An Approach for Change Detection in Multispectral Remotely Sensed Data using Interactive Segmentation

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***Abstract*—to solve the change detection(CD) problem in multitemporal remote-sensing images using interactivesegmentation methods. The user needs to input markersrelated to change and no-change classes in the difference image.Then, the pixels under these markers are used by the supportvector machine classifier to generate a spectral-change map.The most common methodology to carry out automatic unsupervised change detection in remotely sensed imageryis to find the best global threshold in the histogram of the so-calleddifference image.The user first roughly scribblesdifferent regions of interest, and from them, the whole imageis automatically segmented. Toenhance further the result, we include the spatial contextual informationin the decision process using two different solutionsbased on Markov random field and level-set methods. While theformer is a region-driven method, the latter exploits both regionand contour for performing the segmentation task. Experimentsconducted on a set of four real remote-sensing images acquired bylow as well as very high spatial resolution sensors and referring todifferent kinds of changes confirm the attractive capabilities of theproposed methods in generating accurate CD maps with simpleand minimal interaction.referring to different kinds ofchanges show the high robustness of the proposed unsupervisedchange detection approach.**

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***Keywords*— Change Detection (CD),SupportVector Machine (SVM),Maximum LevelSet(MLS),MarkovRandom Field (MRF).**

I. INTRODUCTION

In this letter, we propose to solve the CD problem usingthe concept of interactive segmentation. In particular, we focuson images characterized by a single change. To this end, theuser needs to input markers related to change and no-changeclasses in the DI. Then, the pixels under these markers areused 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 initiallyclassified 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 itsneighborhood often represents an effective way to increasing the accuracy of the result. In this context, we propose to processfurther the obtained CD maps using two different strategiesbased on Markov random field (MRF) and level-set(LS)methods. The former proved to be a powerful and successfulmathematical framework as shown by various works dealingwith different remote-sensing problems. On the other hand,LS methods recently gained popularity in image segmentation.They exhibit interesting advantages over classical segmentationmethods such as thresholding, edge based, and region growingtechniques. Changedetection (CD) is one of the most importantapplications in remote-sensing technology. The aim ofCD is to find pixels that correspond to real changes on theground in pairs of coregistered images acquired over the samegeographical area at two different times. Usually, CD methodsrely on the computation of the difference image (DI) from twocoregistered images, and then, changes are identified by automaticallysegmenting the DI into two regions associated withchanged and unchanged classes, respectively [1]–[4]. However,as these methods are data driven, the fully automatic discriminationbetween changed and unchanged classes is constrainedby the complexity of the statistical distributions characterizingthese classes, their degree of overlap, and initialization.Recently, the utilization of semiautomatic methods withuser's intervention (i.e., interactive segmentation) has becomepopular in the literature of image processing [5]–[9].

II. SYSTEM DESCRIPTION OF THE PROPOSED INTERACTIVE CD METHOD

Let $\mathbf{X}1$ and $\mathbf{X}2$ be two coregistered multispectral remotesensingimages of size $M \times N \times d$ acquired over the samegeographical area at two different times. Let $\mathbf{X}D$ be themultispectral DI of dimension d generated from $\mathbf{X}1$ and$\mathbf{X}2$ (i.e., $XiD= |Xi1- Xi2|$, $i = 1, . . . , d$).The aim of the proposedapproach is to generate a CD map representing thechanges 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.The framework here proposedfalls in the semi-automatic category. In particular, the segmentationis obtained after the user has provided rough scribbleslabelling the regions of interests.First, a couple of coregistered multitemporal remotesensing images acquired at two different dates over the samegeographical area are compared.The result of the comparison isan image usually termed "difference image." In the second keystep, changes are identified by analyzing the difference image.

