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Change detection in synthetic aperture radar images based on unsupervised artificial immune systems☆

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ABSTRACT

In this paper, we propose a novel change detection method for synthetic aperture radar images based on unsupervised artificial immune systems. After generating the difference image from the multitemporal images, we take each pixel as an antigen and build an immune model to deal with the antigens. By continuously stimulating the immune model, the antigens are classified into two groups, changed and unchanged. Firstly, the proposed method incorporates the local information in order to restrain the impact of speckle noise. Secondly, the proposed method simulates the immune response process in a fuzzy way to get an accurate result by retaining more image details. We introduce a fuzzy membership of the antigen and then update the antibodies and memory cells according to the membership. Compared with the clustering algorithms we have proposed in our previous works, the new method inherits immunological properties from immune systems and is robust to speckle noise due to the use of local information as well as fuzzy strategy. Experiments on real synthetic aperture radar images show that the proposed method performs well on several kinds of difference images and engenders more robust result than the other compared methods.

1. Introduction

Image change detection, as described in [1] and our previous papers [2,3], is a process in which the changes between two multitemporal images of the same scene are detected. In recent decades, change detection in remote sensing images has become increasingly important with the development of remote sensing technology [4–11,2,3,12]. Among remote sensing images, synthetic aperture radar (SAR) images are not influenced by sunlight, atmosphere or other weather conditions, and therefore change detection in SAR images has attracted many research interests [9,8,11,10,2,3]. But due to the fact that SAR images are affected by the presence of speckle noise, change detection in SAR images is more difficult than that in optical images as we have discussed in [2].

From our previous works in [2,3], the process of unsupervised change detection in SAR images can be divided into three steps: (1) image preprocessing, which mainly includes co-registration, geometric corrections, and noise reduction; (2) the generation of the difference image (DI), a image that shows the difference of each pixel between the multitemporal images; and (3) segmentation of the DI. In the second step, the log-ratio operator [8] and the mean-ratio operator [10] are usually used because of the multiplicative nature of speckle. In [13], we also proposed the neighborhood-based ratio approach to generate the DI. In the third step, the DI is classified into two classes, the changed and unchanged classes, and two common approaches, the threshold and the clustering approaches, are often adopted. In the threshold approach, a model is to be established and the selection of the optimal threshold is based on several methods, such as the Otsu, the Kittler and Illingworth minimum-error thresholding algorithm, and the expectation–maximization (EM) algorithm [14]. The decision of an accurate model to be fit the two classes is difficult. The clustering approach, however, does not involve such a process to build a model, so it is more flexible. In [2], we proposed a reformulated fuzzy local-information C-means (RFLICM) clustering algorithm for the classification of the DI. The algorithm incorporates the information about spatial context when defining the modified objective function. And in [3], we modified the membership upon a more elaborate analysis of the neighborhood information. The Markov random field (MRF) is applied to the modification of the membership. The two approaches are robust to speckle noise because of the use of the spatial context.

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But the above approaches have two disadvantages: (1) The DI is analyzed through the dependence on the objective functions which are difficult to optimize. And the iterations are carried out according to the complicated and fixed equations, so the result may fall into the local optimum value and the methods may not adjust to several kinds of DIs; (2) The clustering centers depend on the clustering information of the preceding iteration, and i.e. historical information of the previous iterations is not fully retained. So we attempt nature inspired algorithms to complete the task of change detection in this paper. In [12], a method based on genetic algorithms (GA) is proposed for change detection in remote sensing images. The method directly optimizes the binary change detection mask by minimizing a cost function. But the local information is not considered in the cost function which leads the method to be not robust to noise when applied to change detection in SAR images. Here we apply the artificial immune systems to our task. Artificial immune systems (AIS) use the nature immunological properties to establish effective systems in various areas of applications [15–18], including data mining [19], optimization [20–23], and machine learning [24–26]. In this paper, we introduce the unsupervised artificial immune systems (UAIS) to the segmentation of the DI of multi-temporal SAR images. The UAIS have the immunological properties such as clonal selection and immune memory. In the process of UAIS, the antibodies and memory cells are updated according to their affinity with the antigens. And the memory mechanism in UAIS leads the good information to be reserved. But to segment the DIs, it is important to consider the influence of noise. Inspired from RFLICM, we incorporate the local information and fuzzy strategy into the UAIS to improve the precision. Consequently, the UAIS-based change detection method is proposed.

