CHANGE RECOGNITION FOR MULTISPECTRAL REMOTE SENSING IMAGES
BY USING MR METHOD

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ABSTRACT: In this paper we propose to solve the change detection problem in multi temporal remote-sensing images using interactive segmentation methods in Graphical User Interface. The user needs to input markers related to no-change and change classes in the difference image. Then, the pixels under these markers are used by the support vector machine classifier to generate a spectral change map. To enhance further the result, we include the spatial contextual information in the decision process using two different solutions based on (MR method) Markov random field and level set methods. While the first one is a region-driven method, the second one exploits both region and contour for performing the segmentation task. Experiments conducted on a set of four real remote-sensing images acquired by low as well as very high spatial resolution sensors and referring to different kinds of changes confirm the attractive capabilities of the proposed methods in generating accurate CD maps with simple and minimal interaction.

I. INTRODUCTION:
Timely and accurate Change detection of earth features is very important for understanding interaction between human and natural phenomena. Detecting regions of change in images of same scene taken at different times is of widespread interest due to a large number of applications, like land use change analysis, study on shifting cultivation, monitoring of pollution, assessment of burned areas, monitoring of shifting cultivations, burned area identification, analysis of deforestation processes, assessment of vegetation changes, monitoring of urban growth and oceanography. The existing methods for change detection in remotely sensed data can be classified in supervised or in unsupervised manner in the literature several supervised and unsupervised techniques for detecting changes in remote sensing images have been proposed. The supervised methods require the availability of a ground truth for the setup of the system parameters whereas unsupervised approaches perform change-detection without using any additional ground information.

Compared to unsupervised methods supervised approaches result in higher change detection accuracies are more robust to different atmospheric and light conditions at time of acquisition but still unsupervised techniques are more appealing as the ground truth information is not available in many change-detection applications. Most widely used unsupervised change-detection techniques are based on three-steps which are Pre-processing, image comparison and image analysis. In pre-processing step operations like co-registration, noise reductions, radiometric and geometric Corrections are performed. In second step difference image, is generated. After performing first two steps difference image is analyzed using either simple context insensitive or complex context-sensitive to generate final change detection map. Context insensitive techniques based on
image thresholding do not take into account the correlation between neighbouring pixels in the decision process this drawback is overcome with the help of different context-sensitive change-detection procedures. These approaches based on Markov Random Field (MRF) require the selection of a proper model for the statistical distributions of changed and unchanged pixels. To overcome the need of selecting a statistical model for changed and unchanged class distributions, in this article we propose an unsupervised and context-sensitive change-detection technique based on pulse coupled neural network. The presented technique automatically detects the changes in the difference image using a pulse coupled neural network. A neural network approach has been applied for land cover change detection on multitemporal and multispectral images change detection providing good results. Pulse-Coupled Neural Network is a biologically inspired neural network based on cat’s visual cortical neurons. The key advantage of the PCNN model is that it can operate without training needed. Since introduced by Eckhorn in 1990, the model has proven to be powerful tool in digital image.

II. LITERATURE SURVEY:

Change detection (CD) is one of the most important applications in remote-sensing technology. The aim of CD is to find pixels that correspond to real changes on the ground in pairs of coregistered images acquired over the same geographical area at two different times. Usually, CD methods rely on the computation of the difference image (DI) from two coregistered images, and then, changes are identified by automatically segmenting the DI into two regions associated with changed and unchanged classes, respectively. However, as these methods are data driven, the fully automatic discrimination between changed and unchanged classes is constrained by the complexity of the statistical distributions characterizing these classes, their degree of overlap, and initialization. Recently, the utilization of semiautomatic methods with user’s intervention (i.e., interactive segmentation) has become popular in the literature of image processing. They represent a promising solution for enhancing and generalizing the segmentation result. In other words, the user inputs could be valuable in steering the segmentation process in order to obtain accurate results. Usually, interactive-based segmentation methods start by exploiting the user inputs through a set of strokes, lines, scribbles, or curves for generating labeled pixels for object and background termed as seeds. Then, on the basis of these seeds, the segmentation process is carried out using, for example, adaptive weight distances, spline regression, and maximal-similarity-based region merging. Obviously, the more user interactions we have, the more accurate is the result, but ideally, the level of interaction is usually preferred to be simple and minimal.

