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Design of Multi-region SAR Segmentation by Parametric

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Abstract: Synthetic Aperture Radar (SAR) is most important as a natural scenes and image segmentation purpose in Radar field. The image segmentation method name is Context-based Hierarchical Unequal Merging for SAR Image Segmentation (CHUMSIS) .We proposes an approach to represent super pixel context which uses the operation unit instead of pixels. Based on the Gestalt laws, three rules are satisfying under the condition and to manage different kinds of feature extraction from SAR image. The features are including brightness, texture, edges and spatial information of SAR images. While appearing the merging process, a hierarchical unequal merging algorithm is designed by the two stages:1) Coarse Merging Stage(CMS) and 2) Fine Merge Stage. Experiments on synthetic and real SAR images represent in this algorithm can make a balance between computation speed and segmentation accuracy. The proposed method is compared to the two state-of-the-art Markov random field models; CHUMSIS can obtain good segmentation results with short running time.

Key words: synthetic aperture radar (SAR), feature extraction, merging process, image segmentation

I. INTRODUCTION

Radar (Radio detection and ranging), is an electronic system for detection and location of reflecting objects such as aircrafts, ships, spacecraft, vehicle, people and the natural environment.Although modern radars can extract more information of its range, the measurement of range is one of the most important functions. It operates by radiating energy into space and detecting the echo signals reflected from an object or target. Radar can work in antenna alternately transmits and receives pulses at particular microwave wavelengths (in the range 1 cm to 1 m, which corresponds to a frequency range of about 300 MHz to 30 GHz) and polarizations (waves polarized in a single vertical or horizontal plane). Synthetic Aperture Radar (SAR) name comes from that the system uses the movements of the airplane or satellite carrying it to make the antenna system much larger than it resolution.

The moving aircraft or the satellite allows SAR system to repeatedly take pictures from different positions.The receiver processes these signals to make it seem as though they came from a large stationary antenna instead of a small moving one. SAR resolution can be high enough to pick out individual objects as small as automobiles. SAR imaging provides high resolution images of large areas. The intensities of pixels in a SAR image are based on the spatial orientation, roughness, and dielectric constant of the surface imaged. The sensors of synthetic aperture radar (SAR)can penetrate clouds and work under conditions whereoptical sensors are inoperable (such as in bad weather and night time), SAR images find wide applications in resources, environment, archaeology and military uses. To humans, an image is not only a random collection of pixels but
Also a meaningful arrangement of regions and objects. People tend to use high-level features (concepts) to interpret images, while the features automatically extracted using computer techniques are mostly low-level features. CHUMSIS first presegments a SAR imageinto superpixels, which are local, coherent, and homogeneousgroups of pixels under certain constraints. Then, three rules are global constraints to guide the superpixel merging, which follows a top-down fashion in image understanding. The features are used to locally describesuperpixels from a bottom-up fashion. The rules realize a direct and effective way to manage different kinds of features. The former concentrates on the algorithm's computation speed, while the latter pays much attention to segmentationaccuracy.

