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# SAR Image Segmentation Based On Hierarchical Merging Method

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**ABSTRACT-**Image segmentation is an important tool in satellite image processing and serves as an efficient front end to sophisticated algorithm and thereby simplify subsequent processing. It used to extract the meaningful objects lying in the image. The aim of the paper is to obtain the segmentation of the Synthetic Aperture Radar (SAR) image with minimum run time of the algorithm. The algorithm used for the segmentation is named as hierarchical unequal merging algorithm. In this paper instead of pixel, the superpixels are used as operation units. The preprocessing stage consist of formation of superpixel. The analysis of superpixel is performed by using three Gestalt law. In this edge detection, feature extraction are computed from the superpixel content. Based on this the merging of superpixel take place in two phase namely 1) Coarse merging stage 2) Fine merging stage. It will use less running time for the superpixels which are not present in the boundaries of different pattern and more running time in the superpixels which are in doubtful regions. The proposed algorithm is effectively reduces the process of segmentation and computational complexity.

**INDEX TERMS—** Feature extraction, Image segmentation, Region merging, Synthetic aperture radar (SAR**).**

## I. Introduction

Segmentation is the process of dividing a digital image into multiple segments. Aim of segmentation is to make simple and change the identification of an image into something that is more meaningful and easier to analyze. Image segmentation is majorly used to identify the boundaries and objects in given SAR images. More importantly, image segmentation is the process of giving a label to every pixel in an image such that pixels with the similar label share same characteristics. The meaning of context is the information of the area which are given by single pixel, and that single pixel will give the information of the surrounding pixel also. The result of segmentation is the set of segments that consist of the important detail of that image, or a set of contours extracted from the image. Generally the pixels of a particular region are similar with respect to some characteristic such as color, intensity, or texture. SAR images are differentiate the place by roughness and moisture level, which result in different in brightness and textures.

Image thresholding methods are popular due to their simplicity and efficiency. However, traditional histogram-based thresholding algorithms cannot separate those areas which have the same gray level but do not belong to the same part. In addition, they cannot process images whose histograms are nearly unimodal, especially when the target region is much smaller than the background area. The template matching method is simple in principle, but the design of the template always needs much mathematical effort. A clustering method, viewing an image as a set of multidimensional data and classifying the image into different parts according to certain homogeneity criterion, can get much better results of segmentation.

The edge detection method is one of the widely used approaches to the problem of image segmentation. It is based on the detection of points with abrupt changes at gray levels. The main disadvantages of the edge detection technique are that it does not work well when images have many edges, and it cannot easily identify a closed curve or boundary. Region growing algorithms deal with spatial repartition of the image feature information. In general, they perform better than the thresholding approaches for several sets of images. However, the typical region growing processes are inherently sequential. The regions produced depend both on the order in which pixels are scanned and on the value of pixels which are first scanned and gathered to define each new segment. These algorithms have proved to be successful in many applications, but none of them are good for all images or all applications. In remote sensing satellite images, a pixel corresponds to an area of the land space, which may not necessarily belong to a single land cover type. This makes the segmentation more imprecision and uncertainty.

The edge penalty TMF reduce the noise to some extent only. MRF method as high segmentation accuracy and also computational time. The MPM algorithm are not efficient for homogenous and small size images. While the RJMCMC has the segmentation accuracy of 98.28%, but the efficiency is reduced if noise in the image is increased. The pixel based segmentation is good for edge detection but the SAR image is of high density images, therefore this techniques will be slow for computing. Therefore region based segmentation is well suit for SAR image segmentation. Remote sensing satellite images have significant applications in areas such as climate studies, assessment of forest resources, identifying urban, non-urban regions, examining marine environments. Image segmentation plays an important role in remote sensing satellite image processing.

## II. PROPOSED ALGORITHM

The algorithm will follow the steps for performing the segmentation of SAR image.

