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A Multiobjective Optimization Method Based on MOEA/D and Fuzzy Clustering for Change Detection in SAR Images

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***Abstract*—For the presence of speckle noise in SAR images, many change detection methods have been developed to suppress the effect of noise. However, all these methods will result in the loss of image details, and the trade-off between detail preserving and noise removing capability has become an urgent problem remaining to be settled. In this paper, we put forward an innovation for change detection in synthetic aperture radar images. It integrates evolutionary computation into fuzzy clustering process, and considers detail preserving capability and noise removing capability as two separate objectives for multiobjective optimization, and thus transforming the change detection problem into a multiobjective optimization problem (MOP). Experiments conducted on real SAR images confirm that the new approach is efficient.**

Keywords—Change detection；fuzzy clusterin；multiobjective optimization problem (MOP)； Pareto optimal solution；

I. INTRODUCTION

In recent years, synthetic aperture radar technology has been developed rapidly, the spaceborne synthetic aperture radar systems have observed the surface of the earth for years, and have acquired a plenty of multi-temporal ground observation data. Many remote sensing studies have attempted to develop the techniques which can make good use of the information obtained by the synthetic aperture radar systems, including target extraction, object classification, edge detection, interferometry, change detection, etc. In particular, among these studies, the research on change detection technology is the most extensive one.

Image change detection [1], [2] is based on the comparative analysis of two images acquired from the same area at different times, with the purpose of detecting the change region between them. It has been widely used in various fields, such as medical diagnosis [3], [4], remote sensing [5]-[13], and video surveillance [14], [15]. For synthetic aperture radar (SAR) has the characteristics of high resolution, all-weather and all-time, it is a good change detection information source, so the SAR image change detection techniques have a very comprehensive application prospect. In the past decades, SAR image change detection has found a wide range of applications, such as environmental monitoring, crop survey, urban studies, forest monitoring and other fields. Basically, SAR image change detection methods can be divided into two types: image threshold methods and image classification methods. When people identify changed and unchanged areas by virtue of the comparative analysis of two SAR images, the change detection problems usually can be converted to binary classification problems. That is to say, once the difference image of the two images remaining to be detected is obtained, the following step of change detection in SAR images can be considered as a process of image clustering.

However, change detection in synthetic aperture radar (SAR) images encounters more difficulties than optical ones for the presence of coherent speckle noise in SAR images. Most of traditional change detection methods are exquisitely sensitive to the noise, as a consequence, they result in a low detection accuracy. For instance, the widely used fuzzy c-means (FCM) clustering approach, it can preserve the image details information well, but has no robustness to coherent speckle noise since it does not take any spatial information into account.

With the purpose of ameliorating the sensibility of FCM to speckle noise, some other algorithms that think about spatial context information have been proposed. Ahmed, Yamany and Mohamed [16] proposed the FCM_S with modifying the objective function of FCM by introducing an additional term including the local spatial domain information of each pixel. And then Szilagyi, Benyo, Szilagyii and Adam [17] put forward an enhanced fuzzy C-means (EnFCM) algorithm while Cai, Chen and Zhang [18] proposed the fast generalized fuzzy C-means algorithm (FGFCM).

All the three algorithms above have taken the spatial context information into consideration and suppress the effect of speckle noise to a certain degree. However, all these methods have the same shortcoming that they all require an artificial selection of a crucial parameter which indicates a trade-off between the capabilities of detail preserving and noise removing. It is considerably difficult without a priori knowledge about the existing noise in images.

For the sake of improving the methods above, Krindis and Chatzis [19] put forward a robust fuzzy local information C-means clustering algorithm (FLICM) for image clustering.

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It introduces a fuzzy factor into the objective function of the FCM, and the fuzzy factor is free of using any parameter to balance the detail preserving capability and the noise removing capability. Although the FLICM performed a good effect, it has been demonstrated by László Szilágyi in [20] that the iterative algorithm proposed for the minimization of the FLICM objective function is not suitable for the given problem and it does not minimize the objective function.