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II. RELATED WORK

U. Soergel, U. Thoennessen, U. Stilla gives brief information aboutMulti-region SAR segmentation of image processing by using Clustering Segmentation of merging sequence but less accuracy. [1] E.Kuruoglu suggested that the Modelling SAR Images With a Generalization of the Rayleigh Distribution Ercan has image formation of a original parameter occupy but computation time is increased.[2]G. G. Wilkinson, I. Angelopoulos, and T. Moons, Eds. Berlin gives brief details about the Detection of urban features using morphological based segmentation and very high resolution remotely sensed data is used to provide accurate edges but, the design is complex[3] A. Reigber, M. Jäger, W. He, L. Ferro-Famil, and O. Hellwich gives brief information about a review of Detection and classification of urban structures based on high-resolution SAR imagery.It used to provide high sensitivity[4] F. Tupin, H. Maître, J. F. Mangin, J. M. Nicolas, and E. Pechersky suggested that the Detection of linear features in SAR images: Application to road network extraction that has been used by the image formation but it gives less accuracy[5] K. Hedman, B.Wessel, U. Soergel, and U. Stilla contributed that aAutomatic road extraction by fusion of multiple SAR views evaluated by presegment of a interpretation areas but computational complexity[6] F. Tupin, I. Bloch, and H. Maître gives brief description about A first step toward automatic interpretation of SAR images using evidential fusion of several structure detectors that defind by the original image to provide effective performance and robust to noise[7] H. Chaabouni-Chouayakh and M. Duct suggested that Geometrical and topological urban areas characterization using TerraSAR-X data is used by the context of the pre-processing step. It require large time for computation[8] D. Comaniciu and P. Meer gives brief idea about using Mean shift: A robust approach toward feature space analysis. It used to reduce the fault but, sensitivity is less. [9] F. Cellier, H. Oriot, and J. M. Nicolas gives brief information about Introduction of the mean shift algorithm in SAR imagery: Application to shadow extraction for building reconstruction has multiple resources in the particular segment that is used to enchance to detect large images[10] F. Tupin and M. Roux suggested that the Detection of building outlines based on the fusion of SAR and optical features, pixels are pre-segmented by the detection process. It gives accurate classification but difficult to label accurate[11] L. Basly, F. Cauneau, T. Ranchin, and L. Wald brief information about SAR imagery in urban area.It gives accurate classification buy using the image segment It provide high sensitive to detect fluctuation structure[12] T. Esch and A. Roth brief information about Semi-automated classification of urban areas by means of high resolution SAR data by using the classification of a urban areas that is difficult to find the region[13] D. Hoiem, A. A. Efros, and M. Hebert suggested that the Closing the loop on scene interpretation formation of single loop system to uniform sampling noise[14] F. Tupin, B. Houshmand, and M. Datcu suggested that the Road detection in dense urban areas using SAR imagery and the usefulness of multiple views detection processfor images with a high number of segments

III. PROPOSED SYSTEM

The Gestalt theory in three rules are proposed to model the superpixel 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 images, three Gestalt laws are follows: 1) the law of vicinity; 2) the law of similarity; and 3) the law of colour constancy.

A. Law of Vicinity

The rule of vicinity states that two super pixels to be mergedare of spatial vicinity. For any pair of super pixels (si, sj), i _= j,i, j = 1, 2, . . .,Ns, their spatial vicinity is defined by spatialcontext as follows:

$$C1\ (i, j) = \begin{cases} 1, & si \text{ and } sj \text{ are neighbours} \\ 0, & si \text{ and } sj \text{ are not neighbours.} \end{cases}$$

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

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B The Rule of Similarity

The rule of similarity 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 similarity is defined by semantic context as follows:

$$C2(i, j) = \exp \underbrace{\left[-\frac{\| \quad \|}{si + sj} \right.}_{\text{penalty term}} \underbrace{\left. X \right]}_{\text{similarity term}} \| F(i) \quad \|$$

Where F (*i*) is a feature vector extracted from super pixel *si*, | • | is the cardinality of the argument, and || • || is the one norm distance of the argument. To reduce the influence of super pixel size. And the two super pixels differ in size, the smaller the penalty term. 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 super pixel size is very by the extraction. The image segmentation and clustering the original image by the super pixel context in the original SAR image of the pre-segmentation.

For any super pixel *si*, *i* = 1, 2, . . ., *Ns*, its feature vector **F**(*i*) is extracted by the following two steps.

Step 1) Compute the feature vector **F**(*r*, *c*) of any pixel (*r*, *c*) € *si*.

Step 2) Compute the feature vector **F** (*i*) of super pixel *si*, *i* = 1, 2, . . . , *Ns*, by the average of the feature vectors of all pixels belonging to *si*

