WAVELET BASED IMAGE SEGMENTATION OF SAR FLIGHT IMAGES

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Abstract

The presence of speckle in Synthetic Aperture Radar (SAR) images makes the segmentation of such images difficult. A novel method for automatic segmentation of SAR images is proposed. Firstly, a wavelet packet based texture feature set is derived. It consists of the energy of the feature sub images obtained by the over complete wavelet packet decomposition of local areas in SAR image, where the down sampling between wavelet levels is omitted. 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.

Keywords: **Image segmentation, over complete wavelet packet decomposition, texture feature, clustering algorithm.**

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I. INTRODUCTION

Segmentation is a fundamental process in digital image processing which has found extensive application in areas such as content-based image retrieval, medical image processing, and remote sensing image processing. Its purpose is to extract labeled regions or boundaries for targeted objects for subsequent processing such as surface description and object recognition.

A segmentation procedure usually consists of two steps. The first step is to choose a proper set of features which can identify the same-content regions and meanwhile different-content regions; the second step is to apply a segmentation method to the chosen features to achieve a segmentation map.

Texture is an essential key to the segmentation of SAR image. Texture originates from the scale-dependent spatial variability, and is observed as the fluctuation of gray levels in SAR images. It is well known, however, that another source of the fluctuation, speckle, exists in SAR images. Speckle is caused by the interaction of reflected waves from various independent scatters within a resolution cell. Here we consider texture separately from speckle, as Ulaby et al. did in [1].

The notion of scale gives an important hint to texture analysis. Recently, wavelet transform and wavelet packet transform have received much attention as a promising tool for texture analysis [2]-[6], because they have the ability to examine a signal at different scales. The texture feature set derived from the overcomplete wavelet de-composition where the downsampling between wavelet levels is omitted is superior to that derived from the standard (critically downsampled) wavelet decomposition [2], [3].

This is attributed to the property that the overcomplete wavelet decomposition can provide translation invariant features. The work by Chang and Kuo [5], however, indicates that texture features are most prevalent in intermediate frequency bands, thus that the octave band decomposition is not optimal. The trend probably therefore seems to be a concentration on the wavelet packet transform [4], [5], [6], which basically is the wavelet transform with sub band decompositions not restricted to be dyadic. The discrete wavelet packet transform are critically sampled multi rate filter banks. However, critically sampled filter banks typically imply inaccurate texture edge localization [2]. Therefore, in this paper, overcomplete wavelet packet decomposition is employed to extract local texture features from SAR.

Image segmentation can be divided into two catalogs: supervised and unsupervised techniques. Supervised segmentation holds both advantages and drawbacks. One advantage is that one knows in detail how the algorithm works. One of the major drawbacks is that one need to know beforehand how certain phenomena will appear in the images and this information is not always available. Even though the human interpreter often is superior in identifying strange details and phenomena in images, there is still a need to automate this process.

This leads to the concept of unsupervised segmentation or classification of images. Clustering analysis is the main component of unsupervised techniques. Unfortunately, most clustering algorithms, for example the fuzzy C-means (FCM) method [8]-[10], suffer several difficulties: a) sensitive to the initialization; b) inability to find a global minimum and; c) difficulty of deciding how man clusters exist. In this paper, an improved unsupervised clustering algorithm is proposed for image segmentation, which can determine the number of classes automatically.

Wavelets are functions which allow data analysis of signals or images, according to scales or resolutions. The processing of signals by wavelet algorithms in fact works much the same way the human eye does; or the way a digital camera processes visual scales of resolutions, and intermediate details. But the same principle also captures cell phone signals, and even digitized color images used in medicine.