In remote sensing, user-based interaction methods have been developed to address supervised classification problems. The basic idea of these semiautomatic methods known as “active learning” is that, starting from a small and suboptimal training set, additional samples, considered important, are selected in some way from a large amount of unlabeled data (learning set). Then, these samples are labeled by the user and then added to the training set. The entire procedure is repeated until a stopping criterion is satisfied. In this letter, we propose to solve the CD problem using the concept of interactive segmentation. In particular, we focus on images characterized by a single change. To this end, the user needs to input markers related to change and no-change classes in the DI. Then, the pixels under these markers are used for training a support vector machine (SVM) classifier in a similar way to supervised remote-sensing image classification. After training, the pixels in the image are initially classified with SVM as change and
no change. It is a well known fact that the analysis of image pixels under spatial independence assumption may lead to inconsistencies due to several reasons, which include, for example, the coregistration noise. The decision for a pixel by taking into account its neighborhood often represents an effective way to increasing the accuracy of the result. In this context, we propose to process further the obtained CD maps using two different strategies based on Markov random field (MRF) and level-set (LS) methods. The former proved to be a powerful and successful mathematical framework as shown by various works dealing with different remote-sensing problems. On the other hand, LS methods recently gained popularity in image segmentation. They exhibit interesting advantages over classical segmentation methods such as thresholding, edge based, and region growing techniques.

III. EXISTING SYSTEM

The user inputs could be valuable in steering the segmentation process in order to obtain accurate results. Usually, interactive-based segmentation methods start by exploiting the user inputs through a set of strokes, lines, scribbles, or curves for generating labeled pixels for object and background termed as seeds. Then, on the basis of these seeds, the segmentation process is carried out using, for example, adaptive weight distances spline regression and maximal-similarity-based region merging. Obviously, the more user interactions we have, the more accurate is the result, but ideally, the level of interaction is usually referred to be simple and minimal. In remote sensing, user-based interaction methods have been developed to address supervised classification problems. The basic idea of these semiautomatic methods known as “active learning” is that, starting from a small and suboptimal training set, additional samples, considered important, are selected in some way from a large amount of unlabeled data (learning set). Then, these samples are labeled by the user and then added to the training set. The entire procedure is repeated until a stopping criterion is satisfied.

Disadvantages

Then, the pixels under these markers are used for training a support vector machine (SVM) classifier in a similar way to supervised remote-sensing image classification.

After training, the pixels in the image are initially classified with SVM as change and no change. It is a well-known fact that the analysis of image pixels under spatial independence assumption may lead to inconsistencies due to several reasons, which include, for example, the co registration noise.

IV. PROPOSED SYSTEM

Depending on the initialization of the LS function, the minimization of the energy functional of the original CV model could be easily trapped into a local minimum. In particular, this risk is increased when the DI is corrupted by noise due to co registration errors. To reduce this effect, an automatic multiresolution approach termed as MLS. Its basic idea is to analyze the DI at different resolutions, namely, from course to fine resolutions by successively down sampling the image with a factor of two. The spatial down sampling of the DI leads to interesting properties as it provides a less noisy image and reduces the search space and the number of local minima. The combination of SVM and MLS consists in setting the initial contour $\phi_0$ as the SVM
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change map then running the MLS algorithm the sake of comparison, we provide also in Table I the results of two state-of-the-art unsupervised CD methods. The first is based on the fusion of an ensemble of different thresholding algorithms through MRF. The second is the standard MLS method developed where the initial curve is set as small rectangles uniformly covering the entire DI, so that the likelihood of capturing the changed regions can be maximized, which may occur at different positions of the image.

Advantages

The help of these markers, the method calculates the similarity of different regions and merges them according to a maximal-similarity rule. In particular, the authors adopted the Bhattacharyya coefficient to measure the similarity between these regions.

The latter is based on an initial partitioning of the image into homogenous regions using the mean-shift algorithm. Then, the user introduces label information via interactive line markers.

The results of a recent interactive segmentation method based on maximal-similarity region merging (MSRM).

Simulation Results:
V. CONCLUSION:

The potential of a context sensitive unsupervised automatic change detection technique has been observed. This letter has presented two interactive segmentation methods for solving the problem of CD in remote-sensing images. The first is based on the combination of SVM and MRF, while the second combines the SVM and LS methods. The experimental results obtained on four different multitemporal remote sensing data sets have shown that the proposed approach has the following characteristics: 1) It is very attractive in generating accurate CD results with minimum interaction, and 2) it is robust against initial markings compared to the interactive MSRM method. The latter fails when confronted with images characterized by changes situated in different regions of the DI. Future development of this approach is to extend it to the multichannel case that may characterize the DI.

VI. REFERENCE