$$\mathbf{F}(i) = \frac{\sum_{(r,c) \in si} \mathbf{F}(r, c)}{|si|}$$

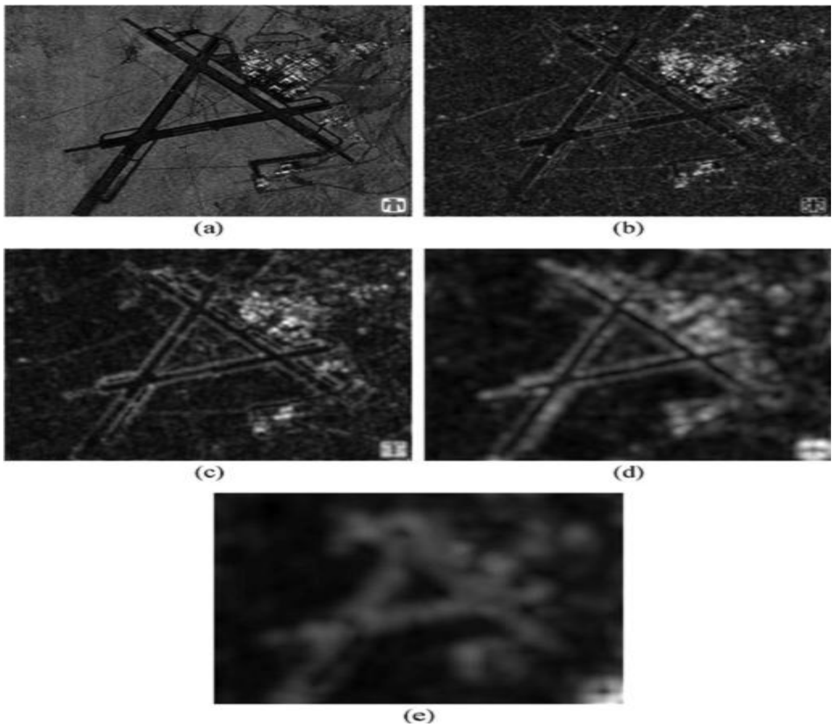

Fig.1. Extracted feature images of a real SAR image for the semantic context.(a) normalized brightness image (b)–(e) isotropic texture images of different scales

C: The Rule of Colour Constancy

The rule of colour constancy 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. The multistate edge representation consists of a group of edge images with different scale. The edge detection is to representation is to increase the robustness to the speckle noises and complex multistate images. The boundary of two super pixels with shorter boundary will be penalized more.H (i,j) in the edge term is measures the edge magnitude between super pixels.

D: Coarse-merge segmentation (CMS)

Hierarchical unequal merging algorithm is designed, which CMS stages. 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 similarity term in computes the 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 image segmentation and clustering the original image by the super pixel context in the original SAR image of the pre-segmentation.

ALGORITHM

1. Find all adjacent pairs of super pixel D1 based on C1.
2. Find the pair of super pixels, and merge them until there are no such pair of super pixels existed.