Wavelets are of real use in these areas, for example in approximating data with sharp discontinuities such as choppy signals, or pictures with lots of edges. While wavelets is perhaps a chapter in function theory, we show that the algorithms that result are key to the processing of numbers, or more precisely of digitized information, signals, time series, still-images, movies, color images, etc. Thus, applications of the wavelet idea include big parts of signal and image processing, data compression, fingerprint encoding, and many other fields of science and engineering. This thesis focuses on the processing of color images with the use of custom designed wavelet algorithms, and mathematical threshold filters. Although there have been a number of recent papers on the operator theory of wavelets, there is a need for a tutorial which explains some applied tends from scratch to operator theorists.

Wavelets as a subject are highly interdisciplinary and it draws in crucial ways on ideas from the outside world. We aim to outline various connections between Hilbert space geometry and image processing. Thus, we hope to help students and researchers from one area understand what is going on in the other. One difficulty with communicating across areas is a vast difference in lingo, jargon, and mathematical terminology. With hands-on experiments, our paper is meant to help create a better understanding of links between the two sides, math and images. It is a delicate balance deciding what to include. In choosing, we had in mind students in operator theory, stressing explanations that are not easy to find in the journal literature.

II. IMAGE SEGMENTATION USING WAVELET TRANSFORM

Following subsections describe algorithms of image segmentation using wavelet transform.

A. Image Features Extraction

Texture is characterized by the spatial distribution of gray levels in a neighborhood. An image region has a constant texture if a set of its local properties in that region is constant, slowly changing or approximately periodic. Texture analysis is one of the most important techniques used in analysis. There are three primary issues in texture analysis: classification, segmentation and shape recovery from texture. Analysis of texture [1] requires the identification of proper attributes or features that differentiate the textures of the image. In this paper, texture segmentation is carried out by comparing co-occurrence matrix features Contrast and Energy of size $N \times N$ derived from discrete wavelet transform overlapping but adjacent sub images $C_{i,j}$ of size 4×4, both horizontally and vertically.

The algorithm of image features extraction involves

a) Decomposition, using one level DWT with the Haar transform, of each sub image Ci,j of size 4×4 taken from the top left corner

b) Computation of the co-occurrence matrix features energy and contrast from the detail coefficients, obtained from each sub image Ci,j

c) Forming new feature matrices.

B. Pixel Differences

After the computation of co-occurrence matrix features, a new matrix with differences is obtained. It is carrying out by calculation the difference between the value by value of features both in horizontal and vertical directions. Then the segmentation band is formed across the texture boundaries.

C. Circular Averaging Filtering

In the image with the segmented band obtained after differences could appear artifacts or spurious spots. When within the same region the high differences of features values appeared, the spots and noise were formed. These spurious elements were removed by applying a circular averaging filter. First the filter with suitable radius was created and then applied for a segmented image to minimize and efface the image.

D. Thresholding and Skeletonizing

The processed image is then thresholded using global image threshold using Otsu's method [6] and black and white image is obtained. Because of the thick boundaries we must thin them on the line of one pixel thickness. To process these specific morphology operations were used. At first operation 'clean' removes isolated pixels - individual 1's that are surrounded by 0's. The second operation 'skel' removes pixels on the boundaries of objects but does not allow objects to break apart. The pixels remaining make up the image skeleton.

III. WAVELET PACKET BASED FEATURE CLASSIFICATION

From the sub band filtering (filter bank) point of view, the difference between the wavelet packet transform and the conventional wavelet transform is that the former also recursively decomposes the high-frequency components, thus constructing a tree-structured multiband extension of the wavelet transform. A two-dimensional (2-D) wavelet packet transform decomposes an image into four sub images. ↓2 denotes the downsampling by a factor of two. The approximated image LL is obtained by low pass filtering in both row and column directions. The detail images, LH, HL, and HH, contain high frequency components. By decomposing the approximated image and the detail images of each level into four sub images iteratively, a complete image quad tree is acquired.

In the "standard" wavelet packet decomposition, the filtered outputs are down sampled by a factor of two, and are a quarter of the size of the previous image. There is neither loss nor redundancy of information between the levels, since the dyadic de-composition is an orthogonal representation of the image. The decomposition is therefore useful for applications such as image coding. The downsampling has, how-ever, a drawback that the decomposition is not translation invariant.

