ASAR IMAGE TARGET RECOGNITION BASED ON THE COMBINED WAVELET TRANSFORMATION

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ABSTRACT:

ASAR image target detection and recognition has been always a hot research. In this paper, on the foundation of the previous studies, a target recognition method based on combined wavelet transformation and cloud model is proposed. According to the good local characteristic, multi-resolution, effectiveness and the sensitivity to both direction and texture of the combined wavelet transformation, the detection method based on combined wavelet restrained the image noise and the errors, such as the object missing and false warning, caused by the use of the detection method based on the brightness alone. Then in order to solve the uncertainty of pixels, especially the object edge, an integrated method named soft segmentation for image segmentation based on the linguistic cloud model, which is a model for the conversion between qualitative and quantitative in the field of artificial intelligence is applied. Accurate target recognition is achieved after further processing eventually, such as mathematical morphology analysis. This integrated mechanism is applied to the ASAR data acquired from Zhuhai, China for carrying on the fish ponds recognition as well as the comparative experiments with classical methods. Results show that this approach can recognize the target more accurately and quick, which indicate that the synthetic scheme for target detection and recognition is flexible and robust and the advantages to the traditional detection operators or crisp segmentation methods are distinct.

1. INTRODUCTION

Since 1970's, various countries, such as America and England, have started to carry on the research on the automatic processing of SAR. One of the typical examples is extracting some significant characteristics from the SAR Imagery, such as region division, target detection and recognition, edge extraction and so on, which are impelled by the rapid development of computer technology. In addition, with the increasing development of radar signal processing technology, the SAR imagery resolution has been largely enhanced, which enables the realization for the automatic target detection of SAR Imagery. ASAR (Advanced Synthetic Aperture Radar) has been the most advanced imaging sensor on ENVISAT - 1 till now， which works in the C band with five kind of imaging patterns, seven kind of imaging strips and alternate polarized imaging function. Furthermore, besides all-weather, all-day and the certain penetrating characteristics like SAR, its data have unique advantages to any other radar sensors (Qingni, 2004).

Target detection and recognition on radar imagery is always the hot but challenging issue during the latest decades, tackled by a series of successful methods (.Lopes etc., 1993; Oliver etc., 1996; Oliver, 1994). However, the radar remote sensing imagery detection not only involves the pure target detection simply, but also involves other instances, as the existence of speckles can also affect the target detection and recognition. In that case, it is needed to suppress the speckles to enhance the recognition accuracy. In the scope of the intensity of echoes, targets may be divided into strong and weak reflecting targets. The weak reflecting targets like fish ponds should belong to the category of target recognition

The wavelet transformation has been one of the applied mathematical branches since later 1980s. Because of its partial, multi-resolution analysis characteristics, the wavelet transformation has already become one of the powerful image signal analysis tools (Szu etc. 2002).The wavelet transformation has also been widely applied to the SAR imagery target detection (Zhengjun, 1999; Ling etc. 2004; Jie etc. 2003).

Besides, there are uncertainty factors of the remote sensing information (Yong, etc. 2004), the traditional crisp segmentation algorithm, can not describe images of uncertainty, especially for the edge pixels. The cloud model brought forward by LI Deyi (Deyi etc., 1998) can be used for the characteristics of a simple and accurate mathematical description of the concept of uncertainty, provides a quantitative and qualitative transformation tools that can effectively achieve the image of the soft partition.

Series of experiments about fish ponds recognition are carried out in this article. To enhance the target recognition accuracy and efficiency, according to the previous studies, a new comprehensive recognition mechanism based on the combined wavelet transformation and linguistic cloud model is proposed. -in this article, experiments on the ASAR imagery of Guangdong, Zhuhai are presented both to validate the feasibility of the comprehensive mechanism and to compare with the traditional methods.