$D1 = \{(si, sj) \mid C1(i, j) = 1, i \_= j, i, j = 1, 2, . . . , Ns \}$

$D2 = \min (\{C3(i, j) \mid C3(i, j) \leq \beta, (si, sj) \in D1\})$

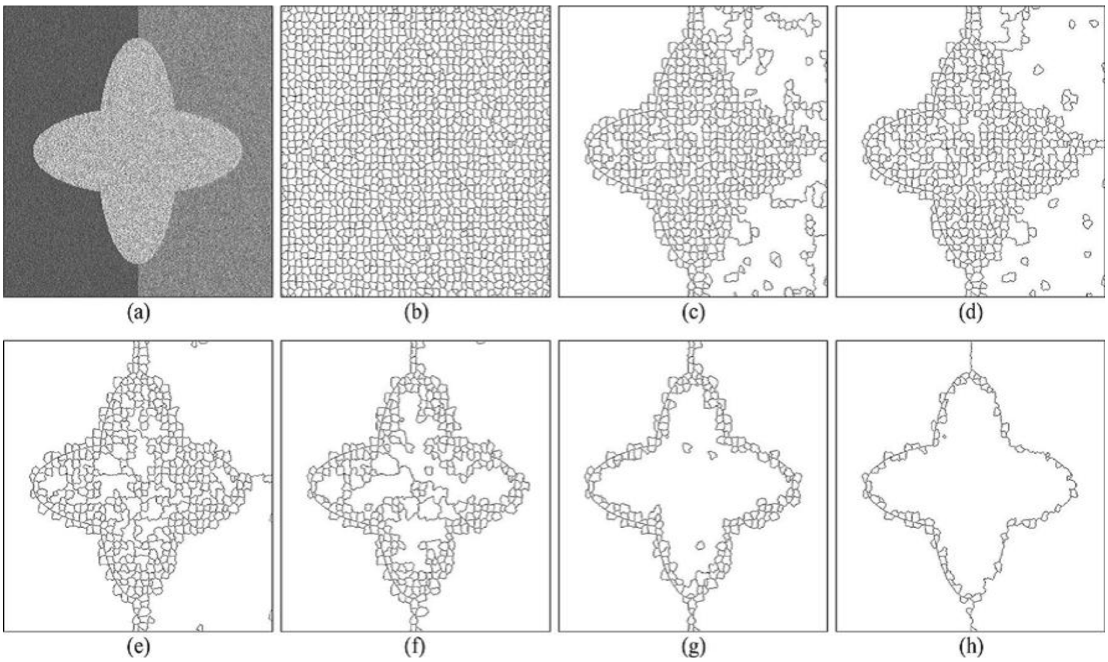

Fig.2. Synthetic SAR image and the intermediate segmentation results of CMS. (a) is the synthetic SAR image. (b) is the super pixels obtained by the preprocessing method. (c)– (h) are the intermediate segmentation results during CMS

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E: Fine-Merge Segmentation (FMS)

AsAs 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 $C1$ as follows:

$$D1 = \{(si, sj) \mid C1\ (i, j) = 1, i \_= j, i, j = 1, 2, \ldots, Ns\}$$

Where Ns is the number of super pixels after CMS. Then, $D1$is divided into Np equally spaced intervals based on semanticcontext $C2$

ALGORITHM

1. Find all adjacent pairs of super pixels D_1 based on $C_{1.}$
2. Divide D_1 into N_p equally spaced intervals based on C_2
3. Sort the pairs of super pixels in each interval based on C_3
4. Obtain the merging sequence D_2 by linking the sorted pairs of super pixels
5. Merge super pixels following the order of D_2 and update after each merging

$$R\text{min} = \min (\{C2\ (i, j) \mid (si, sj) \in D1\})$$

$$R\text{max} = \max (\{C3\ (i, j) \mid (si, sj) \in D2\})$$

The mechanism of FMS can be a sequence of C1 based on the boundary of the merging sequence. The interval number Np will influence them merging value. FMS can sort the pair adjacent pairs of super pixels based on the semantic context C2 and then ranks the pairs of the pixel.FMS will allow the sequence. The pair of Super pixel the merging sequence D2 is different interval numbers Np. The rank of the merging sequence D2, the normalized values corresponding to C2 and C3 , the semantic context determine the merging sequence. 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. The similarity term in computes the 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 image segmentation and clustering the original image by the super pixel context in the original SAR image of the pre- segmentation.

IV. IMPLEMENTATION

Fig3.input image 1

Fig 4. input image 2

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Fig 5.Super pixel

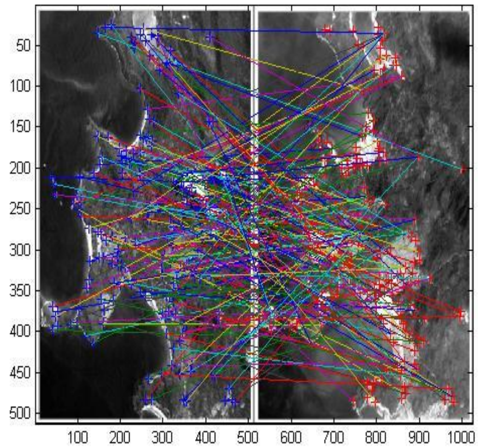

Fig 6. Super pixel context

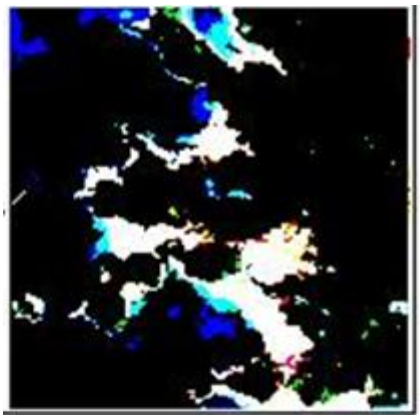

Fig7.After segmentation of FMS

V. CONCLUSION AND DISCUSSIONS

In this work it has been proposed an effective algorithm for image segmentation. This adopted merging work relies on the statistical data modelling with super pixel context. These concepts aim at effective image interpretation of urban area. Simulations have been shown for the performance of super pixel context and CHUMSIS algorithm. This algorithm is used by the content of the super pixel. The pixel that can be implemented by the super pixel context. Segmentation can be adopted by the real SAR images.