The translation-invariance property is indispensable for texture analysis. A solution of this problem is the overcomplete wavelet packet decomposition without the downsampling. The filtered outputs are the same size as the previous images. The over complete wavelet packet decomposition provides robust texture features at the expense of redundancy. Feature extraction using overcomplete wavelet packet transform can extract all band pass information about texture, but accompanying with the default that with the increasing of decomposition level, the number of sub bands increasing exponentially, e.g. for 4 level complete tree structured wavelet transform, there are 341 leave nodes. This will generate high feature dimension, and cause great different in the following classification.

Therefore, from the point of decreasing feature dimension and maintaining the stability of the feature dimension, we use a 2 level overcomplete wavelet packet transform. At level 1, four sub images are chosen to be the feature sub images, and at level 2, only the one with the maximum variance in each sub channel is chosen to be the feature sub images among all of the sub images. Thus, the number of the feature sub images is 8. The energy (i.e., the averaged - norm) of each feature sub images can be a favor-able feature of texture because it indicates dominant spatial-frequency channels of the original image. Our texture feature set is also made up of the energy of feature sub images by the overcomplete wavelet packet decomposition. After an image of a square local area is decomposed, the following averaged energy is calculated, and is assigned to the component of the feature vector of the central pixel in the area.

IV. DISCUSSION

We apply the proposed method to SAR image segmentation and compare the results with other algorithms.

First, we use a 2 level overcomplete wavelet packet transform to obtain eight feature sub images, and compute the energy of each feature sub images. Here we use Daubechies D3 for image decomposition.

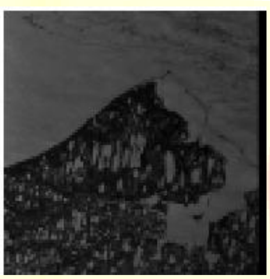

Fig 1. (a)

Fig 1. (b)

Then, the improved clustering algorithm is applied to the chosen features to achieve a segmentation map. Based on experience, the width (σ) of the Gauss function in (2) is set to 0.2, and the constant ξ in (3) is set to 0.01. Fig.4 (a) shows the original SAR image, and fig.4 (b) shows the segmentation result by the proposed algorithm.

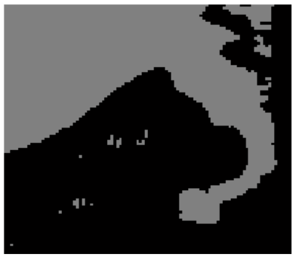 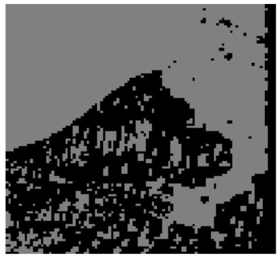

Fig 1. (c) Fig 1. (d)

 

Fig 1. (e) Fig 1. (f)

Fig.1. (a) Original SAR image (b) segmented result by the proposed algorithm (c) segmented result by the FCM method (d) segmented result by the OSTU method (e) segmented result by the split-and-merge method (f) segmented result by the MRF model

Fig.4 (c) ~ (f) shows the results by the FCM [8], [9, [10], the OSTU [11], the split-and-merge method [12] and the MRF model [13] respectively. As Fig.4 illustrates, the result of the proposed method is better than that of the others. In many clustering algorithms, the width (σ) of the Gauss function affects the segmentation results greatly.

 

Fig 2. (c) Fig 2. (d)

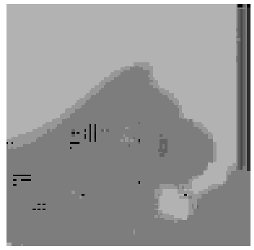

Fig 2. (c) Fig 2. (d)

Fig.2. Affection of σ to the segmentation result, here c denotes number of classes. (a) σ=0.2, c=2 (b) σ=0.14, c=6 (c) σ=0.11, c=10 (d) σ=0.1, c=18.

