A Method for Automatic Target Recognition Using Shadow Contour of SAR Image

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Abstract

SAR image shadow is the geometric distortion caused by scene elevation and downs. Shadow contour of SAR image contains local spatial characteristic of target, the use of a target's shadow contour in synthetic aperture radar (SAR) imaging has garnered much attention for automated target recognition applications. Due to special imaging mechanism, shadow contour of SAR image is not as clear as that of optical image. Aiming at target recognition, this paper presents an SAR image segmentation method based on Partial Differential De-noising and Marker-controlled, and then the automatic target recognition can be carried out on the result of image segmentation. In the proposed method, the SAR image is first pre-processed for de-noising. After it, the shadow contour of SAR image is extracted through Marker-controlled based SAR image segmentation. And then, the characteristic quantity of target contour is represented by Fourier descriptor. Finally, the target recognition is implemented by maximum correlation. Experimental results show that the proposed method can achieve good segmentation result and the target in SAR image can be classified effectively.

Keywords

ATR visit, SAR de-noising, SAR image segmentation, SAR shadow contour.

1. Introduction

Synthetic aperture radar (SAR) is a kind of high-resolution microwave imaging radar. Due to their all-weather, day/night, and long standoff capability, airborne and spaceborne SAR are now widely used. Common SAR has no elevation resolution in vertical plane and the target is located by distance, completely according to geometric relationship; therefore, geometric distortion is produced inevitably in many occasions. SAR image shadow is one kind of geometric distortion; therefore, shadow is a part of SAR target and it contains some spatial structure information of SAR target. Automatic target recognition (ATR) using SAR has become an active research area. The latest theoretical developments in classification methodologies quickly find applications in the SAR ATR design. Joining these efforts, in this paper, we present a new ATR scheme based on SAR image shadow contour. Experiment results show that this method can classify MSTAR data effectively.

Slant range is used in SAR imaging to represent ground distance approximately [1]. If scene width is too wide and spherical wave effect cannot be overlooked, the ground distance represented by slant range contains distortion. The distribution of intersection points between isometric spherical surface and ground at long distance is more intensive than that at short distance. As long as the geometric relation between scene and height of carrier aircraft is known, this kind of geometric distortion can be corrected by calculation. But if the ground has fluctuation and the status of fluctuation is unpredictable, a series of problems will be brought in. In Figure 1, if the interval between spherical waves is equal to range resolution ρ_r, the ground range resolution can be defined as follows: $\rho_{rg} = \rho_r / \cos\psi$, where ψ is the downward view angle of radar. As ψ increases, the ground range resolution becomes worse. When $-\alpha \geq \psi$, the shadow is produced. As shown in Figure 2, thick line indicates the part which cannot be irradiated by radar waves. It's the shadow region without echo wave. The shadow of SAR is different from human visual shadow. The latter is the region which cannot be shined by external light source (such as sun, moon). But it's still in the scope of view angle. Since SAR is active radiation detection equipment, it doesn't need external radiation source. Therefore, only if radiation of SAR itself is blocked, shadow will be produced.

Therefore, it is feasible to perform SAR ATR based on contour characteristic, which can extract SAR image shadow contour while keeping its characteristic and then reflect the local spatial structure characteristic of target. Now many researches about using contour information in target recognition are preset. Wong *et al.* [2] use Cross-plot characteristic in target recognition, Cross-plots of binary patterns are explored. Olson *et al.* [3] proposed

the target objects and images are represented by their edge maps, with a local orientation associated with each edge pixel. This method can recognize specific target in complex background. Belongie *et al.* [4] proposed Shape Matching and Object Recognition Using Shape Contexts. Shape Contexts can solve the problem of correspondences between points on two shapes and aligning transform. Ling [5] use the inner-distance between landmark points to build shape descriptors. The effectiveness of this method is proved by MPEG7 CE-Shape-1, Kimia silhouettes, a Swedish leaf database, and a human motion silhouette dataset. In order for automatic target recognition using shadow contour, Scott Papsont [6] developed the hidden Markov modeling (HMM) of the shadow profile. Main idea is that the basic HMM technique is refined using ensemble averaging, mission-based model selection criteria, multi-look scenarios, and data fusion. In the research of Xu Mu [7]. Timothy Ross [8]contour characteristic also is utilized in recognition.

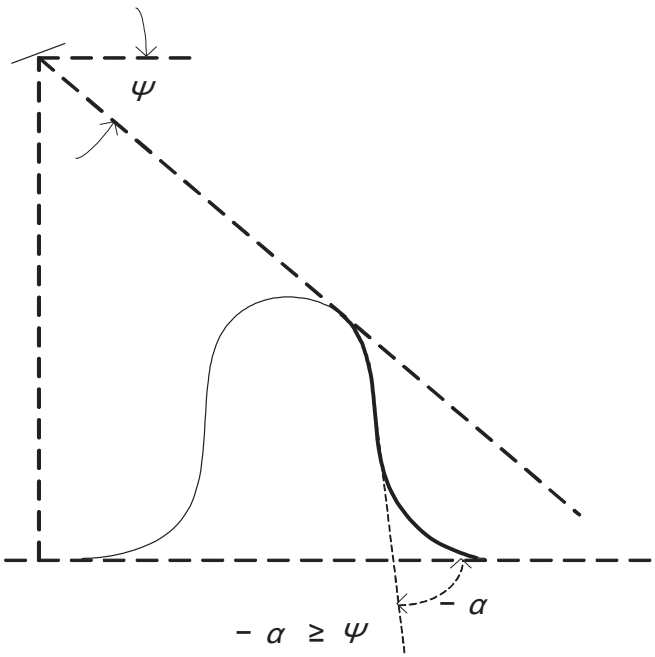

Figure 1: Formation of shadow.