The rest of this paper is organized as follows: Section 2 introduces the background of immune systems and general idea of our method. Section 3 describes the proposed approach in details. Section 4 introduces the experimental settings. Section 5 provides experimental results. Section 6 concludes this paper.

2. Background and general idea

Let us consider two co-registered SAR images, $X_1 = \{x_1(i, j), 1 \le i \le H, 1 \le j \le W\}$ and $X_2 = \{x_2(i, j), 1 \le i \le H, 1 \le j \le W\}$, of size $H \times W$, acquired over the same geographical area at two different times t_1 and t_2, respectively. First we generate the difference image $DI = f(X_1, X_2)$, and then the UAIS-based approach is applied to produce a binary image corresponding to the two classes: the changed and unchanged classes.

2.1. Artificial immune systems

As we all know, it is the immune system that protects us from outside infectious agents, such as viruses, bacteria, and other antigens. Human immune system is a complex adaptive system composed of immune organs, immune cells and immune molecules. Antigens are initial factors of immunoreaction though they are not part of immune system. And the clonal selection theory explains the process of the maturation of antibodies after antigens are recognized by the B cells. The B cells with receptors corresponding to antigens are selected to proliferate. With continuous stimulation of antigens, the cells undergo a hypermutation process in their gene, and those with high antibody–antigen affinity are selected to proliferate again. The process is iterated several times until antibodies are mature. During the process, antibodies match antigens better and better. Only the B cells with highest affinity to the corresponding antigens have chance to enter the population of memory cells. And the B cells with low affinity will disappear eventually. The memory cells can stay in the body for a long time, and recognize similar antigens during the next invasion rapidly.

AIS are mainly inspired from the response between antigens and antibodies, and have been applied to various kinds of applications as described in Section 1. For change detection problems, AIS can adapt to the distribution of the DI without any assumptions due to the clonal selection. They can also reserve good results of previous iterations due to the memory mechanism and recognize the antigen rapidly during the next iteration. Because the segmentation of the DI is an unsupervised process, we use the UAIS. In UAIS, we consider each pixel of the DI as an antigen. In each iteration, the antigen is recognized by memory cells, and we select the corresponding antibodies from the population to proliferate. After the process of hypermutation, the proliferated antibodies are selected to update the population of antibodies and memory cells. The relationship between antibody and antigen depends on the antibody–antigen affinity. From the process, we can see that the UAIS have the following advantages: (1) There are not complex and fixed equations, so they are more flexible than traditional algorithms; (2) they are nonlinear models capable of simulating real and complicated relationships; and (3) they can retain more image information by retaining good clustering information and recognizing the antigens. Due to these properties of UAIS, UAIS is applied to classify the DIs in change detection task.

2.2. Using local information and fuzzy strategy to restrict the impact of noise

The DIs still cannot get over the impact of noise though some operations have been taken during the generation of DIs. Inspired from [27,28], we incorporate local information and fuzzy strategy into the UAIS, so as to reduce the impact of noise and preserve image details.

The characteristic of FLICM [27] is the use of a fuzzy local similarity measure, which is proposed to guarantee noise insensitiveness and preserve image details. The objective function of the FLICM is defined in terms of

$$J_m = \sum_{i=1}^{N} \sum_{k=1}^{c} [u_{ki}^m \left\| x_i - \upsilon_k \right\|^2 + G_{ki}] \tag{1}$$

where υ_k represents the prototype value of the kth cluster and u_{ki} represents the fuzzy membership of the ith pixel with respect to cluster k. G_{ki} is the fuzzy factor that is defined mathematically as follows:

$$G_{ki} = \sum_{j \in N_i} \frac{1}{d_{ij} + 1} (1 - u_{kj})^m \left\| x_j - \upsilon_k \right\|^2 \tag{2}$$

where the jth pixel represents the neighboring pixels around the ith pixel and N_i is the neighborhood of central pixel i. d_{ij} is the distance between i and j and m is a parameter defined by users.

It can be seen that FLICM uses the local information and fuzzy strategy due to the fuzzy factor G_{ki}. With the application of G_{ki}, the membership values of no-noisy pixels and noisy pixels falling into the local window are balanced. Thus, FLICM becomes more robust to outliers.

Inspired by FLICM, to reduce the impact of speckle noise, we add a neighborhood restriction at the antibody–antigen affinity as the introduction to local information. And to use the fuzzy strategy, we introduce a fuzzy membership u_k of the antigen instead of its class label.