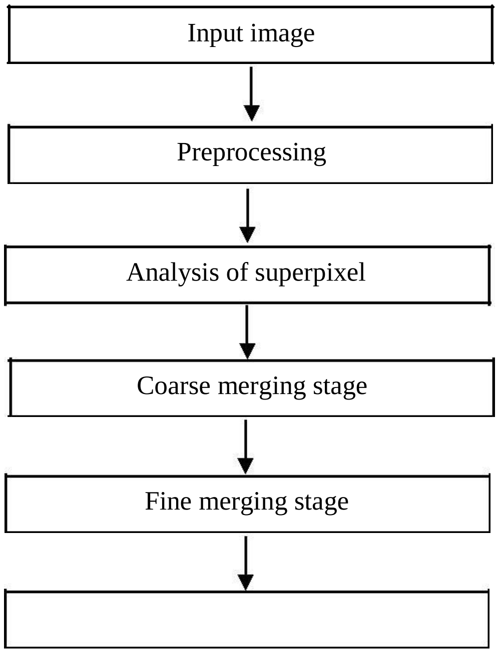



Fig.1 Overall Block Diagram

Flowchart of the Hierarchical unequal merging algorithm is shown in Fig.1, which consist of following steps. First step is the formation of superpixels and then analysis of that superpixel context take place based on the Gestalt theory. Next, CMS and FMS use the superpixel context to merge the superpixels based on different strategies. The superpixel context can accurately describe the contextual relationship between superpixels and further decide the labels of superpixels in the final segmentation. While merging superpixels, a hierarchical unequal merging algorithm is designed, which includes two stages 1) coarse merging stage and 2) fine merging stage. This are the two stages as indicated in Figure 1.The final segmented output is achieved in the fine merging stage.

## III. PREPROCESSING STAGE

Normally the pixels are the basic operation unit in the existing process, but in proposed algorithm the

Superpixels are the basic operation units. The pixel are combined, based on the location, intensity, edges, texture and they form the superpixel. The pixel in the superpixel will have same brightness. Superpixel may reduce the speckle noise and help to increases the speed of the algorithm. For example, if brightness is chosen as the constraint, in this paper, a level-set method called TurboPixels [8] is chosen as the preprocessing method to produce superpixels. In TurboPixels, a user-specified number of seeds are first distributed uniformly over the image plane, and then, the seeds keep dilating to approach the local image structures.

During the dilating process, a Gaussian-smoothing filter is first performed to suppress noise, and then, the gradient of image edges and the curvature of seeds' boundary are taken into the seeds' evolution equation. Since superpixels can reduce the influence of speckle noises, preserve most edges of images, and are approximately uniform in size and shape, they are utilized as the basic operation units in this paper. The superpixels of SAR images produced by TurboPixels [8] are shown in Fig.2. At the preprocessing step, the input SAR image is oversegmented into *Ns* superpixels. The algorithm will next merge the superpixels based on the analysis of superpixel context.

## IV. ANALYSIS OF SUPERPIXELS

The second step of the algorithm is analysis of the superpixel based on the result obtained from the preprocessing step. This are performed by using the Gestalt theory. Context models can improve the accuracy and to decrease the running time [15] of the algorithm. A successful context model is the MRF model [2] but they will take high computation time. In this algorithm the Gestalts law is used to improvement of accuracy of the segmentation and the decrease the running time. Three Gestalt laws are used as the prototypes [10], which are as follows 1) the law of vicinity 2) the law of similarity and 3) the law of color constancy.

### *A.The Rule Of Vicinity*

The rule of vicinity states that two superpixels to be merged are of spatial vicinity [9]. For any pair of superpixels ( ,$s_j$), i, j = 1, 2. . . Ns, their spatial vicinity is defined by spatial context as follows:

$$(i, j) = \begin{cases} 1, & s_i \text{ and } s_j \text{ are neighbours} \\ 0, & s_i \text{ and } s_j \text{ are not neighbours} \end{cases} \quad (1)$$

1

If $_1$ (i, j) = 1, then and $|s_j|$ are of spatial vicinity and satisfy the rule of vicinity and vice versa. In this the near superpixel will be merged to form a single superpixel.

### *B. The Rule Of Similarity*

The rule of similarity states that two superpixels to be merged are similar in content [9]. In this the brightness and texture are analyzed for the SAR image.

$$^{c}\ (i, j) = \exp(-\ \frac{|s_i| - |s_j|}{2\ \|\ \ \|}) \times \|F(i) - F(j)\| \quad (2)$$

Where F (i) is a feature vector extracted from superpixel $s_i$, when the two superpixel of different size will have higher penalty while similar one will have lesser penalty. The similarity is used to find the similarity between two superpixels based on the feature vectors. For any superpixel $s_i$, i = 1, 2. . . Ns. The texture in this is used to find the character of the terrain surface. The feature vector F (i) is extracted by the following two steps.