SAR imaging is different from traditional optical imaging. Due to the specificity of SAR imaging. Speckle noise in SAR image causes SAR image contour difficult to be acquired directly. Big data volume recognition needs standardized contour characteristic. Therefore, our major work is to solve the following two problems: (1) SAR image contour characteristic extraction and (2) contour characteristic standardization.

We present an automatic target recognition method based on SAR image shadow contour. First, we present a segmentation algorithm based on image de-noising and marker-controlled. In this approach, power transformation is employed to transform SAR image data to nearly Gaussian distributed data. Since the anisotropic diffusion equation can keep image structure and have good de-noising performance simultaneously, it is used for de-noising. After the pre-processing operation, the image histogram is divided into three parts, namely, the target region, shadow region, and background region. The global maximum region of the image is assumed to be target region, while global minimum region is assumed to be shadow region. A sliding window is used to find the global maximum and minimum regions of the image, respectively. After the maximum region and minimum region are found, the central point of the sliding window will be marked. When the marker is acquired, a scope can be set around the marker as the target region and image region. In this way, the error segmentation out of interested region can be avoided. After the target and background have

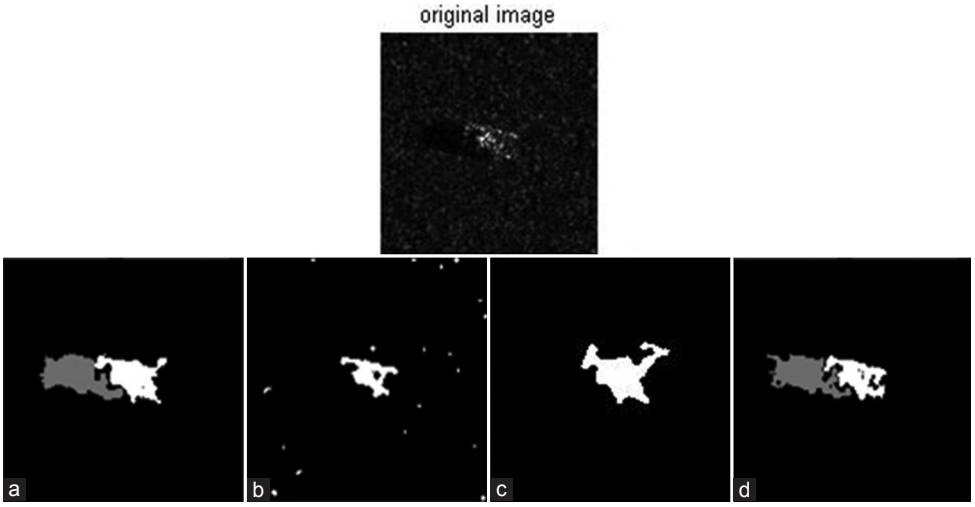

Figure 2: The original image and several segmentation methods (a) Two-parameter constant false alarm rate method; (b) Markov random field model method; (c) Edge-enhanced region grow method and (d) Optimal threshold method.

been separated roughly, the background out of profile parts are collected for statistics. The minimum and maximum of background obtained from statistics is used as the threshold for image segmentation. Finally, a post-processing operation is performed to remove all small objects and artifacts detected with the targets of interest.

On this basis, contour characteristic-based SAR image automatic target recognition is implemented by using Fourier descriptor as the characteristic quantity of target contour and selecting maximum correlation method to construct classifier. The effectiveness of our method is verified by using MSTAR data. The comparison with related research results is also performed.

The rest of the paper is organized as follows. In Section 2, we present related work, including the pose estimation and image-feature representation. The proposed algorithm is described in Section 3. In Section 4, some results of the segmentation of different types of target images are given. The conclusion is drawn in Section 5.

2. Related Work

There are two factors making traditional methods inappropriate for segmenting SAR images. One is impulse noise, and the other is related to the correlation and dependency of adjacent pixel in SAR imagery. The way to dedicate algorithms to segment SAR images should consider the above two aspects.

The methods of SAR image segmentation can mainly be divided into two categories, namely, data-driving algorithm and model-driving algorithm. Data-driving algorithms process data of current image directly. Although prior knowledge is generally used, the data-driving algorithms are not depended on the prior knowledge. But the model-driving algorithms are highly depended on the prior knowledge [9].

The segmentation methods based on model-driving include two-parameter constant false alarm rate (CFAR) method, Markov random field model based method, etc.

In two-parameter CFAR method, pixels in a pre-defined window of background clutter are used to estimate the data's distribution parameters, based on which the threshold is calculated to separate the target and clutter. Then, expansion and corrosion operations from morphology are used to smooth the edge of target image after segmentation. The internal region of target will be filled to compensate some missed pixels with smaller amplitude. But many fake shadows and targets will also be produced, as shown in Figure 2a.

The main idea of Markov random field model-based method is based on the local correlation of image data [10,11]. One two-dimensional random field is used to describe the characteristic of image. The distribution of SAR image data is described by conditional probability. This conditional probability is unrelated to the position of pixels in image. It contains the information about the mutual location of each pixel. When handling explicit segmentation of complex region, this segmentation method can achieve better result. MRF segmentation method only works in partial domain, not considering the whole domain, although it uses the partial correlation information and restricts noise well, making wrongly-distinguishing rare. The wrongly distinguishing phenomenon is very apparent due to the similarity of the texture, as shown in Figure 2b. For the SAR target recognition application, what we concern is to separate the target and clutter. Considering that target is generally with a complex structure, the texture in target region cannot keep ideal correlation property. Therefore, the Markov random field model-based method is not a proper algorithm for SAR target recognition application.

