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Research Article

UNSUPERVISED CHANGE DETECTION FOR MULTISPECTRAL IMAGES

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ABSTRACT

This paper presents a novel approach to unsupervised change detection in multispectral remote-sensing images. The proposed approach aims at extracting the change information by jointly analyzing the spectral channels of multitemporal images without any training data. This is accomplished by using a selective Bayesian thresholding for deriving a pseudo training set that is necessary for initializing an adequately defined binary semisupervised support vector machine (S3VM) classifier. Starting from these initial seeds, the S3VM performs change detection in the original multitemporal feature space by gradually considering unlabeled patterns in the definition of the decision boundary between changed and unchanged pixels according to a semisupervised learning algorithm. The values of the classifier parameters are then defined according to a novel unsupervised model-selection technique based on a similarity measure between change-detection maps obtained with different settings.

Keywords: unsupervised change detection, multispectral, multitemporal, semisupervised support vector machine.

INTRODUCTION

The ever increasing number of operational satellites for Earth observation results in a growing interest of the remote-sensing community in the analysis of images acquired on the same geographical area at different times. This paper focuses the attention on unsupervised change detection in multispectral images. Among them, a widely used technique is the change vector analysis (CVA) [3], [4]. CVA when aaplied to magnitude of SCVs leads to major drawback like loss of information with respect to the original multitemporal and multispectral feature space.

In this paper, we address the aforementioned problem by proposing a method for unsupervised change detection in multispectral images, which has the following properties: i) it performs change detection directly on the original spectral channels of multitemporal images, for increasing the accuracy of the process; ii) it is unsupervised; and iii) it exhibits an intrinsic robustness to the noise affecting multitemporal images.

In this paper, we address the aforementioned problem by proposing a method for unsupervised change detection in multispectral images, which has the following properties: i) it performs change detection directly on the original spectral channels of multitemporal images, thus exploiting all the available information for increasing the accuracy of the process; ii) it is unsupervised; and iii) it exhibits an intrinsic robustness to the noise affecting multitemporal images.

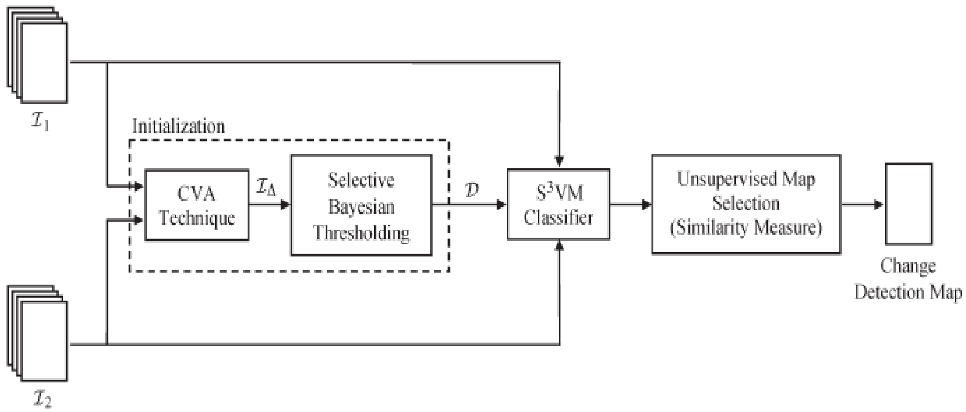


Fig. 1. Block scheme of the proposed approach.

This paper is organized into four sections, the architecture of proposed approach, experimental setup and reports of the results obtained by applying the proposed technique and finally conclusion.

PROPOSED CHANGE-DETECTION APPROACH

Let I1 and I2 be two coregistered multispectral images of size PxQ acquired on the same geographical area at different times t1 and t2, respectively. Let D be the number of spectral channels of each image, and let Ω = {ωu, ωc} be the set of classes of unchanged and changed pixels to be identified. The proposed technique consists of three main parts: i) an initialization to find the seed pixel in an unsupervised way using Bayesian thresholding by thresholding the magnitude of SCVs (pseudo training set); ii) a properly designed S3VM classifier that exploits the pseudo training set and the unlabeled pixels of images I1 and I2 for producing the change-detection map by analyzing the original multidimensional feature space; and iii) a novel similarity measure that is applied to the change-detection maps obtained with different values for the S3VM parameters for deriving, in an unsupervised way, the final change-detection result.

BAYESIAN INITIALIZATION

Let I= {Xp}PxQp=1 be the of PxQ d-dimensional vectors (where d = 2xD) whose components are the channels associated with the generic pth pixel in I1 and I2. I represent the multitemporal data set under analysis achieved by stacking the coregistered multispectral images I1 and I2.

