ISSN 2348 – 9928
IJAICT Volume -1, Issue-3, July 2014 Doi:01.0401/ijaict.2014.01.10 Published Online 05 (05) 2014

A REGION SPLITTING AND HIERARCHICAL UNEQUAL MERGING ALGORITHM FOR SEGMENTATION OF SAR IMAGES

Ms. V.Shalini
PG Scholar
Sri Sakthi Institute Of Engineering and Technology
Coimbatore, Tamilnadu , India.

Ms. P. Subbulakshmi
PG Scholar
Sri Sakthi Institute Of Engineering and Technology
Coimbatore, Tamilnadu , India.

Abstract— In this paper we present an segmentation technique which uses super pixels as the basic unit of operation. The image is first converted into a super pixel image. Then the rules framed by Gestalt based on study of cognitive science are used to extract the features of image such as texture, edges and spatial information. The rule of locality determines the neighboring pixels. The rule of proximity group pixels of same brightness. The rule of consistency is used to identify the boundary for the pixels to be merged. The image is first split using region splitting. Then it is merged in two stages, first abrasively and then finely. In the first stage the pixels within a super pixel are merged and in second stage the pixels along the boundary are merged. The goal of this paper is to obtain segmentation with accuracy.

Keywords- Synthetic Aperture Radar, Image Segmentation Region Splitting, Region Merging.

I. INTRODUCTION

Synthetic aperture radar (SAR) is an active remote sensing system: microwave radiation is beamed down to the earth's surface from a plane or satellite and the sensor detects that reflected signal and forms the SAR images. Images can be obtained from satellites such as ERS, JERS and RADARSAT.

Synthetic aperture radar is used to obtain high resolution images from broad areas of terrain. SAR is capable of operating under inclement weather conditions, day or night. SAR can penetrate clouds and work under conditions where optical sensors are inoperable. Hence SAR images find wide applications in areas such as resources, environment, archaeology, military remote sensing etc.

One of the important roles of SAR system is to collect the information about the ground surface through image reconstruction. Since the ground surface has diverse areas, such as rice fields, wheat fields, grassland, ponds, asphalt roads, desert, and so forth, those areas have to be segmented in the image reconstruction. Thus segmentation problem arises.

SAR image segmentation is to partition an image into regions of different characteristics without intersection. Effective segmentation of SAR images not only can reduce computation cost but also can increase the efficiency for further high-level SAR image processing.

The segmentation methods generally fall under two categories

- Methods emphasizing image features
- Method emphasizing segmentation algorithms

The methods emphasizing image features: Because speckle noises in SAR images lead to random changes in the brightness of pixels, it is often invalid to directly apply traditional segmentation methods to SAR images. Therefore, many researchers pay much attention to extracting efficient SAR image features which include the brightness after denoising, texture, edge and hybrid features.

The methods emphasizing segmentation algorithms: Many algorithms from different mechanisms have been applied to SAR image segmentation, and they include threshold methods, clustering algorithms, statistic-model-based methods, artificial intelligence methods, support vector machines and region growing methods. Three aspects should be carefully considered for SAR image segmentation. They are as follows.

First, features should be able to describe various kinds of characteristics in SAR images. No single feature can completely describe miscellaneous regions and objects in SAR images. Therefore, it is necessary to combine different features to improve the performance of SAR image segmentation.

Second, region should be adopted as the operation unit. Many segmentation algorithms for SAR images were based on the region adjacency graph (RAG).
Third, high-level knowledge should be taken into account for SAR image segmentation. From the studies of human vision it is evident that high level knowledge can facilitate image segmentation.

With respect to these aspects the image is first under segmented into super pixels. Then Gestalts law is used to extract the features such as texture edges, spatial information. The region splitting algorithm is applied. Quad tree decomposition is used to split the images. Then merging is done in two stages. In the first stage of merging the super pixels without ambiguity are merged. This is coarse merging.

ISSN 2348 – 9928
IJAICT Volume -1, Issue-3, July 2014 Doi:01.0401/ijaict.2014.01.10 Published Online 05 (05) 2014

The later stage i.e. fine merging merges the super pixels with ambiguity.