The data-driving SAR image segmentation methods include histogram optimal threshold method, edge detection method, etc.

The edge-enhanced region growing method attempts to find a closed, simply connected region by growing and including all pixels inside the region which meet certain criteria. In the proposed SAR segmentation [11], an edge-based criterion was adopted by computing a threshold for shadow pixels. The stopping rule is based on the energy (the number of pixels belonging to the shadow region), as shown in Figure 2c. The number of pixels depends on human-segmented images.

Another approach to segmentation uses optimal threshold method [12,13]. The segmentation is based on a histogram threshold technique and is able to detect both target vehicles and their shadow; it is built around the use of the mixture-based model selection algorithm to estimate an image histogram with a mixture of normal densities, a linear method for computing multi-level thresholds from a mixture of normal densities. But as shown in Figure 2d, this method cannot attain trim borderline.

3. Marker-controlled SAR Image Segmentation

Impulse noise in SAR image can really challenge traditional, purely intensity-based segmentation techniques, and spatially-based image segmentation methods. In most SAR images, even for a human observer, the edges may be difficult to locate.

Watershed segmentation is a kind of edge detection based segmentation method [14]. Because of noise and local irregularity of gradient, it usually leads to over segmentation. To control over segmentation, the concept of marker-controlled is introduced into watershed segmentation.

To avoid error segmentation, local minimum region is used as the marker of interested region. There are multiple local minimum regions, and thus this kind of marker is prone to be limited to local information. We have investigated this issue and proposed an algorithm denoted by sliding window method which marks an image with target region, shadow region, and background region. For this purpose, a pre-processing step is necessary to make the image de-noising suitable to be approached by sliding window method.

3.1 Pre-processing: SAR Image De-noising

In radar target recognition and detection, the original radar data are transformed to positive real number through pre-processing. Usually, the distribution of these data is of non-normal distribution [13,14]. According to [14], the amplitude of Single View SAR image accords with rayleigh distribution. In such case, the result of optimal detection and evaluation based on these data are not very good. The reason is that the common recognition algorithms or evaluation algorithms used in radar system will have better performance only when the processing data accords with normal distribution. In order to improve the performance of target recognition and detection, it is necessary to transform the data from non-normal distribution to normal distribution or a similar normal distribution.

We try to transform the SAR image from rayleigh distribution to nearly Gaussian distribution. According to [15,16], assuming the original signal is denoted as X, the definition of real signal normalized kurtosis is as follows,

$$K_X \overset{def}{=} \frac{E\{X^4(t)\}}{E^2\{X^2(t)\}} \tag{1}$$

where K_x is called normalized kurtosis. The real signal with normalized kurtosis equal to 3 is called Gaussian signal. According to this model, we acquire the power exponent for transforming rayleigh distribution to Gaussian distribution by deduction.

Define $\gamma = x^v$. γ is the transformed data. The expectation of rayleigh distribution is defined in following equation

$$E(Y^m) = E(X^{mv}) = \int_0^{\infty} X^{mv} \frac{2x}{\alpha} e^{\frac{x^2}{\alpha}} dx \tag{2}$$

If $\frac{x^2}{\alpha} = t$, then $x = \sqrt{\alpha t}, dx = \frac{\sqrt{\alpha}}{2\sqrt{t}} dt$. By simplifying Equation (2), we have

$$E(Y^m) = \alpha^{\frac{1}{2}mv} \int_0^{\infty} t^{\frac{1}{2}mv+1-1} e^{-t} dt = (\alpha)^{\frac{1}{2}mv} \Gamma\left[\frac{mv}{2}+1\right] \tag{3}$$

Substituting (2) into (3), the experimental result is shown in Figure 3. According to Figure 3, when v is near 0.35 and 0.88, rayleigh distribution is similar to Gaussian distribution.

As well known, most SAR images are noised by speckle seriously. Thus before further processing, it's necessary to de-noise the SAR image.

In 1990, Persona and Mali applied anisotropic diffusion equation to image speckle filtering and edge detection [17]. Anisotropic diffusion equation can keep image structure and have good de-noising effect simultaneously. It is widely used in image processing, also including SAR image segmentation field [18-20].

The P-M diffusion equation, proposed by Perona and Malik [17], is as below,

$$\begin{cases} \frac{\partial u}{\partial t} = div(c(|\nabla u|^2))\nabla u \\ c(|\nabla u|^2) = \frac{1}{1+|\nabla u|^2/k^2} \\ u(x,y,0) = u_0(x,y) \end{cases} \tag{4}$$

The basic idea of P-M diffusion equation is as follows: The equation can be looked as a piecewise continuous map bounded by the edge of image. The diffusion carried out on the original image is under the control of