In order to avoid all the above mentioned problems, this paper applies a completely novel approach to the change detection in SAR images. That is a multiobjective optimization method based on MOEA/D [21] and fuzzy clustering for change detection. It integrates evolutionary computation into the clustering process, and considers detail preserving capability and noise removing capability as two separate objectives for multiobjective optimization, and thus transforming the change detection problem into a multiobjective optimization problem (MOP). While other traditional methods can get only a compromise solution, the proposed approach obtains a set of Pareto optimal solutions, and users can choose a more suitable solution from the set according to their different requirements for detail preserving capability and noise removing capability under different circumstances.

The remaining part of this paper is organized as follows. Section II presents the proposed multiobjective optimization method based on MOEA/D and fuzzy clustering for change detection in SAR images. The datasets used in the experiments and experimental results are described in Section III. Finally, a conclusion is summarized in Section IV.

II. PROPOSED METHOD

A. Generation of Difference Images

Here, we let I_1 and I_2 are separately two original images acquired by a synthetic aperture radar over the same geographical area but at two different times t_1 and t_2. And they have the same size of $A \times B$. Then, we apply the frequently-used log-ratio operator to the two original images to create a difference image I_l which preserves the image details well. It can be obtained as follows:

$$I_l = \left|\log(\frac{I_2}{I_1})\right| = \left|\log I_2 - \log I_1\right| \tag{1}$$

where log represents the natural logarithm operator.

Further on, a filtering processing is required to apply to the difference image I_l in order to remove noise, and then we get a filtered image which has been removed most of the image noise. In our method, we employ the neighbour average filtering to implement this procedure and obtain the image I_n as follows:

$$\overline{x_i} = \frac{1}{S}\sum_{i \in N_r} x_i \tag{2}$$

where $\overline{x_i}$ and x_i are the gray values of the i^{th} pixel of image I_n and I_l, respectively, N_r represents a set of neighbors falling into a window of fixed size around x_i, S stands for the total number of set N_r. Actually, the neighbour average filtering can be substituted by an arbitrary filter with good effects at this step.

B. Two Objective Functions Selected for Multiobjective Optimization

As is described in Section I, in the proposed method, we consider detail preserving capability and noise removing capability as two separate objectives for multiobjective optimization, and thus transforming a change detection problem into a multiobjective optimization problem (MOP).

Firstly, from the perspective of image detail preserving, FCM clustering is applied directly to the difference image I_l generated from two original images, and then we consider the cost function of the fuzzy C-means as our first objective function f_1 for the MOP since the image I_l contains all the image details. According to the FCM clustering, the function is defined as:

$$f_1(v_1, v_2) = \sum_{i=1}^{N}\sum_{k=1}^{c} u_{ki}^m \left\|x_i - v_k\right\|^2 \tag{3}$$

where N is the total number of pixels, c stands for the number of clusters, m is a fuzzy exponent and usually selected as 2, u_{ki} is the fuzzy membership degree of the i^{th} pixel with respect to cluster k with $0 \le u_{ki} \le 1$ and $\sum_{k=1}^{c} u_{ki} = 1, \forall i = 1,2,...,N$, and v_k is the average gray value of the center of cluster k. For our change detection problem, we divide the image into unchanged and changed classes, so c is equal to 2. Moreover, the clustering center v_k is obtained by initializing randomly and the fuzzy membership degree u_{ki} is calculated as follows:

$$u_{ki} = \frac{1}{\sum_{j=1}^{c}(\left\|x_i - v_k\right\| / \left\|x_i - v_j\right\|)^2} \tag{4}$$

On the other hand, from the perspective of noise removing, the same cluster analysis is exerted on the filtered image I_n with most of the image noise removed, and the corresponding cost function is selected as the other objective function f_2 for the MOP. It is defined as:

$$f_2(v_1, v_2) = \sum_{i=1}^{N}\sum_{k=1}^{c} u_{ki}^m \left\|\overline{x_i} - v_k\right\|^2 \tag{5}$$

where the symbols represent the same meaning as those in (3) other than $\overline{x_i}$ which has been declared in the previous part A. At this moment, the two objective functions can be combined into a multiobjective optimization problem. It has the following form:

$$\begin{cases} \min F(v_1, v_2) = (f_1, f_2)^T \\ \text{s.t. } (v_1, v_2)^T \in \Omega \end{cases} \tag{6}$$

where $(v_1, v_2)^T$ is a decision vector consisting of the two cluster centers v_1 and v_2, Ω is the decision space of the MOP. As we all know, the fundamental principle of FCM clustering is to acquire a good classification result by minimizing its cost function. Hence, the MOP will be solved as a minimization problem. From all the above, it is reasonable to conclude that a smaller f_1 indicates a better detail preserving capability while a smaller f_2 means a better noise removing capability.