II. SUPERT PIXEL IMAGE

The Super pixels are adopted as the basic operation units instead of pixels. A super pixel is a group of pixels by some constraints such as location, intensity, edge, and texture. For example, if brightness is chosen as the constraint, the pixels belonging to one super pixel have almost the same brightness. For a SAR image, super pixels not only can reduce the influence of speckle noises but also can improve computation speed. Speckles noises are noises that arise due to the effect of interference or radar signals that are reflected by the ground surfaces.

In this paper, a level-set method called Turbo Pixels is chosen as the preprocessing method to produce super pixels. The goal of turbo pixels is to maintain and evolve the boundary between the assigned region, which contains all pixels that are already inside some super pixel, and the unassigned region which contains all other pixels.

In Turbo Pixels, 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 super pixels 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.

The algorithm for turbo pixel formulation consists of the following steps

1. Place initial seeds;
2. Iterate over the following basic steps until no further evolution is possible, i.e., when the speed at all boundary pixels is close to zero,

i. Evolve this boundary for T time steps;

ii. Estimate the skeleton of the unassigned region;

iii. Update the speed of each pixel on the boundary and of unassigned pixels in the boundary's immediate locality.

The next step is to merge the super pixel based on features extracted.

III. ANALYSIS OF SUPER PIXEL CONTEXT

Inspired by the famous Gestalt theory in cognitive science, three rules are proposed to model the super pixel context. The Gestalt theory studies the laws of perceptual organization, which enables people to perceive the structure and composition without knowing any prior information in the image. The Gestalt laws are global constraints to the objects in images and help to group these objects to form a high-level object. Three Gestalt laws are used as the prototypes, which are as follows:

1. The law of locality
2. The law of proximity
3. The law of consistency

The law of locality states that, when objects are physically close to each other, one can merge them together and treat them as a whole, like the black circles in Fig.1(a), which form two groups in a high level. The law of proximity is applied to group the objects with similar shape, color, texture, and so on. Taking Fig.1 (b) for example, it can be noticed in a high level that a region consisting of circles is surrounded by a region consisting of rectangles. The law of consistency states that, when color, intensity, and texture remain relatively stable, the connected regions are treated as a whole region, like the single dark spot in Fig. 1(c). Based on these prototypes, three rules are proposed to represent the super pixel context.

3.1 Rule 1: The Rule of Locality

The rule of locality states that two super pixels to be merged are of spatial locality. For any pair of super pixels (s_i, s_j), i ≠ j, i, j = 1, 2. . . Ns, their spatial locality are defined by spatial context as follows:

C1 (i, j) =1, s_i and s_j are neighbors,

0, s_i and s_j are not neighbors.

If C1 (i, j) = 1, then s_i and s_j are of spatial locality and satisfy the rule of locality and vice versa. The spatial context C1(i, j) describes the relative positions of two super pixels in the image plane. Here it is implemented by deciding whether two super pixels are neighbors or not. It is possible to replace this with specific domain knowledge such as orientation, distance, and adjacency in the terrain surface.

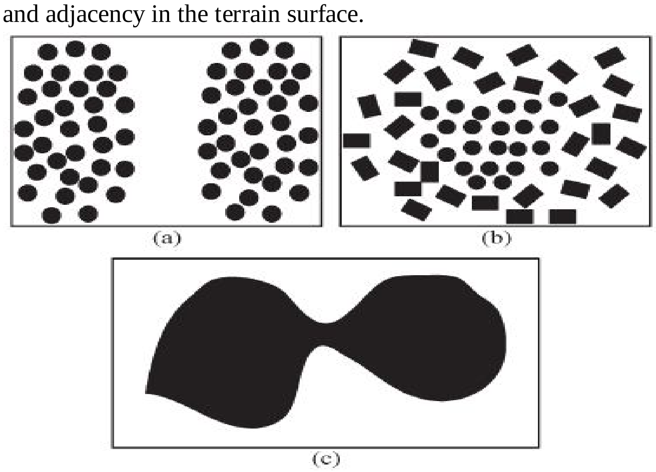


Fig 1: Illustration of three Gestalt laws.
(a) The law of locality.
(b) The law of proximity.
(c) The law of consistency.