2. FRAMEWORK OF COMBINED WAVELET

In order to collect the edge information and partial texture information to suppress the disturbance of target detection, a framework of combined wavelets is proposed, one of which is sensitive to edge characteristic named “Mexican hat mother wavelet” and the other is sensitive to the texture characteristic named “Morlet mother wavelet”. In literature, it had already proven that the combined mother wavelets have good characteristics as the independent wavelet (Szu etc., 2002). This combined wavelet transformation is the isotropic synthesis, with one-dimension definition in x and the y directions as follows:

$$W(x)=\exp(-\frac{x^2}{2})(1-x^2)+\exp(-\frac{x^2}{2})\cos(k_0x)=m(x)+M(x) \quad (1)$$

$$W(y)=\exp(-\frac{y^2}{2})(1-y^2)+\exp(-\frac{y^2}{2})\cos(k_0y)=m(y)+M(y) \quad (2)$$

And then the two-dimensional isotropic combined wavelet filter can be constructed as below:

$$\begin{aligned} W(x,y) &= \exp(-\frac{x^2+y^2}{2})(1-x^2)(1-y^2) \\ &+\exp(-\frac{x^2}{2})\exp(-\frac{y^2}{2})\cos(k_0x)\cos(k_0y) \\ &= m(x)m(y)+M(x)M(y) \end{aligned} \quad (3)$$

Where the first item describes the edge information and the second item describes the texture information.

We suppose the image to be processed be $f(x,y)$ to decompose it by the multi- resolution combined wavelet, which can be described:

$$MW(f)(a,b)=\frac{1}{\sqrt{|a|}}\iint f(t,u)W(\frac{t-b}{a},\frac{u-b}{a})dtdu \quad (4)$$

Where a is an alterable resolution and b=（b1，b2，…）is a set of the displacements.

3. CLOUD MODEL

Cloud model is a model of the uncertain transition between a linguistic term of a qualitative concept and its numerical representation. In short, it is a model of the uncertain transition between qualitative and quantitative.

Let U be the set U={u},as the universe of discourse, and T a term associated with U. The membership degree of u in U to the term T, $C_T(u)$, is a random number with a stable tendency. $C_T(u)$ takes the values in [0,1].A compatibility cloud is a mapping from the universe of discourse U to the unit interval[0,1].That is:

$$C_T(u): U \rightarrow [0,1], \forall u \in u \ u \rightarrow C_T(u) \quad (5)$$

The most useful cloud models are the normal compatibility clouds because normal distribution have been supported by results in every branch of both social and natural sciences (Deyi etc. ,1998).A normal compatibility cloud characterizes the qualitative meaning of a linguistic atom with three digital characteristics:

$$A(E_x, E_n, H_e) \quad (6)$$

Where E_x, E_n and H_e are the expected value, entropy and deviation of the cloud respectively. A given set{ E_x, E_n, H_e } uniquely defines a particular compatibility cloud A. The MEC of the normal compatibility cloud to a linguistic atom A is:

$$MEC_A(u)=\exp[-\frac{(u-E_x)^2}{2{E_n}^2}] \quad (7)$$

Given E_x =0, E_n =3, H_e =0.1 and n=1000, the generated cloud can be described as figure 1.

Figure 1. Cloud generated with CG(0,3,0.1,1 000)

3.1 Cloud Generators

Given three digital characteristics E_x, E_n and H_e to represent a linguistic atom, the forward generator could produce as many drops of the cloud as you like. All the drops obey the properties described above. Figure 2 shows a 1-D cloud generator.

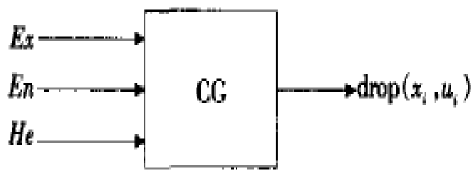

Figure 2. 1-D forward cloud model generator

It is natural to think about the generator mechanism in an inverse way, which is named backward cloud generator. Given a limited set of drops, $drop_i(u_i, \mu_i)$, as samples of a compatibility cloud, the three digital characteristics E_x, E_n

and H_e could be produced to represent the corresponding linguistic atom, which is showing in figure 3.

