

SAR Image Segmentation by Cooperative Populations and Multi-objective Kernel Clustering Indices

Dongdong Yang^{1,a}, Hui Yang^{2,b} and Yuanyuan Liu^{3,c}

¹ Xi'an University of Technology, Xi'an, 710048, China; Shaanxi Huanghe Group Co., LTD, Xi'an;

² The Fourth Engineering Design and Research Institute of Engineer Corps, China PLA General Political Department

³ Shaanxi Huanghe Group Co., LTD, Xi'an, 710043

^addyang@mail.xidian.edu.cn, ^bsingbox258@163.com, ^cxuridongsheng150@163.com

Abstract:

This paper contributes two novel techniques in the context of synthetic aperture radar (SAR) image segmentation by cooperative learning and multi-objective clustering in kernel mapping thereof. First, we introduce an efficient implementation of cooperative evolution by using two parallel implemented populations, which are divided by the Pareto domination and local density dynamic information. Second, in order to obtain the better performance of algorithm in suppressing speckle noise in SAR image, another novelty of the study is introducing the kernel distance measure to the two objective functions. Finally, the proposed algorithm is tested on two complicated SAR images. Compared with four other state-of-the-art algorithms and our method achieve comparable results in terms of convergence, diversity metrics, and computational time.

Keywords: image segmentation and recognition; cooperative learning; multi-objective clustering.

Introduction

Synthetic Aperture Radar (SAR) is an advanced microwave equipment of earth observation, which is paid more attention by remote sensing field for its working at all-weather and all-time, strong permeability, plenty of multi-band and polarization information. SAR images have been applied in many fields including: oil spill detection, ground and sea monitoring, disaster assessment and so on. However, SAR image is generally affected by speckle because of its imaging mechanism. The existence of speckle leads to the degradation of image quality and has a directly impact on the SAR image understanding and interpretation. The

existence of noise deteriorates the quality of images seriously and can conceal important details, leading to the loss of interesting objectives.

Currently, many image segmentation algorithms have been proposed, which can be divided into clustering-based methods [1], graph-partitioning methods [2], morphologic methods [3], and model-based methods [4]. Here, we focus on the fuzzy clustering algorithm by combining newly hot studied nonlocal mean filter, cooperative evolutionary optimization, and multi-objective kernel clustering indices. Multi-objective optimization (MO) has been obtained great interest in evolutionary clustering community. In MO, it usually involves many conflicting and incomparable objectives; therefore, a set of trade-off solutions with different characteristics can be obtained. The clustering objectives usually reflect fundamentally different aspects of clustering solutions. Therefore, the complicated multi-variable relationship among data samples can be discovered and the optimal clustering solution is likely to obtain in MO framework.

As we know, the pixels in SAR images are highly overlapped and corrupted by complicated multiplicative speckle noises. Only one clustering index may be very appropriate for particular type of data sets, but it cannot discover for the types of data sets with complicated and diverse characteristics. Hence, it is necessary to consider multiple clustering objectives and optimize them simultaneously. Besides, a natural approach to tackle high-dimensional optimization problems is to adopt a divide-and-conquer strategy. An famous work on a cooperative coevolutionary algorithm [5] provides a promising approach for decomposing a high-dimensional problem, and tackling its subcomponents individually. Here, we employ the two population evolving strategy to lead the solutions to searching the final optimal segmentation result. The two populations are divided by the Pareto dominance in MO and local dynamic density information. It is noteworthy, once the nondominated solutions become much more, the complicated nondominated sorting could be discarded. The reason is that the diversity of the population can be maintained by the nondominated solutions because the dominated ones are few. Under this condition, the complicated nondominated sorting could be replaced by simple distinction between nondominated solutions and dominated solutions. However, the nondominated solutions are few at the beginning of evolution or at some generation, thereby, the dominated ones could not be ignored under this condition. To the end, an adaptive mechanism in partition is necessary to the optimization process.