ISSN 2348 – 9928
IJAICT Volume -1, Issue-3, July 2014 Doi:01.0401/ijaict.2014.01.10 Published Online 05 (05) 2014

3.2 Rule 2: The Rule of Proximity

The rule of proximity states that two super pixels to be merged are similar in content. For any pair of super pixels (si, sj), i ≠ j, i, j = 1, 2. . . Ns, their proximity is extracted from super pixel si. The penalty term is to reduce the influence of super pixel size. The more greatly two super pixels differ in size, the smaller the penalty term is. Therefore, the semantic context of two super pixels with very different sizes will be penalized more than that of two super pixels with approximate sizes. The similarity term computes the similarity between two super pixels based on the extracted feature vectors.

The semantic context implicitly represents the semantic consistency by describing the similarity of two super pixels in appearance The aim of this fusion strategy is to accurately describe super pixels in SAR images, because brightness and texture are two different important features for radar image interpretation. Brightness describes the strength of the radar reflectivity of the resolution element (pixel), while texture represents the characteristic structure of terrain surface in a finite sampling window. A heuristically designed Gabor filter bank is utilized to obtain feature. The method in first filters the input image by a bank of Gabor filters of different scales ω and orientations θ, and then, the normalized magnitudes of Gabor filter responses are computed as texture images.

3.3 Rule 3: The Rule of Consistency

The rule of consistency states that there is no distinct boundary between super pixels to be merged. For any pair of super pixels (si, sj), i _= j, i, j = 1, 2, . . .,Ns, their feature vector H(i, j) is extracted by the following two steps.

1. Compute the feature vector H(r, c) of any pixel (r, c) ∈ B (si, sj).

2. Compute the feature vector H (i, j) of super pixels si and sj , i _= j, i, j = 1, 2,.,Ns, by the average of the feature vectors of all pixels belonging to B(si, sj)

H(i, j) = Σ(r,c)∈B(si,sj)H(r, c)/|B(si, sj)| ______________(1)

In this method, a multi scale edge representation is designed to extract the feature vector H(r, c). In implementation, the input image is first convolved with a bank of Prewitt kernels, each of which is sensitive to the edges of a scale where I is the input image

IV. REGION SPLITTING

Region splitting segmentation is based on a quad tree partition of an image. It is sometimes called quad tree segmentation. This method starts at the root of the tree that represents the whole image. If it is found non-uniform (not homogeneous), then it is split into four son-squares (the splitting process), and so on so forth. Conversely, if four son-squares are homogeneous, they can be merged as several connected components (the merging process). The node in the tree is a segmented node. This process continues recursively until no further splits are possible. The algorithm for region splitting is given below:

- Initially take the image as a whole to be the area of interest.
- Look at the area of interest and decide if all pixels contained in the region satisfy some similarity constraint.
- If **TRUE** then the area of interest corresponds to a region in the image.
- If **FALSE** split the area of interest (usually into four equal sub-areas) and consider each of the sub-areas as the area of interest in turn.

Then the image is merged in two stages namely coarse merging and fine merging

V. COARSE MERGING SEGMENTATION

Such is the nature that, when people see a new image or scene, they always first coarsely and quickly separate different objects and do not carefully consider the details between objects like boundary, shape, and so on. This process is stimulated by CMS, the main goal of which is to accelerate computation speed. The super pixels that are inside the objects and obvious to be merged are called super pixels without ambiguity, while the super pixels that are located between different objects and doubtful to be merged are called super pixels with ambiguity. The object of CMS is to merge the super pixels with certainty at a very low computation cost.

As for implementation, CMS merges super pixels based on the spatial context and the boundary. CMS first finds all adjacent pairs of super pixels. Then, CMS chooses the pair of super pixels satisfying the merging condition then, a greedy search is made to merge the pairs of super pixels one by one until there are no two super pixels satisfying the merging condition. It can be noticed that the super pixels inside regions are first merged while the super pixels along the boundary are left to FMS. The algorithm of CMS is

- Find all adjacent pairs of super pixel
- Find the pair of super pixels satisfying merging condition and merge them until there are no such pair of super pixels existed.

