive Wallis filter. But, that may cannot do well when GCPs are extracted using other algorithms.

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