III. EXPERIMENTAL STUDY

In order to illustrate the effectiveness of our proposed method, in this section, we will perform the proposed approach on three datasets of real world images with different characteristics in the experiments.

Based on our previous work in [22], we select the Bern, Ottawa and Yellow River Estuary datasets as our change detection images. It's worth noting that, the Yellow River dataset is different from the Bern and Ottawa datasets, for it is very large. Therefore, we cut out a representative part in the experiments. The images remaining to be detected and ground truth of the Bern dataset are shown in Fig. 1, and the two images and corresponding available ground truth of the Ottawa dataset are shown in Fig. 2. Then, the two images cut from the Yellow River dataset and its ground truth image are presented in Fig. 3.

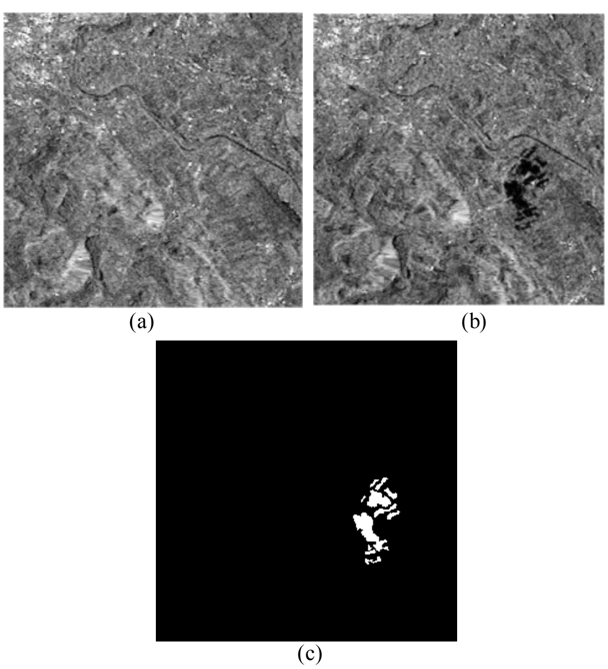

Fig. 1. Images for Bern dataset: (a) Image acquired before flooding in April 1999. (b) Image acquired after flooding in May 1999. (c) Image of the ground truth.

Generally speaking, there are two manners to account for the effects of SAR image change detection problems. One is in a very visual way, that is, to show the final change detection binary maps, and one other way is to calculate the values of some common indexes for evaluation. In our experiments, percentage of correct classification (Pcc) and Kappa coefficient are considered as the primary evaluation indexes. The Kappa coefficient is a measurement of consistency and accuracy on the basis of error matrix, and its value falls usually into the interval $[0,1]$, it is equal to 1 when the final binary map is coincided completely with the image of ground truth.

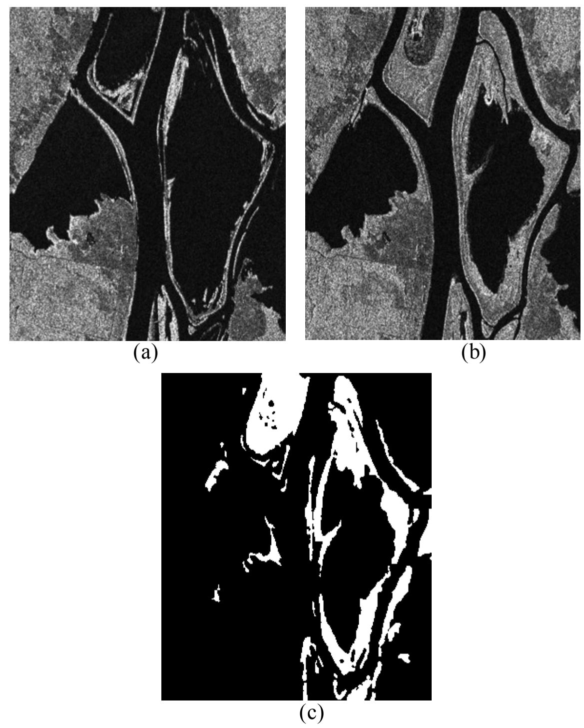

Fig. 2. Images for Ottawa dataset: (a) Image acquired before flooding in July 1997. (b) Image acquired after flooding in August 1997. (c) Image of the ground truth.