- Compute the feature vector F(r, c) of any pixel (r, c) $\in s_i$.
- Compute the feature vector F (i) of superpixel $s_i$, i = 1, 2. . Ns, by the average of the feature vectors of all pixels belonging to $s_i$ F (i) = (r, c) $\in s_i$ F(r, c) $|s_i|$.

For the Gabor filter bank, six orientations $\theta$ are adopted 0◦, 30◦, 60◦, 90◦, 120◦, and 150◦. The scales $\omega$ of the Gabor filter bank are set by an adaptive method, the value of ω will be following as √2/4, √2/8, and √2/16.

### C. *The Rule Of Color Constancy*

The rule of color constancy states that there is no distinct boundary between superpixels to be merged [9]. For any pair of superpixels ($s_i$,$s_j$), i ≠ j, i, j = 1, 2. . . Ns, their boundary is defined as

$$(i, j)=1-\exp(-\frac{1}{\ }) \times (1 - \|\ (\ ,\ )\|) \quad (3)$$

where H (i, j) is a feature vector extracted from the boundary between $s_i$ and $s_j$ , B( $s_i - s_j$) is the set of the pixels on the boundary between $s_i$ and $s_j$ .The penalty term is to reduce the influence of the boundary length. The longer the boundary length is, the larger the penalty.

The boundary of two superpixels with shorter boundary will be penalized more. $\|H(i, j)\|$ In the edge term in measures the edge magnitude between superpixels. The larger the $\|H(i, j)\|$ is, the more prominent the edges between $s_i$ and

are. The domain of $\|H(i, j)\|$is set to [0, 1]. Therefore, when $s_i$ and $s_j$ have long boundary and prominent edges, the boundary $c_3(i, j)$ is small. For any pair of superpixels ($s_i$ $s_j$), i, j =1, 2. . . Ns, their feature vector H (i, j) is extracted by the following two steps.

-  Compute the feature vector H (r, c) of any pixel (r, c) $\in$ B( $s_i - s_j$)
-  Compute the feature vector H (i, j) of superpixels $s_i$ ands$_j$, i, j = 1, 2. . . Ns, by the average of the feature vectors of all pixels belonging to B ($s_i$,$s_j$).

The edge image of scale is computed by the normalized magnitude of horizontal and vertical edge feature images. The multi-scale edge representation consists of a group of edge images with different scales. The aim of the multiscale edge representation is to increase the robustness to the speckle noises and complex multiscale images.

Hierarchical unequal merging algorithm consist of two main stages in the merging which are follow as

- Coarse merging stage and
- Fine merging stage.

In this module the main factor is to the speedup the segmentation algorithm, and the segmentation accuracy is the secondary factor.

### V. COARSE MERGING STAGE

The image are first coarsely and quickly separate different objects in them and do not considering the details between objects like boundary, shape, and so on. The main goal is to accelerate computation speed. The superpixels inside any particular object can easily merged into a common superpixel. In this merging is take place without doubt fullness, while the superpixels that are located in-between different pattern are merged with doubtful, and they are left for the fine merging stage.

The object of CMS is to merge the superpixels without doubtful at a very low computation cost. As for implementation, CMS merges superpixels based on the spatial context $_1$ and the boundary $_3$.CMS first finds all adjacent pairs of superpixels based on $_1$

$$D1 = \{(s_i,s_j) \mid c_1 (i, j) = 1, i \neq j, i, j = 1, 2. . . Ns\} \quad (4)$$

Then, CMS chooses the pair of superpixels based on $c_3$ , satisfying the merging condition as follows

$$\arg\min_{(s_i,s_j)} (\{c_3 (i, j) \mid c_3 (i, j) \leq \beta, (s_i, s_j) \in D1\}) \quad (5)$$

where $\beta$ is the halt condition of CMS, determining the boundary between superpixels. If $_3(i, j) \leq \beta$, then $s_i$ and,$s_j$ have no distinct boundary and satisfy the rule of color constancy and vice versa. The halt condition parameter $\beta$ controls the numbers of superpixels to be merged in CMS. The larger the $\beta$, the more the superpixels that will be merged.