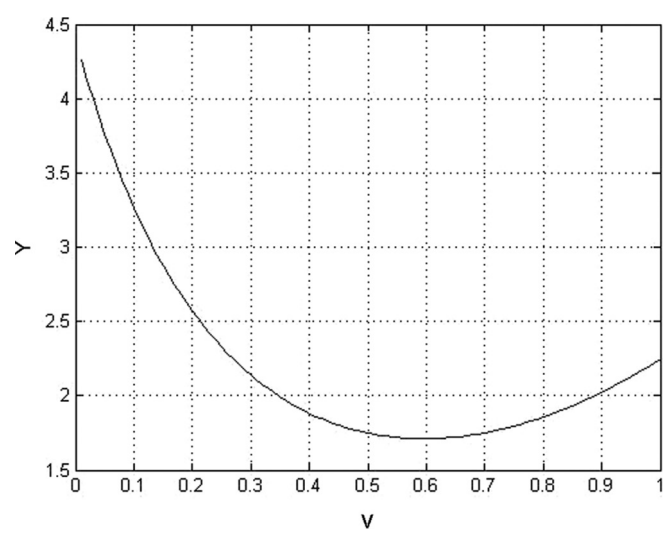

Figure 3: Relationship between V and Y after exponent transformation in rayleigh distribution.

diffusion operator $c(|\nabla u|)$. Selective diffusion smooth is accomplished according to the gradient magnitude of image in P-M model. At the edge area of image, the gradient magnitude is bigger than that of other area of the image. To preserve the edge information, $c(|\nabla u|)$ is set to be a smaller value at edge area in P-M model to obtain weak smooth effect. However, the flat area of image has smaller gradient magnitude. The operator $c(|\nabla u|)$ is set to be a bigger value at flat area, thus strong smooth effect is acquired. The P-M model can carry out weak smooth at edge area and strong smooth at flat area automatically, so the position of image edge can be identified in some degree and the contradiction between de-noising and edge preserving is solved. P-M model can also repair the broken edge contaminated by noise. The form of P-M diffusion equation is identical with the thermal diffusion equation in Physics. Operator $c(|\nabla u|)$ is also called diffusion coefficient. The diffusion velocity, which is controlled by $c(|\nabla u|)$, is changed according to the gradient magnitude in different direction. To be distinguished from directionless isotropic diffusion equation, this equation is called anisotropic diffusion equation.

Power transformation transforms SAR image from nearly Rayleigh distribution to nearly Gaussian distribution. Partial differential de-noising centralizes each region of the target, background and shadow of image. Especially, the gray scale of shadow region becomes very centralized. Therefore, as long as the position of target and shadow are located roughly, and the threshold is determined according to gray scale statistics of target, shadow, and background, the segmentation of SAR image can be achieved.

3.2 References

In this section, a Marker-Controlled based optimal threshold segmentation method is proposed. Because the unit used for statistics is not single pixel, but region, it can mark the interested region and not be limited to local information.

A sliding window is introduced to find the marker [21]. The initial value of the sliding window is the background of edge area. The sliding window will traverse the whole image and collect statistics of all pixels to find the global maximum and minimum regions of the image. This kind of marker will not be limited to local information. Because the sliding window is focused on local information, the influence of noise is excluded. The sliding window should not be too big; otherwise, the shadow will be contained in target. Since the target and shadow are close, big window will bring mutual influence to the average gray scale in window and cause error locating. The following figure shows that a 9 × 9 sliding window (the resolution of SAR image used in experiment is 0.3 × 0.3. The size of sliding window is about 1/5 or 1/4 that of target. It is used to find the global maximum and minimum regions of the image. After the maximum and minimum is found, the central point of the sliding window will be marked.

From Figure 4c, we can see that after the SAR image is processed by partial differential de-noising, the internal distribution of target, shadow, and background is already relatively even. The target region, clutter region, and shadow region cannot be separated efficiently on condition that histogram is used for threshold segmentation, which can be seen from Figure 5. Some strong points in background still can lead to error segmentation. After the marker is acquired, a scope can be set around the marker as the target region and image region. In this way, the error segmentation out of interested region can be avoided. The follow-up morphological filter used for processing the error segmentation is also unnecessary.

After the target and background have been separated roughly, the background out of profile is divided into four 20 × 20 pixels parts for collecting statistics. The minimum and maximum of background obtained from statistics are used as the threshold for image segmentation. To avoid over segmentation and too coarse

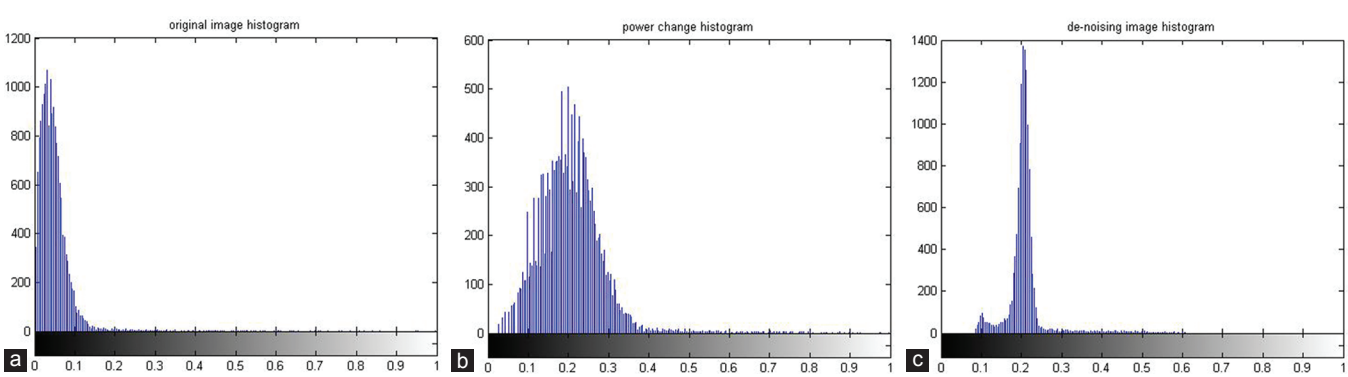

Figure 4: (a) The histogram of original image in Figure 3; (b) The histogram of power transformation in Figure 7 and (c) The histogram of de-noising image in Figure 7

segmentation, the pixel range should be set for the two parts generated by segmentation.

