

A Novel Approach for Change Detection in Multispectral Remotely Sensed Data

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Abstract—In this letter, we propose to solve the change detection (CD) problem in multitemporal remote-sensing images using interactive segmentation methods. The user needs to input markers related to change and no-change classes in the difference image. Then, the pixels under these markers are used by the support vector machine (SVM) 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 Markov random field and level-set methods. This paper presents an interactive algorithm for segmentation of natural images about an area, city, vegetation field etc.,.

Keywords—Change Detection (CD), Support Vector Machine (SVM), Maximum Level Set (MLS), Markov Random Field (MRF).

I. INTRODUCTION

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 [1]–[4]. 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.

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*.

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 co

registration 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.

II. DESCRIPTION OF THE PROPOSED INTERACTIVE CD METHOD

Let X_1 and X_2 be two coregistered multispectral remote sensing images of size $M \times N \times d$ acquired over the same geographical area at two different times. Let XD be the Multispectral DI generated from X_1 and X_2 . The aim of the proposed approach is to generate a CD map representing the changes that occurred between the two acquisition dates of the two images. The following algorithm provides a general view of the proposed method. Detailed descriptions are given in the next subsections.

Algorithm: Interactive CD

Start

Input: X_1 and X_2

Output: CD map Y

- 1) Compute the DI
 - 2) Mark change and no-change regions in the DI
 - 3) Build a training set using the pixels under these Markers
- End

III. CHANGE AND NO-CHANGE REGION MARKINGS

Given the DI, the user needs to specify pixels related to change and no-change classes. To this end, the user can input the interactive information by drawing markers in the form of lines, strokes, or curves on the DI. Fig. 1 shows an example using line markers. After marking, a learning set $D =$

$\{(\mathbf{x}_i, y_i)\}_{i=1}^n$ is generated from the multispectral DI, where n represents the number of samples, \mathbf{x}_i is the feature vector of dimension d , and $y_i \in \{1, -1\}$ is the corresponding pixel label. Change pixels under green marker are assigned label "1," whereas no-change pixels under blue marker are assigned label "-1."

IV. EXAMPLES OF REMOTELY SENSED INPUT IMAGES

The below figures shows a Remotely Sensed Images of same geographical area taken at different intervals of time 2004 and 2010 respectively



Fig. 1. Images taken at 2004 and 2010 respectively.

V. DIFFERENCE IMAGE IN REMOTELY SENSED DATA

In this paper we can say that the Change Detection is obtained using the Difference Image as shown below. First, a couple of co-registered multitemporal remote sensing images acquired at two different dates over the same geographical area are compared. The result of the comparison is an image usually termed "difference image." The user first roughly scribbles different regions of interest, and from them, the whole image is automatically segmented. This

softsegmentation is obtained via fast, linear complexity computation of weighted distances to the user-provided scribbles.

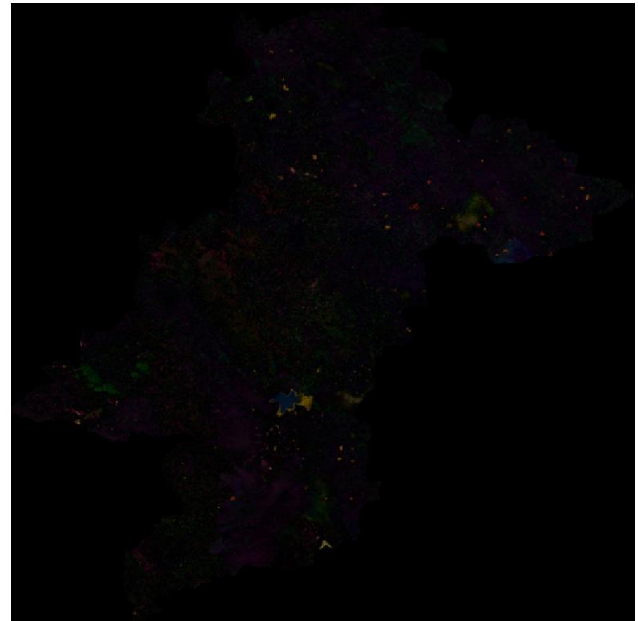


Fig. 2. Difference Image (DI).

VI. INPUT MARKERS ON DIFFERENCE IMAGE

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*. The markings on the Difference Image (DI) as shown below.

Given the DI, the user needs to specify pixels related to change and no-change classes. To this end, the user can input the interactive information by drawing markers in the form of lines, strokes, or curves on the DI. Fig. 1 shows an example using line markers. After marking, a learning set $D = \{(\mathbf{x}_i, y_i)\}_{i=1}^n$ is generated from the multispectral DI, where n represents the number of samples, \mathbf{x}_i is the feature vector of dimension d , and $y_i \in \{1, -1\}$ is the corresponding pixel label. Change pixels under green marker are assigned label "1," whereas no-change pixels under blue marker are assigned label "-1." The learning set $D = \{(\mathbf{x}_i, y_i)\}_{i=1}^n$ is given as input to a binary SVM classifier. The latter is among the most popular supervised kernel-based classifiers available in the literature. Compared to standard classification methods, it relies on the margin maximization principle that makes it less sensitive to over fitting problems.