If $\beta$ is too large, CMS will merge too many superpixels and result in errors. If $\beta$ is too small, CMS is not computation cost of FMS. $\beta$ is set as $\beta$ = 70%. That is, CMS will merge nearly 70% pairs of superpixels for synthetic SAR images. And the output image is given as input to the fine merging stage.

### FINE MERGING STAGE

In contrast with CMS that quickly merges the superpixels without doubtful, FMS adopts a strategy to accurately merge the superpixels with doubtful superpixel. The accuracy of the segmentation is mainly depend on FMS only. The FMS adopts all three rules to merge the superpixel. In FMS the all adjacent pairs of superpixels are merged based on the spatial context $_1$ as follows:

$$D1 = \{(s_i, s_jj) \mid c_1 (i, j) = 1, i \_= j, i, j = 1, 2, .. Ns\} \quad (6)$$

Then, in each interval, FMS sorts the adjacent pairs of superpixels based on the boundary $c_3$ in a non-decreasing order as follows

= ({ 3( , )| 2(s , s ) ∈ }) (7)

2 ($s_i$, ) i j

This is a new sequence of the adjacent pairs of superpixels, which is named merging sequence *D*2. FMS will follow the order of *D*2 to merge superpixels. FMS first sorts the adjacent pairs of superpixels based on the semantic context $c_2$ and then ranks the pairs in each interval according to the boundary$c_3$.

Therefore, when two pairs of superpixels have very different($c_2$), they will be allocated in different intervals. In addition, the pair of superpixels with lower ($c_2$) will be merged first. In another situation, when two pairs of superpixels have approximate($c_2$), they will be in the same interval. In this situation, the pair of superpixels with lower $c_3$ will be first merged. It set to make sure that ($c_2$) in each interval are nearly the same and have slight variability. From this the final segmentation output is obtained.

## VII. RESULTS AND DISCUSSION

The preprocessing is performed for the input images which is of Ku-band SAR image of the area of China Lake Airport

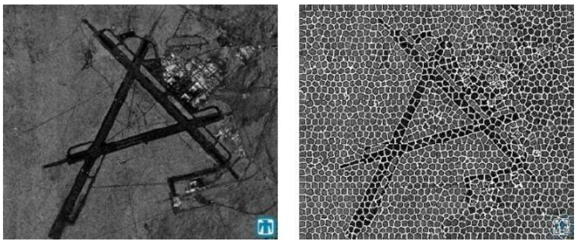
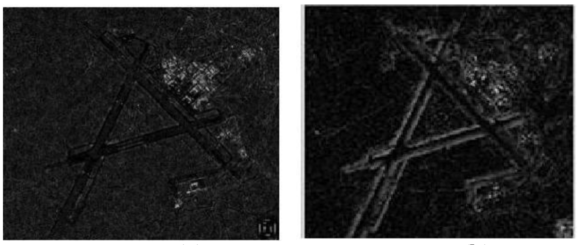


Fig.2. (a) Input SAR Image of Chinalake airport
(b) Superpixels formed for input images

The required number of superpixel are obtained from the preprocessing stage. The output image of preprocessing is then used for the contextual analysis.



(a) (b)

(c)

Fig.3. Different scales of texture images for the input (Chinalake) image.

From the Gestalts second law the features of the input image are identified. This is performed by using the Gabor filter bank. For that different scales ω are √2/4, √2/8, √2/16 and orientations θ will be 30◦, 60◦, and 90◦.The edge representation is to increase the robustness to the speckle noises and to identify the edges of the image.

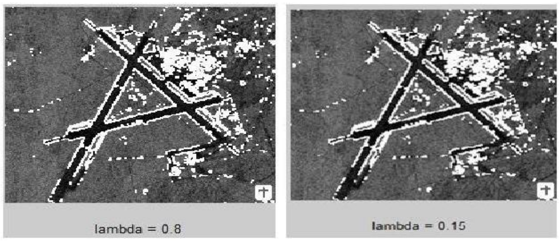



Fig.4. Edge representation of input image for the different

image. The final segmented output gives the edges of the objects, present in the input image. The accuracy of final segmentation is also depends on the superpixels formed in the preprocessing step. The future work will be in improving the accuracy of the superpixel formation and to further reduction in computational time.

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