A sliding window is introduced to find the mark. The initial value of the sliding window is the background of edge area. The sliding window will traverse the whole image and collect statistics of all pixels to find the global maximum and minimum regions of the image. This kind of mark will not be limited to local information. Because the sliding window is focus on local information, the influence of noise is excluded.

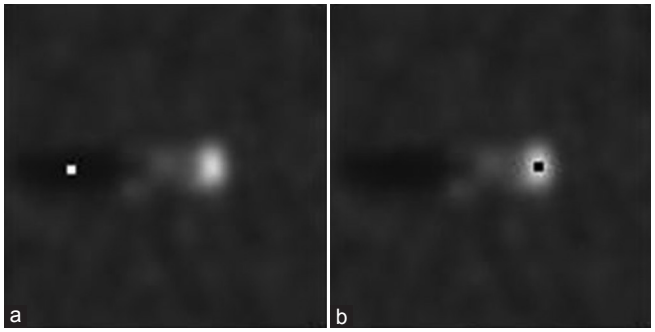

Figure 5: Sliding window mark (a) Minimum region and (b) Maximum region (for good visual effect, 3 × 3 pixels mark is showed in figure).

Following figure shows that a 9 × 9 sliding window is used to find the global maximum and minimum regions of the image. After maximum and minimum is found, the central point of the sliding window will be marked.

Figure 6 is a flow chart of edge detection; we can see the result in Figure 7, it can be seen that after processed by power change and partial differential de-noising, the target, shadow, and noise of SAR image have been separated. If the discontinuous region is generated after segmentation, other regions will be abandoned, considering the requirement of follow-up recognition, for background part, except for the region containing extreme value point. For target part, the threshold is improved properly. If discontinuous regions still exist, considering the complexity of target scattering, these regions will be preserved.

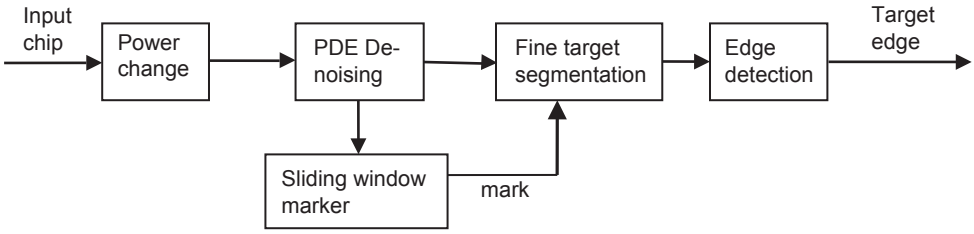

Figure 6: Flow chart of edge detection.

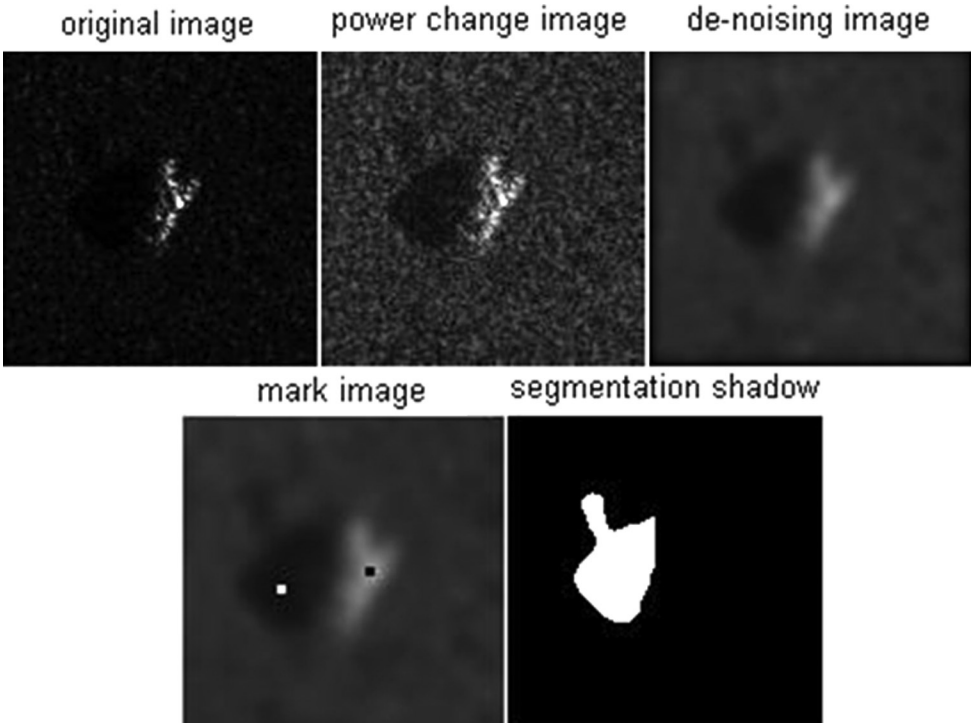

Figure 7: Example of intermediate result in edge-detection procedure.

