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A new Automatic Segmentation for Synthetic Aperture Radar Images

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ABSTRACT

The multiplicative nature of the speckle noise in SAR images has been a big problem in SAR image segmentation. A novel method for automatic segmentation of SAR images is proposed. Firstly, we use wavelet energy to extract texture features, use regional statistics to extract gray-level features and use edge preserving mean of gray-level features to ensure the accuracy of classification of pixels near to the edge. Three representative kinds of features of SAR image are extracted, so the segmentation ability is enhanced. Then an improved unsupervised clustering algorithm is proposed for image segmentation, which can determine the number of classes automatically. Segmentation results on real SAR image demonstrate the effectiveness of the proposed method.

1. INTRODUCTION

Synthetic Aperture Radar (SAR) images taken from airborne or space platforms can have high spatial resolution, but are affected by the speckle phenomenon which makes the extraction of the useful information a difficult task [1].

Segmentation is a low-level description on which image understanding is based. It prepares for high level concepts such as shape and adjacency. Accurately segmented image are easier to interpret, and the performance of objects recognisition is better.

The gray-level, edge and texture information are the three dominating information in SAR images. The presence of speckle noise reduces the efficiency of traditional segmentations based on gray-level feature. Many traditional techniques of segmentation which rely on measures based on differences between pixel intensities suffer from noise when applied to SAR images [2]. Some filtering schemes have been proposed for removing speckle, such as the Lee multiplicative filter [3]. However, existing speckle filtering algorithms can effectively reduce the speckle effect but unfortunately also, to some degree, smear edges and blur images. This is why traditional segmentation methods sometimes do not perform very well in edgeareas.

This paper proposed a new segmentation method without noise filtering. The method proposed combines gray-level, edge and texture information, and can determine the number of classes automatically.

2. FEATURE EXTRACTION

Texture feature

Texture is an important additional feature for classification purposes. Texture involves the spatial distribution of gray-levels in a local region. It contains important information about he structural arrangement of surfaces and their relationship to their neighboring surfaces.

Here we use wavelet energy to extract texture feature of SAR image. Each pixel responses to a neighborhood with N pixels in length and N pixels in width. Every neighborhood is transformed by wavelet and responses to 3 high frequency and 1 low frequency components subbands (as fig1 illustrates). Wavelet energy is defined as

$$e = \frac{1}{N \times N} \sum_{x,y=0}^{N\times N-1} \left| s(x,y) \right|^2 \qquad (1)$$

, where, $s(x,y)$ is the coefficient of component subband. A Daubechies3 wavelet was used [4]. That is, each pixel responses to 4 wavelet energies.

Gray-level feature

Due to deduce the impact of the speckle, we use regional statistics to extract gray-level features. Here we use mean and standard deviation of gray-level in the neighborhood.

Edge feature

Traditional segmentation methods based on regional information sometimes do not perform very well in edge areas. One of the reasons is that neighborhood in edge areas contains two or more classes of pixels, which make the center pixel very difficult to be classified. To ensure the accuracy of segmentation in edge area, we define a edge preserving mean of gray-level features

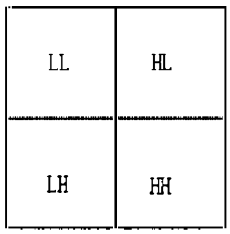


Fig.1. wavelet frequency subbands

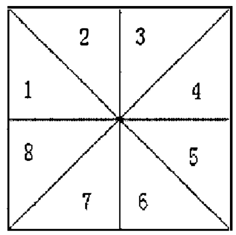


Fig.2. eight direction region

As fig.2 illustrates, suppose the center gray-level is x, which region G_i is divided into eight sub-areas S_k. Suppose the mean of gray-levels of the region is a_i, and the mean of each sub-area is $t_k(k=0,1,2,3,4,5,6,7)$, then the sub-areas can be divided into two sets H_i and L_i

$$H_i = \{S_k : t_k \geq a_i, S_k \in G_i\} \tag{2}$$

$$L_i = \{S_k : t_k < a_i, S_k \in G_i\} \tag{3}$$

Then the edge preserving mean of gray-level features is

$$e_i = \begin{cases} g_h & if abs(g_h - x) < abs(g_l - x) \\ g_l & if abs(g_h - x) \geq abs(g_l - x) \end{cases} \tag{4}$$

, where, g_h and g_l are the center point of H_i and L_i respectively.