VI. FINE MERGING SEGMENTATION

As for implementation, FMS adopts all three rules to guide the super pixel merging. FMS first finds all adjacent pairs of super pixels based on the spatial context then, in each interval, FMS

ISSN 2348 – 9928
IJAICT Volume -1, Issue-3, July 2014 Doi:01.0401/ijaict.2014.01.10 Published Online 05 (05) 2014

sorts the adjacent pairs of super pixels based on the boundary in a non decreasing order. The algorithm of FMS is

- Find all adjacent pairs of super pixels
- Sort the pair of super pixel in each interval.
- Obtain the merging sequence.
- Merge super pixels and update after each merging.

FMS first sorts the adjacent pairs of super pixels based on the semantic context and then ranks the pairs in each interval according to the boundary. Therefore, when two pairs of super pixels have very different, they will be allocated indifferent intervals. In addition, the pair of super pixels with lower semantic context will be merged first. In another situation, when two pairs of super pixels have approximate consistency, they will be in the same interval. In this situation, the pair of super pixels with lower semantic context will be first merged. Therefore, the semantic context globally determines the merging sequence while the boundary locally adjusts the order of the merging sequence. Every time, the pair of super pixels to be merged in FMS not only is similar in content but also has smooth boundary, which is plausibly similar to the perceptual organization regulation of human being. It can be noticed that the interval number will influence the merging sequence.

VII.SIMULATION RESULTS

The three algorithms are further tested with two real Ku-band SAR images from Sandia National Laboratories. The SAR image shown in Fig.2 captures the area of China Lake Airport in California with 3-m resolution and 522 × 446 size. This SAR image has three classes: runway (dark), buildings (bright), and farms (gray). The difficulty in segmenting this image comes from the small buildings that are randomly distributed in the farms and the large intra class variations of the farms. Some areas of the farm are quite similar to the buildings or the runway by subjective observation.

Input image

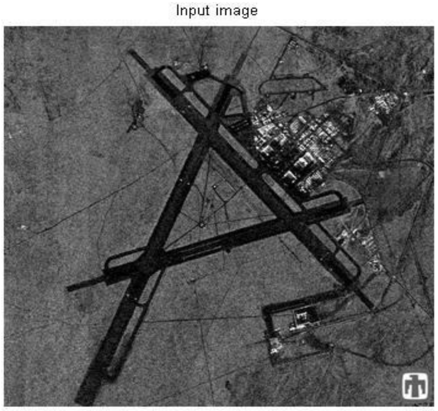


Fig 2: Input image

At the preprocessing step, the input SAR image is over segmented into super pixels where all the pixels in one super pixel have the same label. The proposed algorithm will next merge the super pixels based on the analysis of super pixel context. The super pixel image of input is shown in Fig 3.

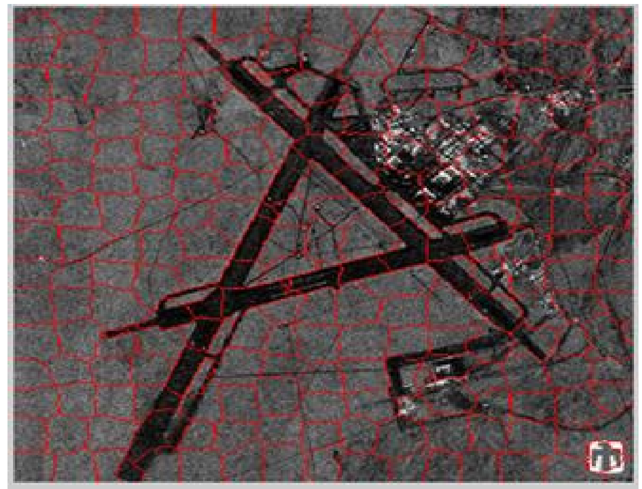
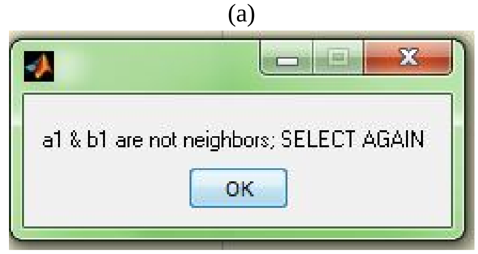


Fig 3 : Super pixel image

Rule 1: The Rule of Vicinity

The rule of vicinity states that two super pixels to be merged are of spatial vicinity. In this paper, it is implemented by deciding whether two super pixels are neighbors or not. Two super pixels are selected, if they are neighbors then the dialog box shown in figure 4a will occur, else figure 4b will be displayed