4. The Target Recognition Based on SAR Shadow Contour

There are many contour-based recognition methods [1-5], and each method has its application scope. Because SAR target is hard object without big deformation, Cross-plot characteristic is not used. The time consumed by HMM method is too long. SAR target has bed segmented in the second section hand the edge maps characteristic is lost. Similarly, because landmark points are difficult to be ascertained, inner-distance method is not used in this paper. Because contour has been acquired through segmentation, our description method needs to meet following conditions: 1) express contour characteristic effectively; 2) normalize the characteristic length; and 3) suitable for characteristic recognition. Fourier descriptor is used in our method. Fourier descriptor can describe SAR shadow contour effectively and low-frequency portion accounts for more than 90 percent energy. Therefore, only 30 descriptors are needed for effective contour description. This method can normalize the characteristic length, also more suitable for characteristic recognition. Following are detail description of this method.

4.1 Fourier Descriptor

The shadow contour is acquired through above image segmentation. Contour characteristic can reflect the local spatial information of target. We select Fourier descriptor to describe the contour information of shadow. The basic idea of Fourier descriptor is as following. Closed boundary in two-dimensional plane has total K boundary points. Use complex number to represent the boundary points (x0, y0), (x1, y1), …, (x K- 1, yK- 1), that is, s (k) = x (k) +j y (k), k = 0,1,2, …, K – 1. In this way, two-dimensional sequence is transformed to one-dimensional sequence.

Fourier transform of s(k) is described in following equation.

$$a(u) = \frac{1}{k}\sum_{k=0}^{k-1} s(k)e^{-j2\neq uk/k},\ k = 0,1,2,\ldots,k-1 \tag{5}$$

a(u) is called the Fourier descriptor of boundary. s(k) can be restored by performing inverse Fourier transform on a(u).

$$s(k) = \frac{1}{k}\sum_{u=0}^{k-1} a(u)e^{j2\neq uk/k},\ k = 0,1,2,\ldots,k-1 \tag{6}$$

By using partial Fourier coefficients to replace all Fourier coefficients, the reconstruction of contour can be achieved. For example, only four P coefficients are used to reconstruct image contour.

$$a(u) = \frac{1}{k}\sum_{k=0}^{k-1} s(k)e^{-j2\neq uk/k}\ \ k = 0,1,2,\ldots,k-1 \tag{7}$$

High-frequency components of Fourier transform correspond to contour detail, while low-frequency components correspond to basic shape of contour. Therefore, the image contour can be reconstructed by using a small number of low-frequency Fourier coefficients.

Determining the number of items of Fourier descriptor.

The amplitude of Fourier descriptor after centralization of shadow contour is depicted in Figure 8. It can be seen that major energy of Fourier transform is concentrated on small number of low-frequency coefficients.

The reconstruction result of shadow contour using different number of items of Fourier descriptor is shown in Figure 9. It can be seen that fore 30 low-frequency components can represent shape characteristic of contour effectively.

4.2 The Design of Classifier

Maximum correlation coefficient classifier is used in our method. Maximum correlation coefficient method (also known as correlation matching method) originates from classical pattern recognition algorithm – template matching method. It can also be called the template matching method containing range profile domain translation compensation. For test range profile $X(n)$ and template $X_T(n)$, if corresponding frequency domain profile is $X(\omega)$ and $X_T(\omega)$, respectively, the maximum correlation coefficient can be obtained by frequency domain quick convolution algorithm [22-23].

$$d(X, X_T) = \max\left|\int \mathbf{X}(\omega)\mathbf{X}_T^*(\omega)\exp(j\omega n)d\omega\right| \tag{8}$$

Among above equation, * indicates conjugate operator. The key problem of using maximum correlation coefficient method is how to select template. Due to the target sensitivity of SAR image, enough templates are needed to describe the echo wave of target at different posture. Therefore, selecting the template which has relative

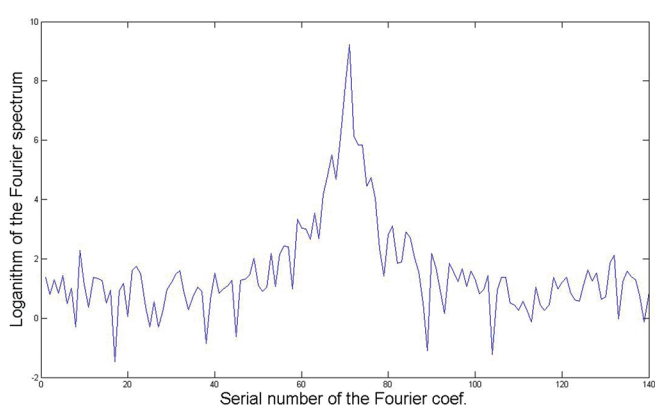

Figure 8: Serial number of the Fourier.

robustness to the change of target posture can reduce the number template used by recognizer.

5. Experimental Results

We validate the proposed ATR system on the MSTAR public release database. The task is to classify three distinct types of ground vehicles: BTR70, BMP2, and T72. There are seven serial numbers for the three target types: one BTR70 (sn-c71), three BMP2's (sn-9563), and three T72's (sn-132). For each serial number, the training and test sets are provided, with the target signatures at the depression angles 17° and 15°, respectively. The sizes of the training and test datasets are given in Table 1.

We divide the data into two groups. Three kinds of imaging data BTR70, BMP2, and T72 at elevation angle 17°are selected as training sample data. As shown in Table 1. In accordance with each 10°azimuth, three kinds of data are separated into 36 templates, respectively. Total 108 templates are formed from three kinds of target. The data to be recognized are three kinds of data BTR70, BMP2, and T72 at elevation angle 15°. According to preceding processing steps, matching between samples to be recognized and 108 templates are performed. The recognition results are listed in Table 2. The comparison with existing experimental results is shown in Table 3.