The Procedure of the SAR Image Segmentation Algorithm

We want to present an efficient and effective two-objective automatic SAR image segmentation framework. The basic procedure of the SAR image segmentation framework is illustrated in Fig. 1. Clearly, it can be divided into two stages. The first stage is the preprocessing operations, including speckle noise removing by nonlocal mean filter and watershed transformation (WT) is employed to partition SAR image into disjoint small local patches or "super-pixels". The second stage consists of an efficient multi-objective

clustering algorithm in MO and kernel induced mappings, which can implement the fine segmentation on the produced denoising images in the first stage.

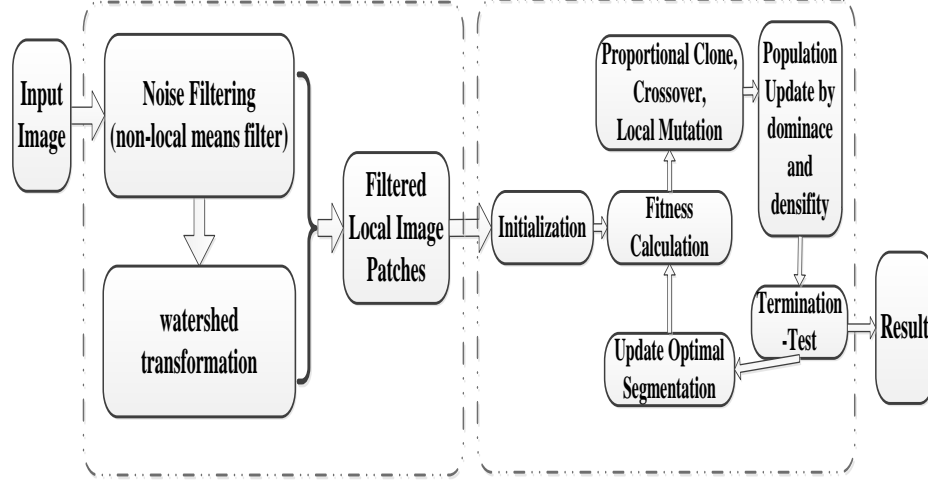


Fig. 1 the procedure of the SAR image segmentation algorithm.

Nonlocal means filter. The redundancy information in images is adequately exploited by nonlocal means filter, which means that every small patch in an image have many similar patches in the same image. As a result, the speckle randomly distributed in the image can be suppressed by these similar local patches. If \mathbf{I} is an image with noises, $x(i)$ is the observed image and $u(i)$ is the noise removed image by nonlocal means filter, the denoising operator can be defined as the weighted average of the pixels in the original image.

$$NL(i) = \sum_{j \in I} w(i, j) x(j) \quad (1)$$

$$w(i, j) = \frac{1}{\mathbb{N}(i)} e^{-\frac{\|v(NB_i) - v(NB_j)\|_{2,a}^2}{h^2}}, \mathbb{N}(i) = \sum_j e^{-\frac{\|v(NB_i) - v(NB_j)\|_{2,a}^2}{h^2}} \quad (2)$$

The weights in equation (1) measure the similarity of pixel i and their neighborhoods NB_i . $v(NB_i)$ is the vector of neighboring pixel around i . a is the standard deviation of the Gaussian kernel, and h controls the decay of the exponential function.

Two kernel clustering indexes. The searching process of current clustering algorithms using fuzzy set theory is usually guided by certain clustering validity index. Nevertheless, since we have no prior information of the optimal partitions, the multiple directions or indices can supply different searching paths and more solutions with different characteristics can be obtained. Here, more than one

objective functions are used to guide the segmenting process. The definition of two-objective clustering could be formulated as follows.

$$XB^{kernel} = \frac{\sum_{k=1}^K \sum_{i,j=1}^n u_{kj}^2 (1 - \aleph(x_j, z_k))}{n \min_{i,j} (1 - \aleph(z_i, z_j))}, \text{ and } J_m^{kernel} = \sum_{j=1}^n \sum_{k=1}^K u_{pj}^2 (1 - \aleph(x_j, z_k)) \quad (3)$$

u_{kj} is the element of fuzzy partition matrix U and z_k, z_i are the cluster centers of current partitions, which can be defined by following two equations. In kernel distance measure between two pixel x_i and x_j , it can be calculated through the widely used Gaussian kernel function is defined by the followings, where σ is the bandwidth