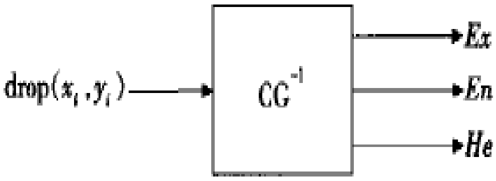

Figure 3. 1-D backward cloud generator

The combination of the two kinds of generators can be used interchangeably in images segmentation.

3.2 Synthesized Cloud

A synthesized cloud is used to synthesize linguistic terms into a generalized one and it can be described as a concept tree where each leaf node is a cloud model.

Suppose there are two neighbour linguistic atoms $A_1(E_{x1}, E_{n1}, H_{e1})$ and $A_2(E_{x2}, E_{n2}, H_{e2})$, over the same universe of discourse U.A virtual atom $A(E_x, E_n, H_e)$ may be created by synthesizing the two atoms using the following definition:

$$E_x = \frac{E_{x1}E_{n1}{}' + E_{x2}E_{n2}{}'}{E_{n1}{}' + E_{n2}{}'} \quad (8)$$

$$E_n = E_{n1}{}' + E_{n2}{}' \quad (9)$$

$$H_e = \frac{H_{e1}E_{n1}{}' + H_{e2}E_{n2}{}'}{E_{n1}{}' + E_{n2}{}'} \quad (10)$$

Where $E_{n1}{}'$ and $E_{n2}{}'$ are calculated as follows. Suppose $MEC_{A1}(u)$ and $MEC_{A2}(u)$ are the mathematical expected curves of A_1 and A_2 respectively. Let

$$MEC_{A1}(u) = \begin{cases} MEC_{A1}(u), \text{ when } MEC_{A1}(u) \geq MEC_{A2}(u) \\ 0 \quad\quad , \text{ otherwise} \end{cases}, \quad (11)$$

$$MEC_{A2}(u) = \begin{cases} MEC_{A2}(u), \text{ when } MEC_{A2}(u) \geq MEC_{A1}(u) \\ 0 \quad\quad , \text{ otherwise} \end{cases}, \quad (12)$$

then,

$$E_{n1}{}' = \frac{1}{\sqrt{2}} \int_U MEC'_{A1}(u)du,$$

$$E_{n2}{}' = \frac{1}{\sqrt{2}} \int_U MEC'_{A2}(u)du \quad . \quad (13)$$

It can be deduced that the parent node generated by synthesizing two clouds is still a cloud model and it serves as a leaf node for higher level cloud synthesizing, which continues until a root node of the universal concept tree is generated.

4. EXPERIMENTS AND ALGORITHMS ANALYSIS

ASAR-VV data from Zhuhai, Guangdong, China on April 6, 2004 is used to implement the comprehensive method for fish ponds recognition in the paper. Figure 4 shows the original image. From the original image we can see that the brightness of the fish ponds is close to the river but the textures are different a lot. According to the characteristic of the original image, a comprehensive mechanism, considering both the brightness and texture characteristic of the target to be recognition as well as the uncertainty of the target edge, is implemented in this paper. In order to optimize the recognition result ,a series of mathematical morphological operators are used .Meanwhile some comparative experiments with classical segmentation methods are implemented.