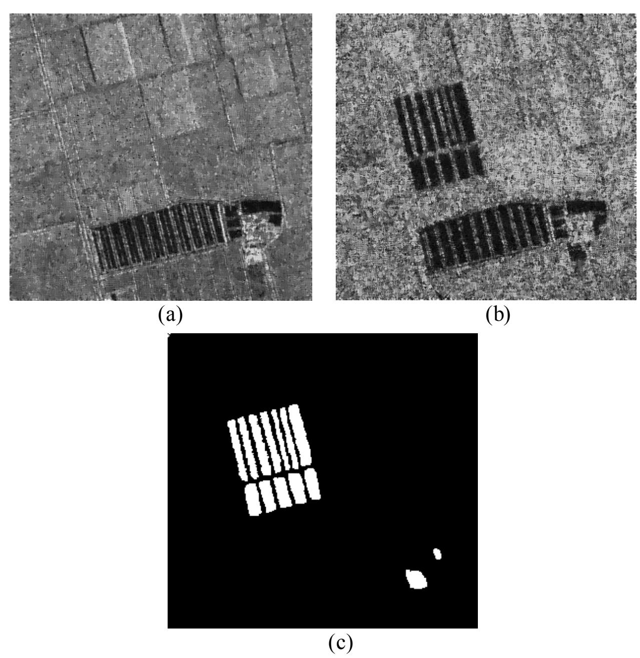

Fig. 3. Images for Yellow River dataset: (a) Image acquired in June 2008. (b) Image acquired in June 2009. (c) Image of the ground truth.

For the three datasets, we select a 3×3 window to implement the neighbour average filtering and get the filtered difference images. Meanwhile, the number of subproblems decomposed by MOEA/D is set to 100.

After applying our approach to the Bern dataset, we get a uniformly-distributed Pareto front including one hundred Pareto optimal solutions with different effects of detail preserving and noise removing. The Pareto front for Bern dataset is shown in Fig. 4, and six different change detection maps selected randomly from all the results are present in Fig. 5.

By comparing the six images in Fig. 5, we can find a fact that Fig. 5 (a) and (b) contain less speckle noise than the other four but fail to detect some crucial changed regions since the loss of image details. However, on the contrary, Fig. 5 (e) and (f) have detected more changed regions but include more noise. And the Fig. 5 (c) and (d) indicate that the effects of detail preserving and noise removing fall in between the two cases above. All these phenomena show that all the solutions have different detail preserving and noise removing capabilities.

Similarly, we employ our approach to deal with the Ottawa dataset and reach its evenly-distributed Pareto front which is present in Fig. 6. The set of Pareto front is also composed of one hundred Pareto optimal solutions with different effects of detail preserving and noise removing. Six different change detection maps selected randomly from the set are shown in Fig. 7. It is obvious that there are less speckle noise than the other four in Fig. 7 (a) and (b), but some real changed regions are not detected. On the other hand, more changed regions are detected successfully while more noises are left in Fig. 7 (e) and (f), which manifests a weaker noise removing capability but a better detail preserving capability in this case. The effects in Fig. 7 (c) and (d) have indicate different capabilities of detail preserving and noise removing which fall in between the two cases above.