3. SEGMENTATION BASED ON CLUSTERING

Image segmentation can be divided into two catalogs: supervised and unsupervised methods. Supervised segmentation methods may get better results, but they require training data and can not be applied in real time environments. Clustering algorithm [5] is the main component of unsupervised methods. Fuzzy C mean (FCM) is a common and useful algorithm whose results suffer from the choosing of initial clustering centers. And another drawback is that the number of classes must be determined before FCM runs. Here a novel clustering algorithm is presented which can determine the number of classes automatically. The core idea is that the data have the big relationship are always similar. The steps of the novel clustering algorithmas follow:

Suppose $X = \{x_1, x_2, \ldots, x_n\}$ is the set of input vectors, each vector is $x_i = \{x_i(1), x_i(2), \ldots, x_i(p)\}$, then

1. define $v_i(i=1,2,\ldots,n)$ and let $v_i = x_i$
2. compute the relationship between v_i and v_j

$$r_{ij} = \exp\left(-\frac{\|v_i - v_j\|^2}{2\sigma^2}\right), \; i=1,2,\ldots,n,$$
$$j=1,2,\ldots,n \tag{5}$$

3. change the relationship between v_i and v_j

$$r_{ij} = \begin{cases} 0, & if\ r_{ij} < \xi \\ r_{ij}, & otherwise \end{cases} \tag{6}$$

,where, ξ is a little positive real number

4. compute $w_i = \{w_i(1), w_i(2), \ldots, w_i(p)\}$ as follow

$$w_i = \frac{\sum_{j=1}^{n} r_{ij} v_j}{\sum_{j=1}^{n} r_{ij}}, \; i=1,2,\cdots,n \tag{7}$$

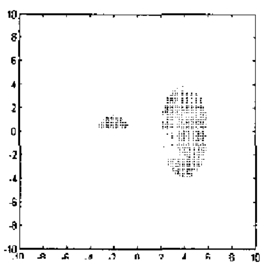
5. If all w_i are identical to v_i, goto step 6, otherwise let $v_i = w_i$ and return to step 2.
6. The input vectors with the same convergent vectors $v_i(i=1,2,\ldots,n)$ is classified into the same class. And the convergent vectors are the clustering centers. The number of the classes is just the number of convergent vectors with different values.

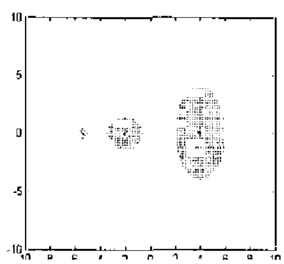
Each pixel responses to a neighborhood with N pixels in length and N pixels in width. When we apply proposed clustering algorithm to SAR image segmentation, we extract regional feature vectors with 7 components $\vec{x} = (x_1, x_2, \ldots, x_7)$. x_1 x_4 denotes LL,LH,HL,HH wavelet energies as fig.1 illustrates. x_5 and x_6 are the gray-level mean and standard deviation of region pixels. x_7 is the edge preserving mean of gray-level features.

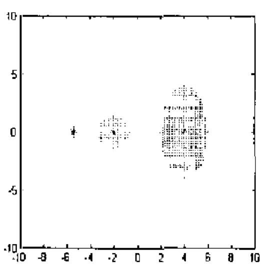
From above clustering algorithm, we notice that a $n^2 \times n^2$ relationship matrix is computed in every flop. When number of input vectors is less, the memory and computing cost problem is not obvious. But when it is applied in image segmentation which needs to classify every pixel, the large memory space demanded always goes beyond the real physics memory which will cause the computation impossible. So we developed an improved method which just computes one row vectors each flop. That is from step2 to step5 we just compute

$$r_j = \exp\left(-\frac{\| v - v_j \|^2}{2\sigma^2}\right), \; j = 1,2,\ldots,n \tag{8}$$

The memory space demanded and computation cost is reduced. A example is given to validate this. Fig.3(1) is artificial data and Fig.3(2), (3),(4) are the former method clustering result, improved method clustering result and FCM clustering result respectively. From Fig.3, we can see both the former method and improved method can classify the data correctly. Whereas FCM classifies some data falsely (the * points denote the location of the clustering centers). Table 1 shows the running time comparison with different image size. We can see that as the input vectors number increases, the improved method take less computing time than former one.


