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Fuzzy clustering algorithms for unsupervised change detection in remote sensing images

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ABSTRACT

In this paper, we propose a context-sensitive technique for unsupervised change detection in multitemporal remote sensing images. The technique is based on fuzzy clustering approach and takes care of spatial correlation between neighboring pixels of the difference image produced by comparing two images acquired on the same geographical area at different times. Since the ranges of pixel values of the difference image belonging to the two clusters (*changed* and *unchanged*) generally have overlap, fuzzy clustering techniques seem to be an appropriate and realistic choice to identify them (as we already know from pattern recognition literatures that fuzzy set can handle this type of situation very well). Two fuzzy clustering algorithms, namely fuzzy *c*-means (FCM) and Gustafson–Kessel clustering (GKC) algorithms have been used for this task in the proposed work. For clustering purpose various image features are extracted using the neighborhood information of pixels. Hybridization of FCM and GKC with two other optimization techniques, genetic algorithm (GA) and simulated annealing (SA), is made to further enhance the performance. To show the effectiveness of the proposed technique, experiments are conducted on two multispectral and multitemporal remote sensing images. A fuzzy cluster validity index (Xie–Beni) is used to quantitatively evaluate the performance. Results are compared with those of existing Markov random field (MRF) and neural network based algorithms and found to be superior. The proposed technique is less time consuming and unlike MRF does not require any a priori knowledge of distributions of changed and unchanged pixels.

1. Introduction

In remote sensing applications, *change detection* is the process aimed at identifying differences in the state of a land cover by analyzing a pair of images acquired on the same geographical area at different times [58,61]. Such a problem plays an important role in different domains like studies on land use/land cover dynamic [10], monitoring shifting cultivations [6], burned area identification [4], analysis of deforestation processes [24,30], assessment of vegetation changes [8], monitoring of urban growth [47] and oceanography [43]. Since all these applications usually require an analysis of large areas, development of completely automatic and unsupervised change detection techniques is of high relevance to reduce the time required by manual image analysis.

Change detection in remotely sensed data may be done either in supervised or in unsupervised manner [1,3,5,7,8,13,17,21,24,32,33,36,46,47]. In supervised techniques, a set of *training patterns* is required for learning the

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classifier. In real-life, it is difficult to have data containing spectral signatures of changes from which *training patterns* can be generated. In unsupervised techniques, there is no need of *training data*. Thus the usefulness of unsupervised techniques is more than supervised ones for this problem. We may think of unsupervised change detection problem as a clustering one where the task is to discriminate the data into two groups *changed* and *unchanged*.

When an user has two multitemporal images in hand to detect *changes* between them, it may happen that the images are not consistent or comparable because of misregistration [11,65] (*i.e.* the two images may not be coregistered [7]) and radiometric and geometric errors [66]. Moreover, some noise may be present. Hence before analyzing the images for detecting changes, a certain degree of (pre) processing is needed [7]. Thus, in literature [58,61], three steps are suggested to be performed sequentially for unsupervised *change detection*. They are (i) pre-processing, (ii) image comparison and (iii) image analysis. In step (i), operations like coregistration, radiometric and geometric corrections and noise reduction are done to make the two multitemporal images compatible. To remove the effects of sensor errors and environmental factors, radiometric corrections are needed [7,66].

In step (ii), the two pre-processed images are taken as input and compared pixel by pixel and thereafter another image is generated, called the difference image (DI). To generate the DI, we may consider: (a) only one spectral band (*i.e.*, Univariate Image Differencing - UID) [61], (b) multiple spectral bands (*i.e.* Change Vector Analysis - CVA) [5,61], (c) vegetation indices (Vegetation Index Differencing - VID) [61,64] etc. Tasseled Cap Transformation [18] is also a popular method. The most popular of these is the CVA and used in our study. We have chosen CVA because by using this technique reflectance properties of various land cover types can be combined.

After performing the above two steps (pre-processing and image comparison and thereby generating the DI) *change detection* is done on the DI. Either context-insensitive or context-sensitive procedure is adopted [21] for this. Histogram thresholding [5,46] is of the first kind. The threshold value may be detected by manual trial-and-error (MTET) process or by automatic techniques by analyzing the statistical distribution of the DI. In these cases spatial correlation between the neighboring pixels is not taken into account. Most of the context-sensitive techniques [1,3,5,36] are based on MRF, require the selection or estimation of a model for the statistical distributions of *changed* and *unchanged* classes, and can overcome the drawbacks of context-insensitive approaches mentioned earlier. Algorithms (like Expectation–Maximization (EM) [14]) are required for estimating the class distributions assuming different standard distributions e.g., Gaussian [5], generalized Gaussian [1] and mixture of Gaussians [3]. A few context-sensitive techniques using neural networks are also suggested recently [21,22,24,54].

To the best of the authors' knowledge, the use of fuzzy clustering for change detection in remotely sensed images has not been reported in the literature. So, in order to overcome the limitations imposed by the need of selecting or estimating a statistical model for *changed* and *unchanged* class distributions, we propose unsupervised, distribution free and context-sensitive change detection techniques based on fuzzy clustering [2] approach. Our attempt here is to recover the *changed* and *unchanged* regions of the DI by constructing two clusters. Normally the pixels of the DI belonging to two clusters *changed* and *unchanged* are not separable by sharp boundaries (as they are highly overlapped). As fuzzy clustering technique is more appropriate and realistic to separate overlapping clusters [66], we have chosen fuzzy clustering techniques to have a better judgement of the two groups. From our results it is also noticed that fuzzy clustering is a better choice than crisp clustering (as the crisp version yields worse results). In this regard we have used two fuzzy clustering algorithms namely fuzzy *c*-means [2] and Gustafson Kessel [26]. There are several fuzzy cluster validity indices available in the literature to evaluate fuzzy clustering results. We have used one of the popular measures proposed by Xie and Beni [69] which considers both intra cluster compactness and inter cluster separation. We have used Mahalanobis norm while evaluating the outcome of GK type clustering as in [39].

As clustering processes are sensitive to their initializations and thus have a tendency to get stuck to local optima, we have combined them with two well known other optimization techniques namely genetic algorithms (GAs) [23] and simulated annealing (SA) [67] with a hope to have improved performance.

In this work we emphasis on the physical interpretation of the utility of these two fuzzy clustering algorithms for change detection without going into deep mathematical details. We have stated some elementary formulae in Section 2.2 to describe the fuzzy clusterings without deviating from this very goal. We also tried to analyze how and to what extent efficiencies of the used techniques could be enhanced by adjusting the parameters of the fuzzy algorithms or by hybridizing them with other optimization techniques. Our main concern here is to deal with an environment having overlapping irregular shaped and unstructured clusters.

To assess the proposed technique, experiments are carried out on two real world data sets and compared the results with those obtained by already published techniques [5,21] for solving the same problem of change detection on the same data sets. The proposed technique is found to be superior with respect to both error and time requirement.

This paper is organized as follows: Section 2 provides a brief description of a few crisp and fuzzy clustering algorithms. Section 3 is about genetic algorithms and simulated annealing as a search procedure. Section 4 is about validity measures for fuzzy clustering. Section 5 describes the proposed *change detection* technique. The data sets used in the experiments and the results obtained are described in Sections 6 and 7, respectively. Finally, in Section 8, conclusions are drawn.

2. Clustering

Cluster analysis [31,34] partitions a data set into a reasonable number of disjoint groups, where each group contains similar patterns. The partitions should be such that patterns are "homogeneous" within the clusters and "heterogeneous"