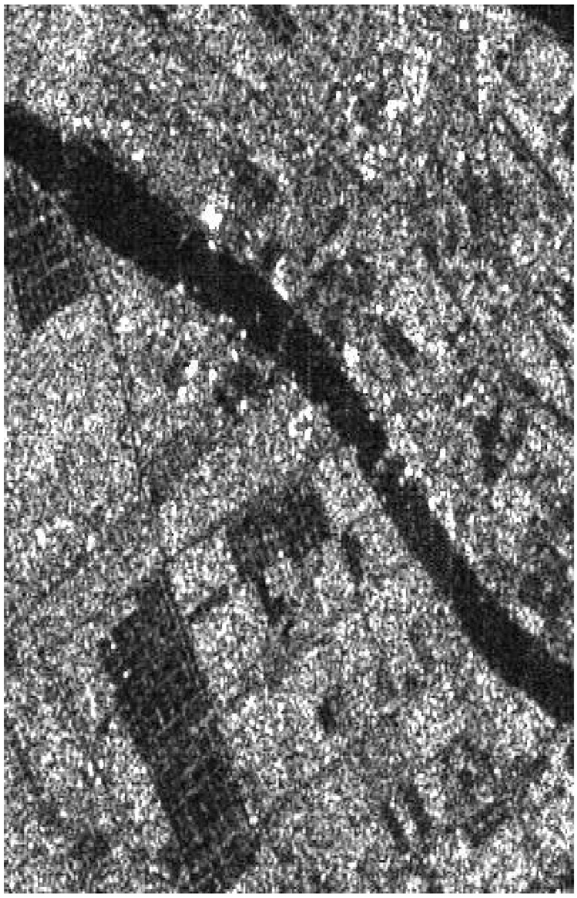

Figure 4 .ASAR-VV data from Zhuhai, Guangdong, China

4.1 Process of target recognition in this paper

4.1.1 Designing combined wavelet and image preprocessing: First construct combined wavelet and carry on combined wavelet decomposing on the input image, then obtain coefficients matrix of all levels. Secondly construct coefficient images by data obtained from the first step, choose one of the coefficient images as the input for the next step. Here the choice of wavelet coefficient gradation number is very essential, since the different target always manifests best in some special coefficient images.

4.1.2 Generating cloud model: First the training samples are selected by the way of Human-Computer Interaction from the coefficient image. Then a cloud model is created by backward cloud generator with the Gray-value of the training samples, which is the mapping from quantitative to qualitative. As a result the training samples can be denoted by cloud models (E_x, E_n, H_e).

4.1.3 Creating the universal concept tree: Given the cloud models generated through the last step as the leaf nodes, a complete universal concept tree is created by cloud synthesizing level by level. Then detecting the target by maximum determinant criterion. It is well known that the properties of the cloud generator that $\mu_i (i = 1, 2..., n)$ are random numbers with stable tendency rather than fixed values. Therefore, the same attribute with the overlapping area of two neighbour clouds may be assigned to different clouds at different occasions, which is just like what humans do, thus the soft partition method can simulate human beings thinking better than the crisp partition methods. In our experiment, we first compute the compatibility of every pixel to some certain cloud model and then we get the outputs $\mu_1, \mu_2, ..., \mu_n$, which are the compatibility values of every pixel x to $A_1, A_2, ..., A_n$ respectively. In the paper, $\mu_i (i = 1, 2..., n)$ are produced by the formula below:

$$u_i(x) = e^{-\frac{(gray - E_{xi})^2}{2 E_{ni}^2}} \tag{14}$$

Where gray is the gray-value of the input image, E_{xi} is the expected value of the corresponding cloud model, E_{ni} is the corresponding entropy and $u_i(x)$ is the compatibility of x to the cloud model numbered as i. The maximum compatibility value is retrieved and x is assigned to A_i if μ_i is the maximum .As a result, each pixel assigned into certain category , which is illustrated in figure 5.

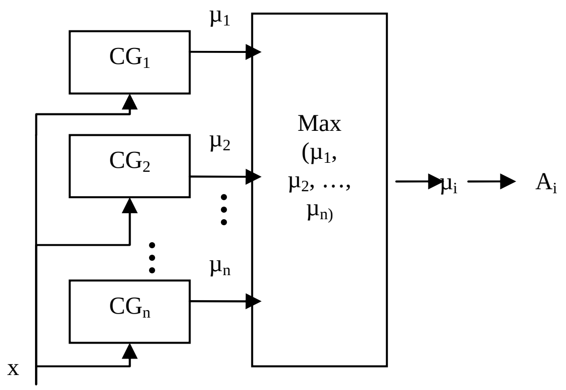

Figure 5.The mechanism for assigning an pixel to a cloud model

4.1.4 Optimizing the segmentation results: Using mathematical morphology operators to optimize the result obtained above, to integrate or eliminate some fragments According to the direction and texture characteristics of different targets detected, different mathematical morphology operations are used to obtain the most satisfactory result. At last, the recognizing result is achieved by correlating analysis between the original and the morphological result.