From the proposed clustering algorithm, we notice that the specified value of σ affects the relationship of data set, and affects the number of clusters (as fig.5 illustrates). Besides, due to the difference of gray-level distribution of different image, the same σ may obtain different results. So the choosing of σ is very important, which need further research.

V. CONCLUSION

In this paper, a wavelet packet based texture feature set has been introduced. The texture feature set is made up of the energy of feature sub images by the overcomplete wavelet packet decomposition of a local area in an image, where the downsampling between wavelet levels is omitted. The overcomplete wavelet packet decomposition provides translation-invariant features at the expense of redundancy. In addition, the proposed clustering algorithm can automatically determined the number of classes, which is much better than the fuzzy C-means (FCM) method. Segmentation results on the real SAR image demonstrate the effectiveness of the proposed method.

REFERENCES

[1] Ulaby, F.T., Kouyate, F., Brisco, B., Williams L.: Textural Information in SAR Images. IEEE Trans. Geosci. Remote Sensing. Vol. 24 (3) (1986), pp. 235-245.

[2] Unser, M.: Texture Classification and Segmentation Using Wavelet Frames. IEEE Trans. Image Processing. Vol. 4 (11) (1995), pp. 1549-1560.

[3] Fukuda, S., Hirosawa, H.: A Wavelet-based Texture Feature Set Applied to Classification of Multifrequency Polarimetric SAR Images. IEEE Trans. Geosci. Remote Sensing. Vol. 37 (1999), pp. 2282-2286.

[4] Laine, A., Fan, J.: Texture Classification by Wavelet Packet Signatures. IEEE Trans. Pat-tern Anal. Mach. Intel. Vol. 15 (11) (1993), pp. 1186-1190.

[5] Chang T., Kuo, C.-C.J.: Texture Analysis and Classification with Tree-Structured Wavelet Transform. IEEE Trans. Image Processing. Vol. 2 (4) (1993), pp. 429-441.

[6] Saito, N., Coifman, R.R.: Local Discriminant Bases and Their Applications. J. Mathemati-cal Imaging and Vision. Vol. 5 (4) (1995), pp. 337-358.

[7] Wong, C.C., Chen, C.C.: A Hybrid Clustering and Gradient Descent Approach for Fuzzy Modeling. IEEE Trans. on SMC-Part B. Vol. 29 (6) (1999), pp. 686-693.

[8] Canno, R.L., Dave, J.V., Bezdek, J.C.: Efficient Implementation of the Fuzzy C-Means Clustering Algorithm. IEEE Trans. Pattern Anal. Mach. Intel. Vol. 8 (1986), pp. 248-255.

[9] Bezdek, J.C., Ehrlich, R., Full,W.: FCM: The Fuzzy C-Means Clustering Algorithm. Com-puters and Geosciences. Vol. 10 (1984), pp. 191-203.

[10] Kamel, M.S., Selim,S.Z.: New Algorithms for Solving the Fuzzy Clustering Problem. Pattern Recognition. Vol. 27 (1994), pp. 421-428.

[11] Otsu, N.: A Threshold Selection Method from Gray Level Histograms. IEEE Trans. Syst., Man, Cybern. Vol. 9 (1979), pp. 62-66.

[12] Wu, X.: Adaptive Split-and Merge Segmentation Based on Piecewise Least Square Ap-proximation. IEEE Trans, Patt. Anal. Machine Intel. Vol. 25 (8) (1993), pp. 808-815.

[13] Panjwani, D.K., Healey, G.: Markov Random Field Models for Unsupervised Segmenta-tion of Textured Color Images. IEEE Trans. Pattern Anal. Mach. Intel. Vol. 17 (10) (1995), pp. 939-954.