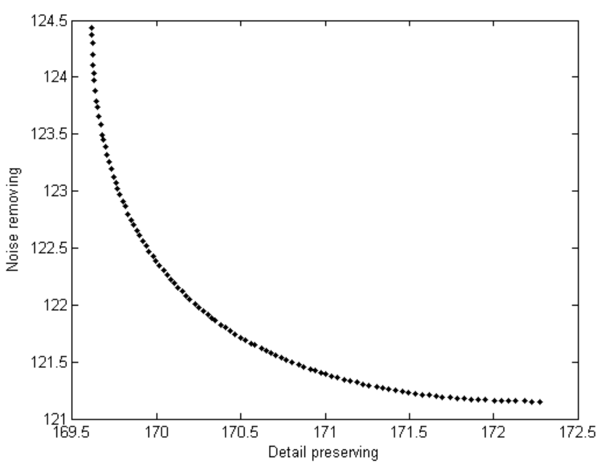

Fig. 4. Pareto front for Bern dataset

Finally, we conduct an experiment on the Yellow River dataset by using our approach. As a consequence, a evenly-distributed Pareto front is obtained and it is shown in Fig. 8. In the same way, the set of Pareto front is also composed of one hundred Pareto optimal solutions with different effects of detail preserving and noise removing.

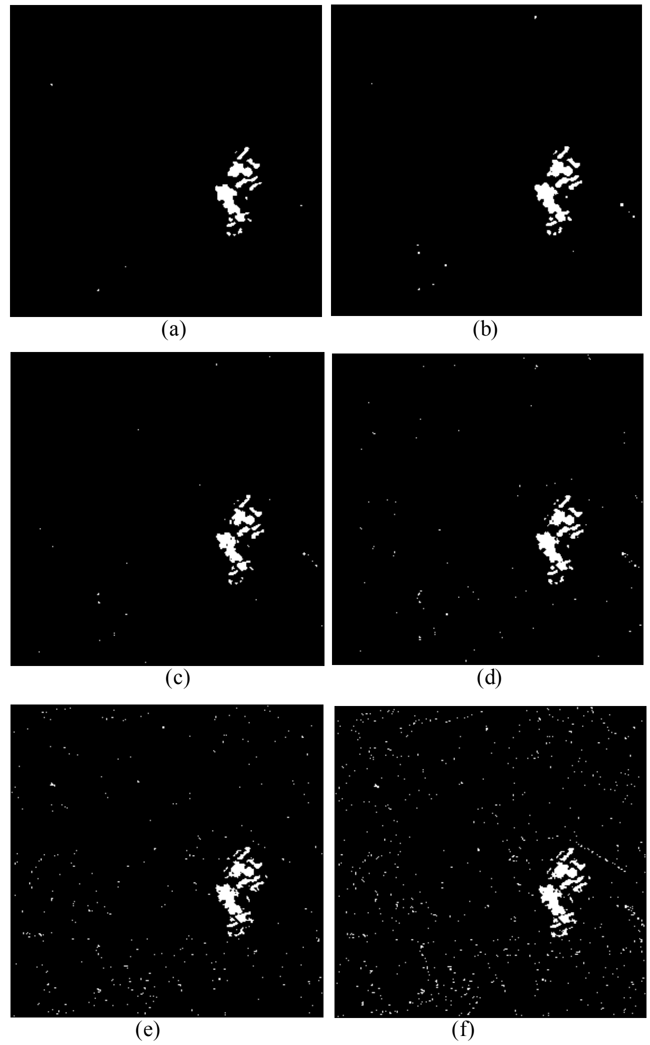

Fig. 5. Six different change detection maps selected randomly from all the results of the Bern dataset.

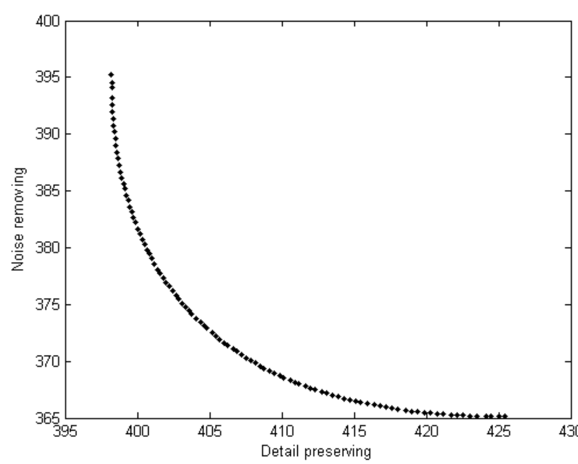

Fig. 6. Pareto front for Ottawa dataset.