III. ALGORITHM STEPS AND DATA FLOW DIAGRAMS

- **Algorithm**

Step 1: Read multispectral remote sensing Image.
Step 2: Change and no change region markings.
Step 3: Change pixels under green marker are assigned.
Step 4: No change pixel under green marker are assigned.
Step 5: Finally regions are marked.
Step 6: Perform pixel analysis with SVM.
Step 7: start margin maximization.
Step 8: Then spectral-change map is generated.
Step 9: Got analyzed pixels.
Step 10: Perform spatial analysis with MRF.
Step 11: Minimization of final change detection map.
Step 12: Apply the Platt procedure to the SVM.
Step 13: Got spatial analyzed image.
Step 14: Perform spatial analysis with LS.
Step 15: Splitting and merging of curve.
Step 16: SVM and MLS consists in setting the initial contour.
Step 17: Change detection.
Step 18: End.

- **Data Flow Diagrams**

A Data Flow Diagram (DFD) is a graphical representation of the "flow" of data through an information system. Data Flow models are used to show how data flows through a sequence of processing steps. The data is transformed at each step before moving on to the next stage. These processing steps or transformations are program functions when Data Flow diagrams are used to document a software design. DFD diagram is composed of four elements, which are process, data flow, external entity and data store. The DFD can be decomposed into three levels such as level 0, level 1.

Data Flow Diagram – Level 0

The level- 0 is the initial level DFD and it's generally called as the context level diagram. It is common practice for a designer to draw a context-level DFD first which shows the interaction between the system and outside entities. Thiscontext-level DFD is then exploded to show more detail of the system being modelled.

Figure1: Level 0Data Flow Diagrams

Data Flow Diagram – Level 1

The Level-1 DFD gives more information than the level-0 DFD. The figure below shows the Level-1DFD

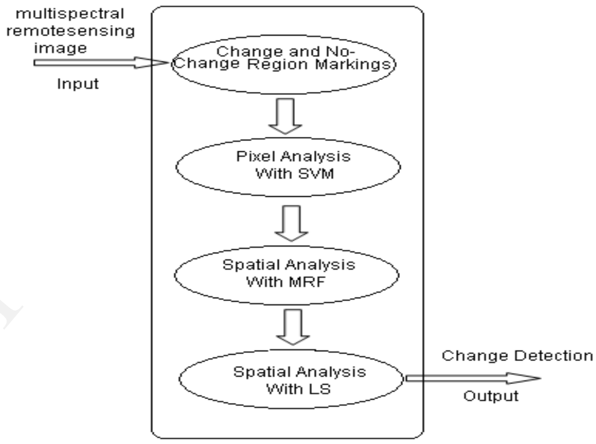

Figure2: Level 1 Data Flow Diagrams

The functions of this system are as follows:

- Read multi spectral remote sensing image.
- Change and No-Change Region Markings
- Pixel Analysis With SVM
- Spatial Analysis With MRF
- Spatial Analysis With LS

  Change detection.

IV. EXAMPLES OF REMOTELY SENSED INPUT IMAGES

The below figures shows a Remotely Sensed Imagesof same geographical area of Channagiri taken at different intervals of time 2002 and 2012 respectively

Figure 3: Taken at 2002

Figure4: Taken at 2012

V. DIFFRENCE IMAGE

The Difference Image is obtained by subtracting the pixel values of TWO images, Hence the Difference Image is as shown in figure 5

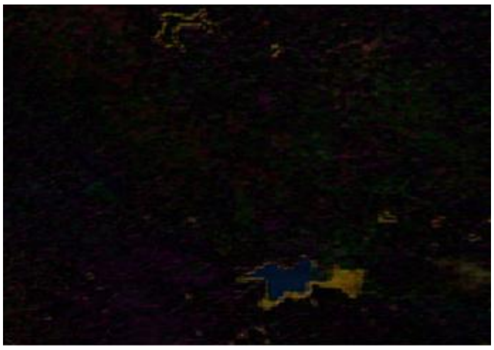

Figure 5: Difference Image

The input markers on the Difference Image as shown in figure 6.

A Single Change Detection as shown in figure 7.

A Multiple Change Detection as shown in figure 8.