$$u_{k,i} = \frac{1}{\sum_{j=1}^K \left(\frac{1 - \aleph(z_k, x_i)}{1 - \aleph(z_k, x_j)} \right)^{2/(m-1)}}, \text{ and } z_k = \frac{\sum_{i=1}^n (u_{k,i})^m x_i}{\sum_{i=1}^n (u_{k,i})^m}, 1 \leq k \leq K \quad (4)$$

$$\aleph(x_i, x_j) = \exp\left(-\|x_i - x_j\|^2 / (2\sigma^2)\right) \quad (5)$$

Cooperative strategies by Pareto dominance and local density. How to use the domain the local information of image pixels to guide the partition process of image segmentation is still worthy of further study. Here, we employ Pareto dominance to divide the current population into to sub-population, called non-dominated solutions and dominated solutions. These two populations are designed to exchange their information by each solution's local density. If the nondominated solutions are few, thus, premature convergence could occur easily if much computational budget is assigned to them. Therefore, both the dominated solutions, locating at the sparse area, are required to contribute their information for global search. If the number of nondominated solutions becomes large in population, these solutions could hold the diversity of the population; therefore, it is almost redundant to assign different ranks to individuals in the population. The solutions with larger value of crowding distance could get more computational budget to be reproduced. The local density is measured by the k-nearest neighbor product in the literature [6].

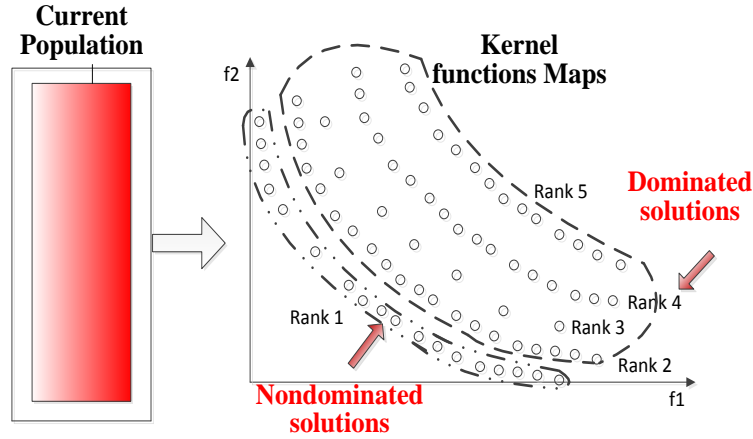
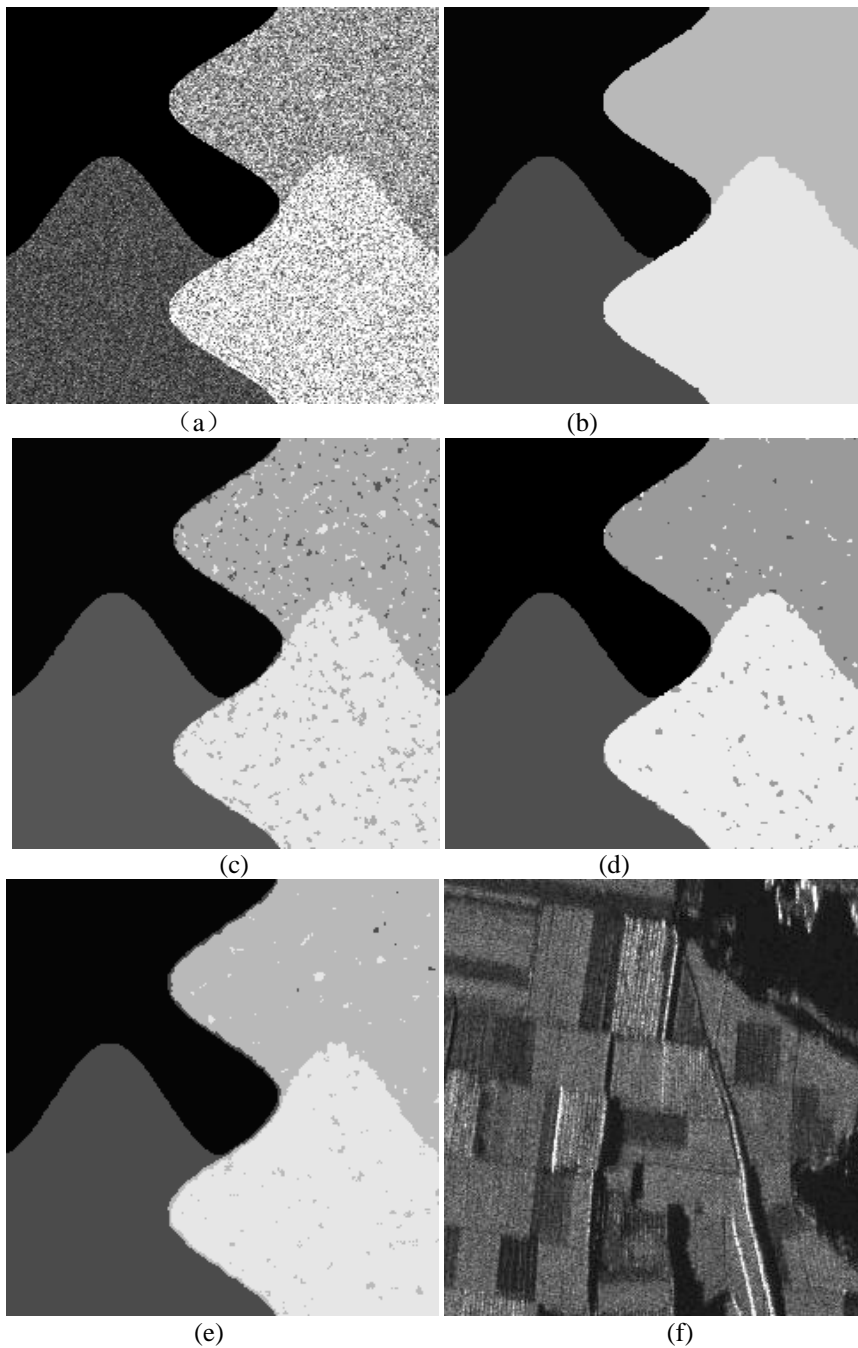