Six different change detection maps selected randomly from the set are shown in Fig. 9. And from Fig. 9, we can draw a conclusion that the six images also have different detail preserving and noise removing capabilities.

In order to demonstrate the availability of the proposed approach in depth, after running the program many times, we calculate the average ranges of the values of Pcc and Kappa corresponding to all the Pareto optimal solutions acquired, and the results are recorded in Table I.

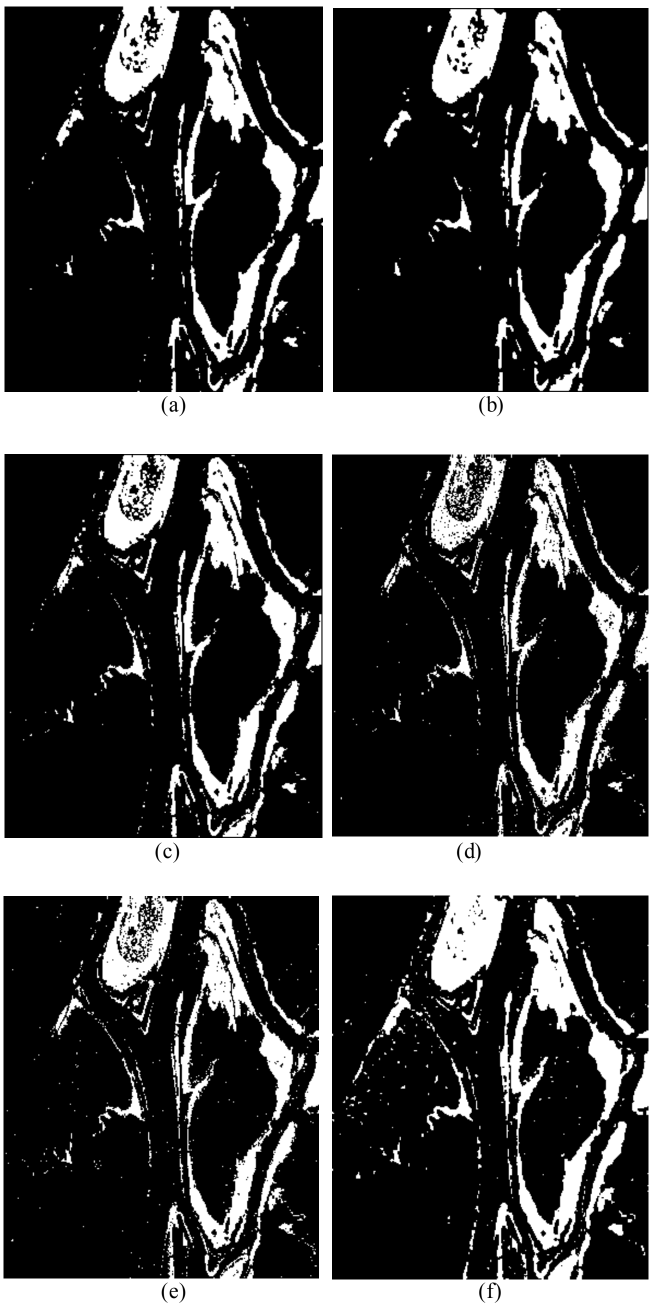

Fig. 7. Six different change detection maps selected randomly from all the results of the Ottawa dataset.

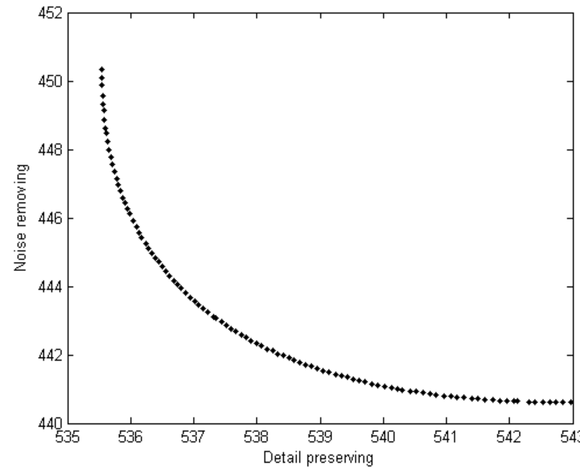

Fig. 8. Pareto front for Yellow River dataset.