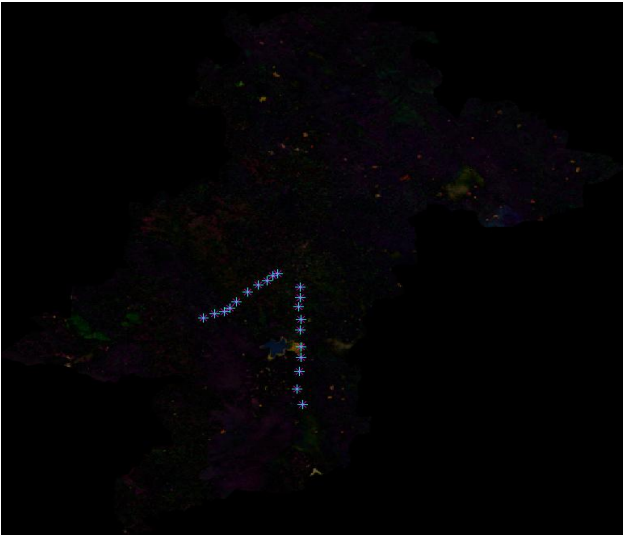


Fig. 3. Input markings on DI.

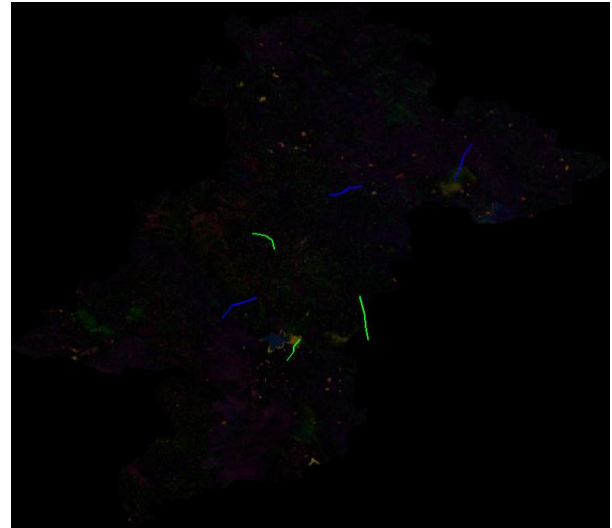


Fig. 5. Multiple change detection

VII. ANALYSIS AND SIMULATION RESULTS

The results reported in this letter are based on a single interaction step at the beginning, where the user selects only two markers. One marker line is used for the change and no change classes, respectively.

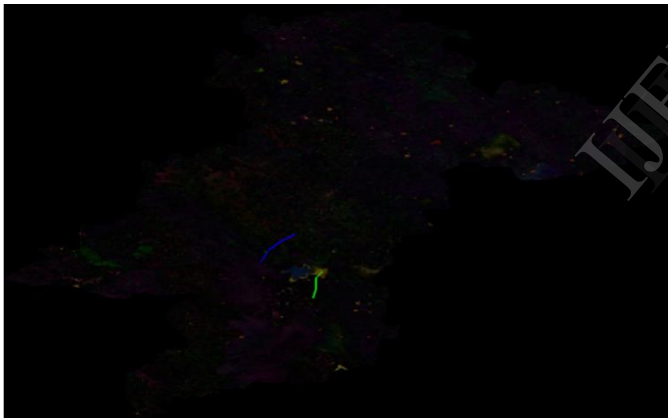


Fig. 4. Single Change Detection

This will allow us to assess the capability of the proposed method in capturing changes situated in different regions of the image with minimal marking. And further step is to find the Error Rate, False Alarm Rate and Missed Alarm Rate Which are having a definition of Error Rate (PE : total number of wrongly classified pixels over the total number of pixels) False-Alarm Rate (PF : number of unchanged pixels classified as changed pixels over the total number of unchanged pixels) and Missed-Alarm Rate (PM : number of changed pixels classified as unchanged pixels over the total number of changed pixels).

The first error measure is typically considered as a global detection performance criterion, whereas the two last measures are more specific criteria whose importance depends on the application. Support Vector Machine-Maximum Level Set (SVM-MLS) is the proposed algorithm. The proposed project is environmental friendly and the proposed algorithm is used to detect the changes that are occurred in the Multispectral Remotely Sensed Data.

VIII. CONCLUSIONS

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 multi temporal 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 MSR method. The latter fails when confronted with images characterized by changes situated in different regions of the DI.

ACKNOWLEDGMENT

The authors would like to say thanks to Professor D Basavalingappa who is a Head Of the Department of ECE, GMT, Davangere. for providing the multispectral images used in the experiments.

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