Fig. 2 the cooperative strategy by Pareto dominance and local density.

The experiments study

The SAR image with multiplicative noise is used for comparison. Besides, two famous variations of FCM: FLICM [1] and KWFLICM [4], and one graph partitioning methods: spectral clustering ensemble (SCE) [2], are used here. The involved parameters are here: iteration number is 100, the scale of population is 20, cloning proportion is 5, cross probability is 1, and mutation probability is 0.3. The iterations of two variations of FCM is 200, and stopping threshold is 10^{-4} .

The segmentation results of the four algorithms on the two images are shown in Fig. 3. We can see that our algorithm obtained the satisfying segmenting results among the four algorithms. There are many misclassified spots in the segmentation results of FLICM and KWFLICM. The reason may be that the filters used in these two algorithms are not suitable for the speckle in SAR image. Besides, The real SAR image consists of four typical ground objects: three types of crops and several regions of water. Visually, the difficulty of the classification task lies in how to distinguish the light gray crops, dark gray crops, and black water clearly and accurately. We can see that black water and dark gray crops are mixed together by FLICM and SEC.



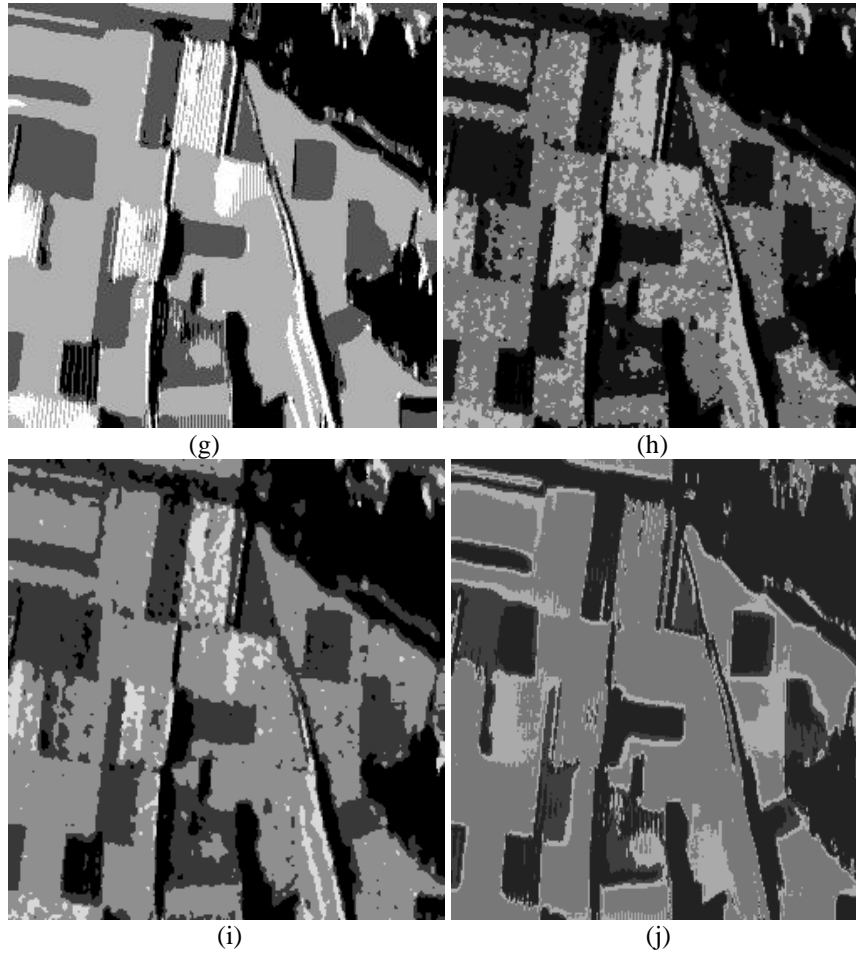


Fig. 3 The segmentation results of the synthesized image with four categories (512x512 in Fig3.(a)) and the real SAR image with four categories (256x256 in Fig3.(f)). (b)-(e) Segmentation results of the synthesized image by our algorithm, FLICM, KWFLICM, and SCE respectively; (g)-(j) Segmentation results of the real SAR image by our algorithm, FLICM, KWFLICM, and SCE respectively.

Besides, in order to implement a fair comparison of the running time, the source codes of the four algorithms were implemented in Matlab 2014 on an HP Workstation xw9300 (2.19 GHZ, 16 GB RAM; Hewlett-Packard, Palo Alto, CA). Their average segmentation results are 99.77 (0.01) for our algorithm, 79.12 for

FLICM, 123.12 for KWFLICM, and 144.33 for SCE. Over-considering the experimental results in Fig3, the proposed algorithm seems to give relatively better results in region consistence and boundary discrimination.

Conclusions

Here, we have presented a novel SAR image segmentation algorithm, including nonlocal mean filter, cooperation evolution and kernel clustering functions.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (Grant No. 61403304), the Project of Department of Education Science Research of Shaanxi Province, China (Grant No.14JK1511) and the Project of Science Research Plan in Xi'an of China (No.CXY1439 (5)).

References

- [1] S. Krinidis, and V. Chatzis: *IEEE Trans. on Image Processing*, vol. 19, no. 5, pp. 1328-1337, 2010.
- [2] X.R Zhang, L.C. Jiao, F. Liu, and M.G Gong: *IEEE Trans. on Geoscience and Remote Sensing*, vol. 46, no. 7, pp. 2126–2136, 2008.
- [3] C. Lemarechal, R. Fjortoft, P. Marthon, E. Cubero-Castan, A. Lopes, in: *Proceeding of the SPIE*, vol. 3497, 1998, pp. 111–121.
- [4] M. G. Gong, Y. Liang, J. Shi, W.P Ma, and J.J. Ma: *IEEE Trans. on Image Processing*, vol. 22, no. 2, pp. 573-584, 2013.
- [5] D. D. Yang, L.C. Jiao, R.C. Niu, and M.G. Gong: *Computational Intelligence*, vol. 30, no. 1, pp. 115-144, 2014.
- [6] X.D.Li, X. Yao: : *IEEE Trans. on Evolutionary Computation*, vol. 16, no. 2, pp. 210-224, 2012.