(a)



(b)

Fig 4: Illustrating rule of vicinity
a. Two pixels are neighbors
b. Two pixels are not neighbors

Rule 2: The Rule of Similarity

The rule of similarity states that two super pixels to be merged are similar in content. The contexts considered are brightness

ISSN 2348 – 9928
IJAICT Volume -1, Issue-3, July 2014 Doi:01.0401/ijaict.2014.01.10 Published Online 05 (05) 2014

and texture. Brightness describes the strength of the radar reflectivity of the resolution element (pixel), while texture represents the characteristic structure of terrain surface in a finite sampling window. Fig. 5a shows four isotropic texture images of different scales ω of Gabor filter for the first super pixel. Fig 5b shows for the second super pixel.

(a)

(b)

Fig 5: Extracted feature images of a real SAR image for the semantic context. Isotropic texture images of different scales for

(a) First super pixel

(b) Second super pixel.

Rule 3: The Rule of Color Constancy

The rule of color constancy states that there is no distinct boundary between super pixels to be merged. λ is the scale parameter of the Prewitt kernel. With the increase of λ, the size of the Prewitt kernel increases, and the scale of the extracted edges increases, which, in effect, reduces the influence of speckle noises, the multi scale edge representation of a real SAR image is shown in Fig. 6. Here the vertical and horizontal orientations are seen.

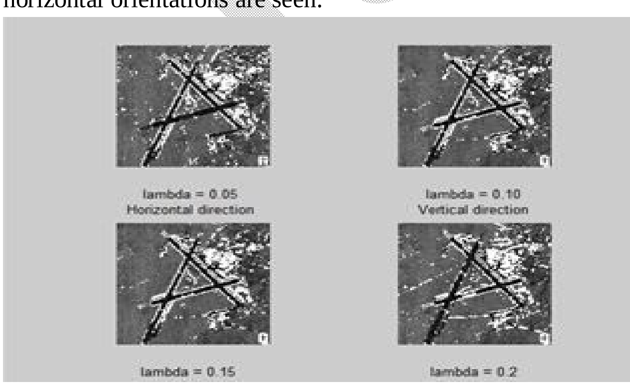


Fig 6 : Multi scale edge representation of a SAR image with different scales.

The image split using quad tree decomposition is shown in figure 7

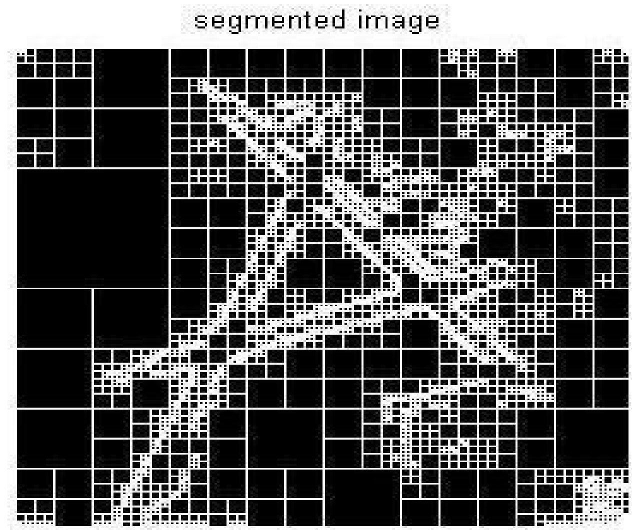


Fig 7 : region split image

The super pixels that are inside the objects and obvious to be merged are called super pixels without ambiguity, while the super pixels that are located between different objects and doubtful to be merged are called super pixels with ambiguity. The coarse merged image is shown in figure8. It can be found that the super pixels within regions have been merged during CMS and only the super pixels with ambiguity are left for FMS.