(1)artificial data


(2)former method result


(3) improved method result

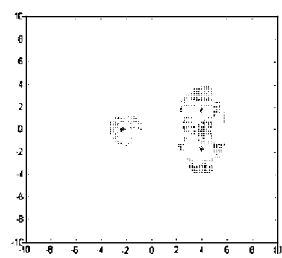

(4)FCM result

Fig.3. artificial data and clustering results

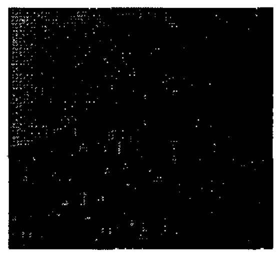
Size of image	Running time second	
	Former method	Improved method
40×40	24.47	11.45
50×50	39.91	28.37
60×60	75.16	53.84
70×70	194.66	120.75
80×80	401.76	221.41
90×90	Out of memory	420.67

Tab.1. Running time comparison between former method and improved mehtod

4. EXPERIMENT

We apply our method to SAR image and compare the result with other algorithms. Here we set $\sigma = 0.2$ $\xi = 0.01$. Fig.4 (1) is the original SAR image, and fig.4 (2) is the segmentation result of proposed algorithm. Fig.4 (3) ~ (6) are the results of FCM [8, 9, 10], OSTU [11], split-and-merge segmentation [12], MRF segmentation [13] respectively. As Fig.4.illustrates, the result of proposed method is better than others.

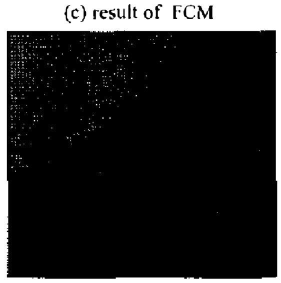
In many clustering algorithms, standard deviation of gauss function, σ, affects the segmentation results greatly. From proposed clustering algorithm, we notice that σ affects the relationship of data, and affects the number of classes (as fig.5 illustrates). Besides, due to the difference of gray-level distribution of different image, the same σ may get different results. So the choosing of σ is very important, which need further research.


(a) original SAR image


(b) result of proposed algorithm


(c) result of FCM


(d) result of OSTU


(e) result of split-and-merge segmentation

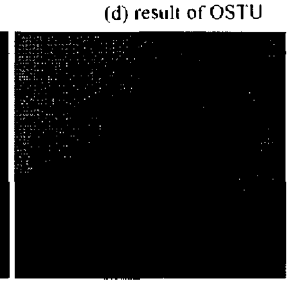
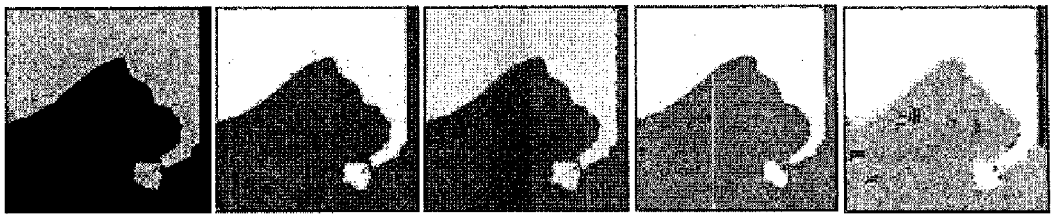

(f) result of MRF segmentation

Fig.4. comparison with different algorithms



1 σ 0.2, c=2   2 σ 0.16, c=4   3 σ 0.14, c=6   4 σ 0.11, c=10   5 σ 0.1, c=18

Fig.5. affection of σ to the segmentation result,
Here c denotes number of classes

5. CONCLUSION

Based on effective feature extraction and novel algorithm, an unsupervised SAR image segmentation method is proposed. Considering three dominating information: gray-level, edge and texture information make SAR image accurate segmentation possible. And the proposed clustering algorithm can automatically determined the number of classes, which is much better than FCM. Segmentation results on real SAR image demonstrate the effectiveness of the proposed method. Further research is focused on choosing σ.

6. ACKNOWLEDGEMENT

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7. REFERENCES

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