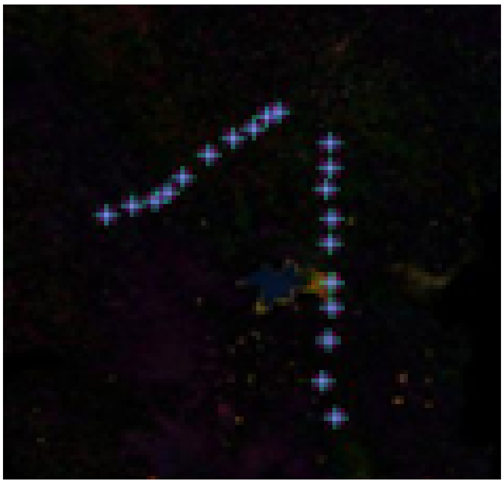

Figure6: Input markers on DI

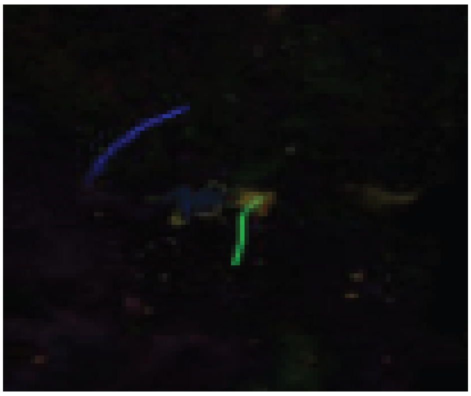

Figure7: Single Change Detection Map

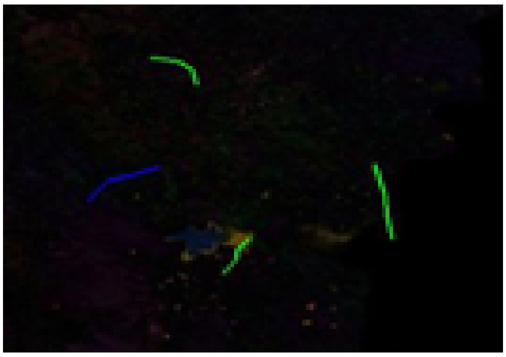

Figure8: Multiple Change Detection Map

VI. SIMULATION RESULTS AND ANALYSIS

The THREE important parameters are consider in this paper to analyze the simulation results, they are

- Error Rate
- False Alarm Rate
- Missed Alarm Rate

Error rate (P_E: total number of wronglyclassified pixels over the total number of pixels).

False-alarmrate (P_F : number of unchanged pixels classified as changedpixels over the total number of unchanged pixels).

Missed-alarm rate (P_M: number of changed pixels classifiedas unchanged pixels over the total number of changed pixels).

The output of a SVM Classifier as shown in figure 9.

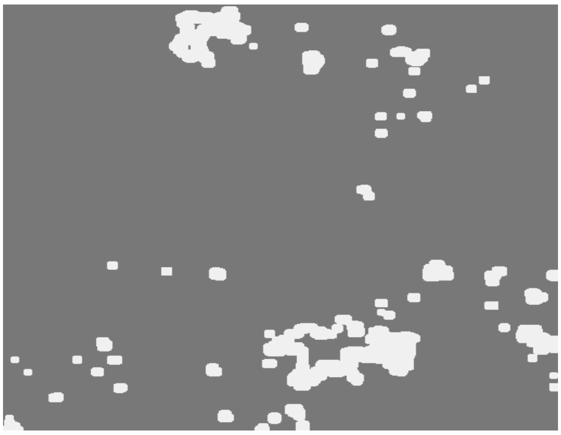

Figure9: SVM Classifier Output

The final Change Detected map as shown in figure10.

Figure10: Change Detected output shown in Black colour
The Error Rate, False Alarm Rate and Missed Alarm Rate as shown in Table1 for Channagiri Images.

Method	Channagiri image		
	ER	FAR	MAR
SVM-MLS	1.5	3.0	1.2

VII. CONCLUSION

The experimental results obtained on one set of multitemporal remote sensing data sets have shown that theproposed approach has the following characteristicsThe output is very attractive in generating accurate CD results with minimal interaction.it is robust against initialmarkings compared to the interactive MSRM method.Basically there are TWO methods to solve the CD problem in Remotely Sensed Data. First is based on the combination of SVM-MLS, while the second combines the SVM-MRF methods.

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