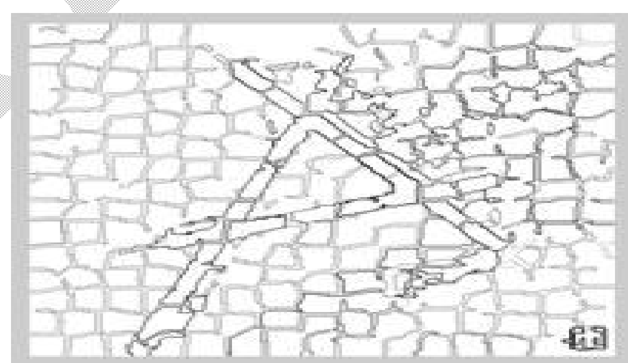


Fig 8: Coarse merged image.

In contrast with CMS that quickly merges the super pixels without ambiguity, FMS adopts a sophisticated strategy to accurately merge the super pixels with ambiguity. Therefore, the accuracy of the final segmentation result is mainly decided by FMS.

The fine merged output is shown in fig 9. The boundaries between different regions have been accurately located, particularly for the boundary of the runway. Moreover, the small buildings have also been exactly segmented out.

ISSN 2348 – 9928
IJAICT Volume -1, Issue-3, July 2014 Doi:01.0401/ijaict.2014.01.10 Published Online 05 (05) 2014

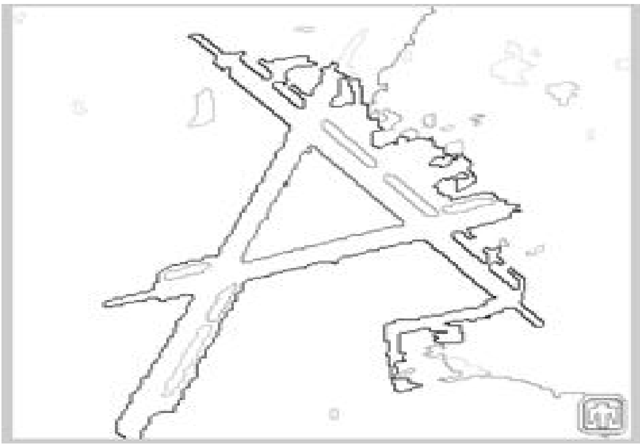


Fig 9: Fine merged image

VIII. CONCLUSION

In this paper we present a segmentation technique which uses super pixels as the basic unit of operation. The image is first converted into a super pixel message. Then the rules framed by Gestalt based on study of cognitive science are used to extract the features of image such as texture, edges and spatial information. The rule of locality determines the neighboring pixels. The rule of proximity group pixels of same brightness. The rule of consistency is used to identify the boundary for the pixels to be merged. The image is merged in two stages, first abrasively and then finely. In the first stage the pixels within a super pixel are merged and in second stage the pixels along the boundary are merged. As a result we obtain segmentation with accuracy.

The paper uses merging algorithm alone for segmentation Better results can be obtained by using region splitting also. This will be considering in future work.

References

[1] A. Levinshtein, A. Stere, K. N. Kutulakos, D. J. Fleet, S. J. Dickinson, and K. Siddiqi, "TurboPixels: Fast superpixels using geometric flows," IEEE Trans. Pattern Anal. Mach. Intell., vol. 31, no. 12, pp. 2290–2297, Dec. 2009.

[2] A. Oliva and A. Torralba, "The role of context in object recognition, Trends Cognitive Sci., vol. 11, no. 12, pp. 520–527, Dec. 2007.

[3] A. Desolneux, L. Moisan, and J. M. Morel, From Gestalt Theory to Image Analysis: A Probabilistic Approach. New York: Springer-Verlag, 2007.

[4] A. Jain and F. Farrokhnia, "Unsupervised texture segmentation using Gabor filters," Pattern Recognit., vol. 24, no. 12, pp. 1167–1186, 1991.

[5] R. Duda, P. Hart, and D. Stork, Pattern Classification, 2nd ed. New York: Wiley-Interscience, 2001.

[6] D. Clausi and M. Jernigan, "Designing Gabor filters for optimal texture separability," Pattern Recognit., vol. 33, no. 11, pp. 1835–1849, Nov. 2000. [34] X. He, R. Zemel, and D. Ray, "Learning and incorporating top-down cues in image segmentation," in Proc. ECCV, 2006, vol. 1, pp. 338–351.

[7] A. Hanbury, "How do superpixels affect image segmentation?" in Proc. 13th Iberoamerican Congr. Pattern Recognit., 2008, vol. 5197, pp. 178–186.