4.2 Results and analysis

Figure 6 shows the result of recognition based on traditional segmentation method with double thresholds of image brightness. From figure 6 we can see that the result is trashy as it contains the river whose brightness is near to the brightness of fish ponds in some extent, which makes it difficult for them to be separated further.

The result shown in figure 7 rectifies the false target by texture analysis based on co-occurrence measures as preprocessing and performing segmentation with thresholds iterating. However, there is still serious target missing, for instance, the fish pond near the river disappeared with the river. On the other side, the result shown in figure 8 indicates that the detecting and recognizing ability of comprehensive mechanism based on combined wavelet transform, morphology operations and linguistic cloud model, which is combining the advantages of the algorithms proposed above, has enhanced greatly. For one side, the river has not been included in the result .For the other, the phenomenon of targets missing has been reduced a lot. In addition, the area of the fish ponds recognized by the comprehensive mechanism is measured by geometric method and compared with the actual area surveyed on the spot. The total error rate is below ten percent, which is mainly caused by the speckle noise of ASAR image and the training samples is selected based on experience with some unavoidable inaccuracy. The result shows that the integrated mechanism used in this paper is effective and robust.

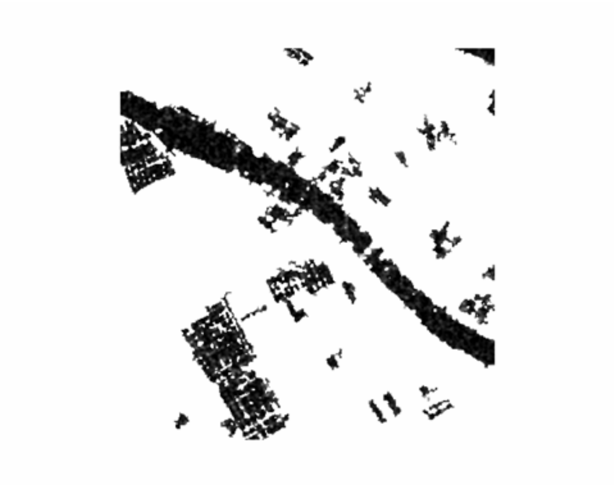

Figure 6. Result of segmentation with threshold of the gray-values

Figure 7. Result of recognition based on the iteration of thresholds and traditional texture analysis

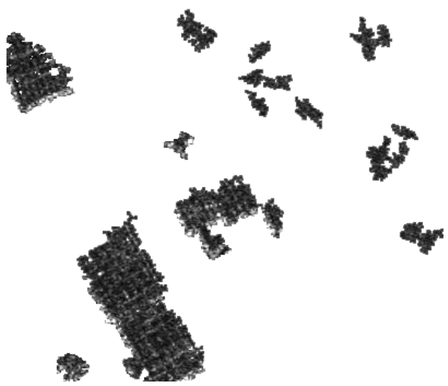

Figure 8 Result of recognition by the comprehensive mechanism proposed in this paper

5. CONCLUSIONS AND DISCUSSION

Because of the multi-resolution, partial, sensitivity to both boundary and texture of the combined wavelet and flexibility of morphology operations, the method based on combined wavelet transform and mathematical morphology can increase the separability of the target from other objects effectively and comprehensive methods perform better when there are more than one targets to be detected, especially when their gray-values are approached. Moreover, the linguistic cloud model is introduced to enhance the existing algorithms for image segmentation. The mathematical representation of 1-D linguistic atoms with three digital parameters for uncertainty is given to explore the essential uncertainty with randomness. Cloud model based on generalization allows the overlapping area between neighbour linguistic terms, and it is a soft mechanism for segmentation. Compared with the classical crisp segmentation methods, such as Otsu (Otsu, 1979) and method by iterated thresholds, the ability of recognition mechanism proposed in this paper has been improved largely. However, as a result of the limitation of sole data source, they are not the most perfect, so that fusion of multiple source remote sensing information should be studied to increase the target recognition accuracy in the future. Besides the comprehensive method proposed in this article can also be used for image classification by which we will complete the recognition of other targets, and this will be discussed in details in the future.

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