The result of this effort can be the starting point to develop the second module. The next step is to develop or improve the SAR interpretation methodology with different segmentation algorithm. The segmentation method that can be improved by the super pixel context.

REFERENCES

1. "Context based Hierarchal Unequal Merging for SAR in Segmentation Algorithm" U. Soergel, U. Thoennessen, U. StillaFGAN-FOM Research Institute for Optronics and Pattern Recognition, IEEE, transc, Feb 2013

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2. "Modeling SAR Images With a Generalization of the Rayleigh Distribution Ercan" E. Kuruoglu, *Member*, IEEE, and Josiane Zerubia, Fellow, Dec 2010

3. "Detection of urban features using morphological based segmentation and very high resolution remotely sensed data," in G. G. Wilkinson, I. Kanellopoulos, and T. Moons, Eds. Berlin,vol.43,no. 3,pp.43-76,Oct 2010

4. A. Reigber, M. Jäger, W. He, L. Ferro-Famil, and O. Hellwich, "Detection and classification of urban structures based on high-resolution SAR imagery," in Proc. Urban Remote Sens. Joint Event, Paris, France, 2008.

5. F. Tupin, H. Maître, J. F. Mangin, J. M. Nicolas, and E. Pechersky, "Detection of linear features in SAR images: Application to road network extraction,"IEEE Trans. Geosci. Remote Sens., vol. 36, no. 2, pp. 434– 453, Mar.2007

6. K. Hedman, B.Wessel, U. Soergel, and U. Stilla, "Automatic road extraction by fusion of multiple SAR views," in Int. Arch. Photogramm. RemoteSens., May 2006.

7. F. Tupin, I. Bloch, and H. Maître, "A first step toward automatic interpretation of SAR images using evidential fusion of several structure detectors,"IEEE Trans. Geosci. Remote Sens., vol. 37, no. 3, pp. 1327–1343, March 2006.

8 . H. Chaabouni-Chouayakh and M. Datcu, "Geometrical and topological urban areas characterization using TerraSAR-X data,"in Proc. IEEEIGARSS, Boston, MA, 2005, pp. IV-157–IV-160.

9. D. Comaniciu and P. Meer, "Mean shift: A robust approach toward feature space analysis,"IEEE Trans. Pattern Anal. Mach. Intell., vol. 24, no. 5, pp. 603–619, May 2004.

10. F. Cellier, H. Oriot, and J. M. Nicolas, "Introduction of the mean shift algorithm in SAR imagery: Application to shadow extraction for building reconstruction," in EARSel, Porto, Portugal, Aug 2003.

11. F. Tupin and M. Roux, "Detection of building outlines based on the fusion of SAR and optical features," ISPRS J. Photogramm. Remote Sens., vol. 58, no. 1/2, pp. 71–82, Jun. 2003.

12. L. Basly, F. Cauneau, T. Ranchin, and L. Wald, "Sar imagery in urban area," inProc. 19th Symp.EARSeL—Remote Sens. 21st Century, J.-L. Casanova, Ed. Valladolid, Spain, Jun. 1999, pp. 563–568.

13.T. Esch and A. Roth, "Semi-automated classification of urban areas by means of high resolution SAR data," inProc. 20th ISPRS, Istanbul, Turkey, 1999.

14. D. Hoiem, A. A. Efros, and M. Hebert, "Closing the loop on scene interpretation," in Proc. IEEE Comput. Soc. Conf. CVPR, Anchorage,Nov1998 .

15. F. Tupin, B. Houshmand, and M. Datcu, "Road detection in dense urban areas using SAR imagery and the usefulness of multiple views," IEEE Trans. Geosci. Remote Sens., vol. 40, no. 11, pp. 2405–2414, Sep 1998.