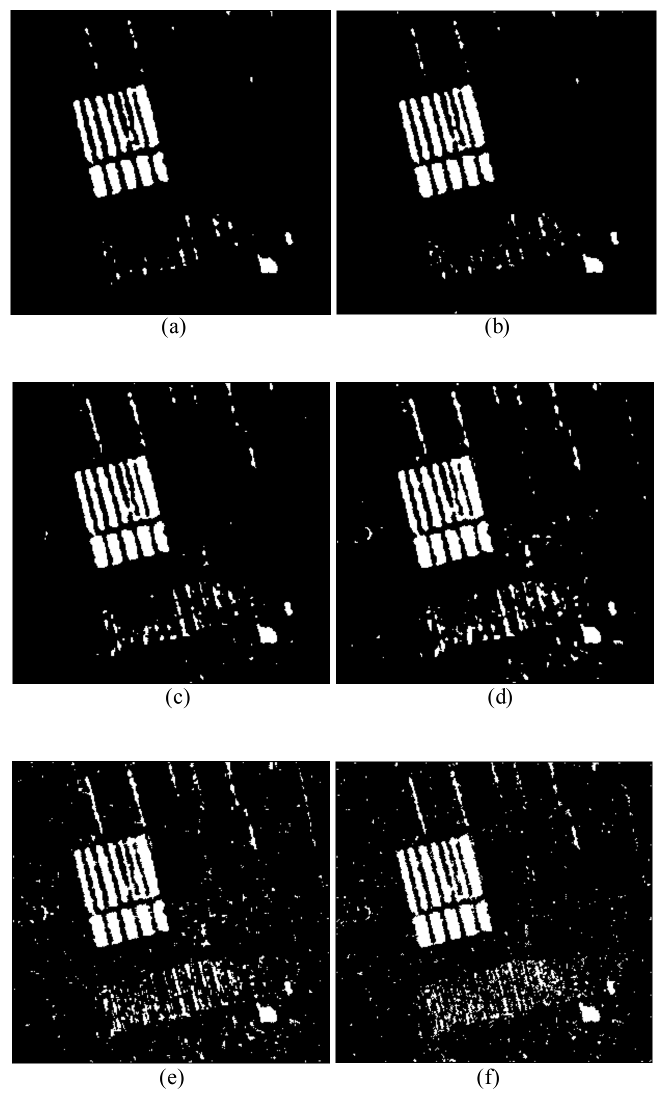

Fig. 9. Six different change detection maps selected randomly from all the results of the Yellow River dataset.

TABLE I
THE RESULTS OF THE PROPOSED METHODS ON THE THREE DATASETS

	Kappa	***Pcc***
Bern dataset	0.7257-0.8436	99.20%-99.57%
Ottawa dataset	0.8861-0.9073	96.94%-97.68%
Yellow River dataset	0.6728-0.7968	95.58%-97.66%

To sum up, from Fig. 5, 7, and 9, it is apparent that our approach has better visual effects on Bern, Ottawa and Yellow River datasets. One hundred effective solutions with different effects of detail preserving and noise removing for each dataset in our experiments are obtained, so that they can be selected by users according to different requirements.

In the meantime, the average values of Pcc and Kappa listed in Table I are high enough for explaining good classification results acquired by the proposed approach.

IV. CONCLUSION

In this paper, a novel approach for SAR images change detection is put forward. It converts the change detection problem into a multiobjective optimization problem (MOP) by considering the image detail preserving and noise removing as two separate objectives that remain to be optimized. As a consequence, the proposed approach obtains a set of Pareto optimal solutions corresponding to all the decomposed subproblems. Experimental results exhibited that our approach had obtained good visual effects on datasets with distinct features. At the same time, the high average values of the Pcc and Kappa indicated good classification results for change detection in SAR images.

In addition, although the new approach has performed a good effect on change detection problems, it has some little weaknesses to a certain degree. Therefore, we intend to combine the MOEA/D with the update of membership degree matrix in order to improve the effects further in the near future.

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