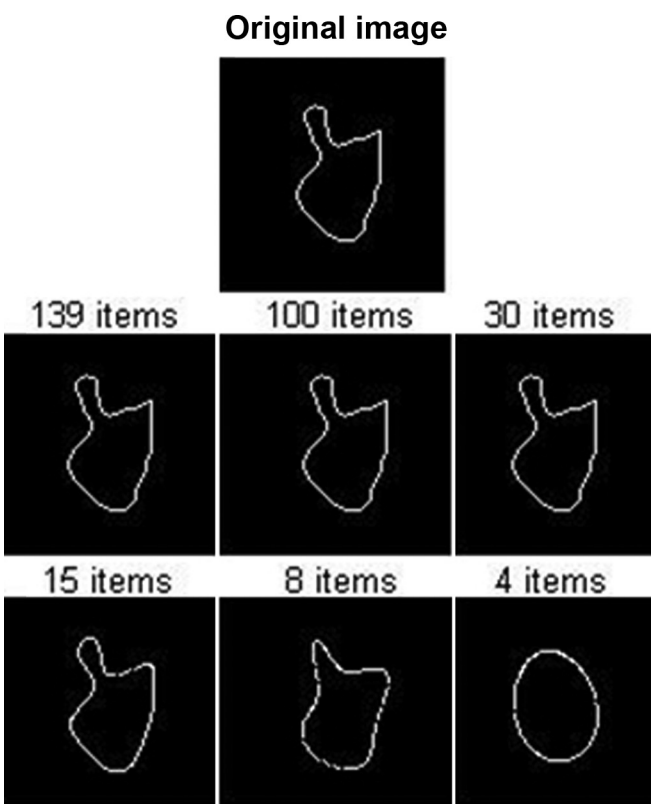

Figure 9: The rebuilding result under different number of Fourier descriptors.

We present details of the application of the algorithm using some intermediate results [Figures 10-12]. For each Figure, we show the original image, the de-noising image, and the segmentation result. The shadow outline is also presented.

From experimental result, it can be seen that recognition result of this paper is obviously better than traditional gray characteristic matching method. It proves that the robustness of contour characteristic is better than that of gray characteristic. Compared with the target contour based recognition methods in references, the recognition result of this paper is also better. There is little difference between recognition method of this paper and the recognition methods in references, while the major difference exists in pre-processing steps. In our method, partial differential de-noising is performed before segmentation in pre-processing. Anisotropy effect of partial differential repairs the edge which is not clear. Therefore, the contour becomes clear and smooth. From above grayscale image, it can be seen that the data of shadow are more centralized than that of target, which make it more suitable for segmentation. Due to above reason, the recognition rate of our method is improved.

6. Conclusions

In this paper, we propose an effective SAR image segmentation method. The first step of this method is using power transformation to transform the distribution of

Table 1: Summary of the MSTAR database

	Training set		Testing set	
	Serial number	Size	Serial number	Size
BTR70	sn-c71	233	sn-c71	196
BMP2	sn-9563	233	sn-9563	195
T72	sn-132	232	sn-132	196

BTR is an eight-wheeled armored personnel carrier; BMP is an infantry fighting vehicle; T72 is a Soviet second-generation main battle tank

Table 2: Recognition result of method in this paper

	sn-c71	sn-9563	sn-132	Recognition rate (%)
sn-c71	183	6	7	93.77
sn-9563	24	171	0	87.69
sn-132	14	25	157	80.51

Table 3: Recognition rate comparison between this paper and related references

	sn-c71 (%)	sn-9563 (%)	sn-132 (%)	Recognition rate (%)
Method of this paper	93.8	87.7	80.5	87.3
Reference [5]	-	-	-	71.95
Reference [6]	87.5	86.2	73.7	81.7
Reference [7]	85.9	-	76.7	81.3
Reference [8]	Simulation data	72	76.7	81.3

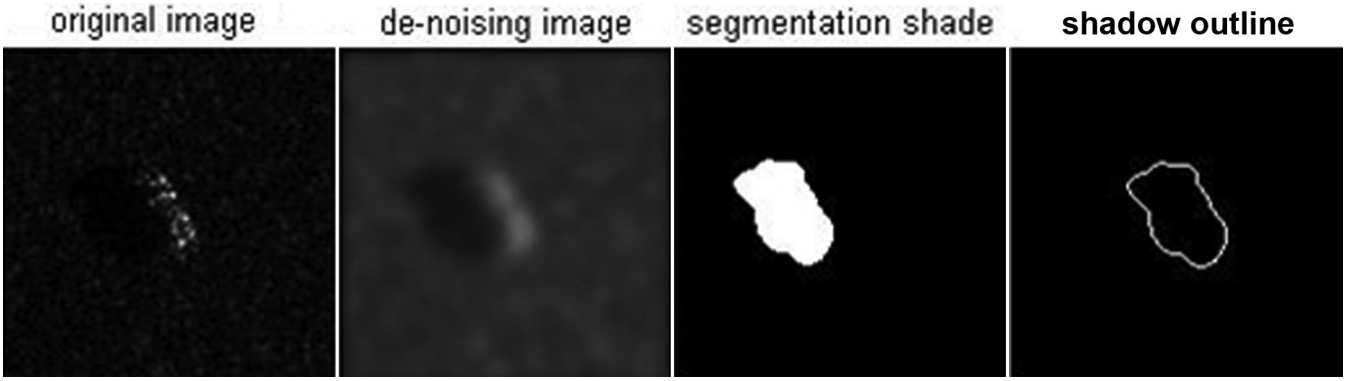

Figure 10: Example of the application of the Marker-controlled based SAR segmentation on BTR-70 target image.

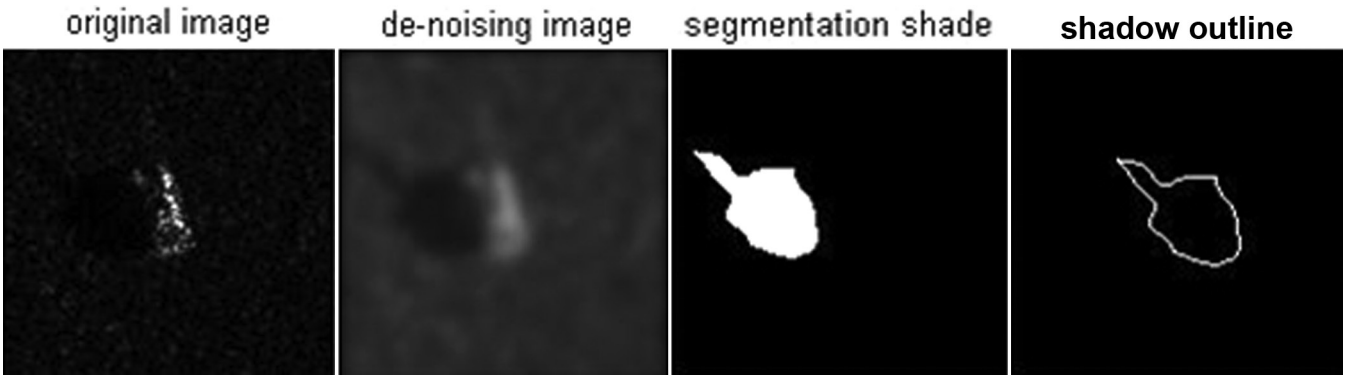

Figure 11: Example of the application of the Marker-controlled based SAR segmentation on Ts72 target image.

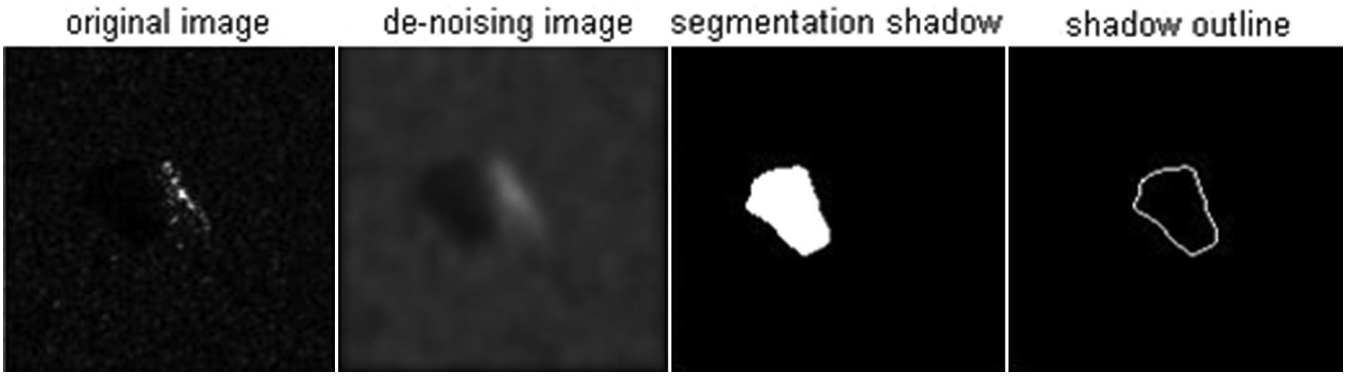

Figure 12: Example of the application of the Marker-controlled based SAR segmentation on BMPsn target image.

SAR image data into nearly Gaussian distribution. And then, the SAR image is processed by de-noising. After de-noising, the target, background, and shadow of original SAR image can be acquired. The internal of each part is relatively smooth. A sliding window is introduced to mark the target and shadow. After the rough scope around marker is set, the background is divided into several regions. Statistics of sample data in each region is collected to evaluate the distribution parameter of background and determine the segmentation threshold. After initial segmentation, we collect statistics of the range of pixels from two generated part and adjust the threshold according to statistics dynamically. The merits of our method include the low computational complexity, less error or over segmentations, and easy to determine the interested region.

With the improvement of SAR image resolution, the shadow contour can become clear gradually. The contour can reflect the local spatial structure of target. In this paper, we present a de-noising-based SAR shadow automatic segmentation method, and use contour characteristic to perform target recognition on segmentation result. The effectiveness of the proposed method is verified by the measured data-based experimental result. Shadow contour is an effective characteristic for SAR image target recognition. The segmentation method is simple and the amount of data is small;

therefore, the recognition speed is fast. Due to the complexity of target to be recognized, good recognition result can't be achieved by only using a single characteristic. Therefore, solution of the problem depends on using multi characteristic synthetically. Shadow is part of radar target. If shadow characteristic is used effectively, furthermore, characteristic of shadow and target are used jointly, SAR target characteristic can be reflected fully, and good recognition performance can be achieved.

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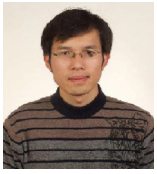

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