The first step of the proposed unsupervised approach to change detection aims at identifying a pseudotraining set D = {Xl ,Yl} made up of pairs (xln, yln) to be used as seed patterns for initializing the S3VM, where Xl = { xln, xln Є I} and Yl = { yln, yln Є Ω} (Yl is the set of pseudolabels corresponding to seed patterns in Xl). As we detect these patterns in an automatic and unsupervised way, we propose to identify Xl by applying the CVA technique to I1 and I2 and by selectively thresholding the magnitude IΔ of SCVs. Threshold-selection technique is based on the Bayesian decision theory.[8], [9], [15]. The application of these techniques requires the explicit estimation of the statistical parameters of classes of changed and unchanged pixels (i.e., the class-prior and class-conditional probabilities). As we are dealing with an unsupervised changedetection problem, these statistical quantities are estimated from the observed statistical distribution of the magnitude of the SCVs according to the expectation–maximization (EM) algorithm [9]. However, if we apply the Bayesian threshold to IΔ, we obtain a change-detection map affected by errors resulting from the uncertainty that characterizes pixels with a magnitude value that is close to the threshold. This region around the threshold is called uncertain region and separated from correctly labeled pixels. Therefore, Xl is defined as

Xl ={xln | iΔ n ≤T- δ1and iΔ n≥ T+ δ2 }PxQ n=1 (1)

where iΔ n is the magnitude of the nth SCV in IΔ and where δ1 and δ2 are positive constants that tune the left and right boundaries, respectively, of the margin of uncertain pixels around the threshold value T. It is worth noting that, in general, the margin can be approximated as symmetric with respect to the threshold; thus, we can assume δ1 = δ2 = δ.

According to the properties of SCVs, pseudolabels of pixels in Xl are assigned as follows:

yln = { ωu, if iΔn ≤ T – δ1

ωc, if iΔn ≥ T + δ2 . (2)

Fig. 2. Example of distribution of the magnitude of SCVs p(iΔ) and of definition of the uncertainty region.

CHANGE DETECTION BASED ON S3VM

The main idea of the second step of the proposed technique is to define a discriminant function in the original Multitemporal feature space of the multitemporal images, which can accurately separate changed pixels from unchanged ones. The proposed S3VM technique is based on the following two main phases: 1) Initialization and 2) Semisupervised Learning.

Phase 1—Initialization: Let D(i)= {X(i),Y(i)} and X∗(i) denote the pseudo training set and the unlabeled set at the generic iteration i, respectively. The first phase corresponds to the initial step of the entire process (i = 0). We have that D(0) = {X(0),Y(0)} ≡ {Xl,Yl} and X∗(0) ≡ Xu. The learning cost function of a standard supervised SVM is used to obtain an initial separation hyperplane based only on pseudotraining data (xln,yln)Nn=1. According to standard SVM notation, the labels ωu and ωc are represented with values "+1" and "−1," respectively (i.e., ylnЄ{ωc, ωu} ≡ {+1,−1}).

Phase 2—Semisupervised Learning: The second phase of the proposed S3VM starts with iteration i = 1 and represents the core of the algorithm. At the generic iteration i, pseudolabels yu are given to unlabeled pixels belonging to X∗(i) Є Xu according to the current separation hyperplane. These pixels are called pseudolabeled patterns. As support vectors are the only patterns that affect the position of the discriminant hyperplane, unlabeled samples which fall into the margin and are closest to the margin bounds have the highest probability to be correctly classified. Accordingly, the ρ pseudolabeled samples lying into the margin that are closest either to the lower or the upper margin bound are selected and denoted as semilabeled patterns. The set containing all the semilabeled samples defined at iteration i is called H(i). Patterns of H(i) and their corresponding semilabels are then merged with X(i) and Y(i), respectively. Let J (i) represent the set of all the pixels selected from Xu, which have been always assigned the same label until iteration i. Let S(i), represent the set of samples belonging to J (i−1) whose labels obtained according to the separation hyperplane at iteration i are different than those at iteration i − 1. Patterns belonging to S(i) are reset to the unlabeled state and moved again into X∗(i). In this way, it is possible to reconsider these patterns for several iterations.

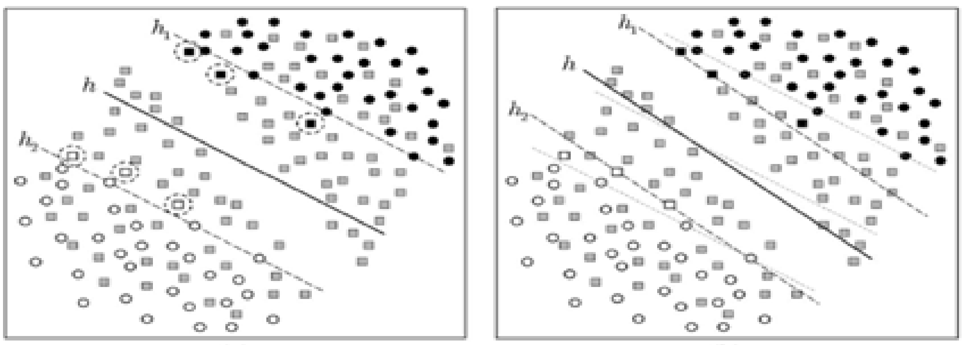
NOVEL UNSUPERVISED MODEL-SELECTION PROCEDURE BASED ON A SIMILARITY MEASURE

In the design of the S3VM architecture, it is necessary to select the values of the parameters of the considered kernel functions. This phase is called model selection of the classifier. In the proposed architecture, we analyzed the following two different strategies: i) model selection based on seed pixels included in the pseudo training set and ii) model selection based on a novel procedure that exploits both the pixels included in the pseudo training set and a similarity measure between the change-detection results on unlabeled pixels. The first trivial strategy does not allow a fine tuning of the model. The second strategy, which represents a novel methodological contribution of this paper, integrates the first one with an analysis of the effects of different models on the change detection map. To identify generic pair of solutions Si and Sj compute a measure of similarity Hij of the change-detection results on the P x Q pixels as follows:

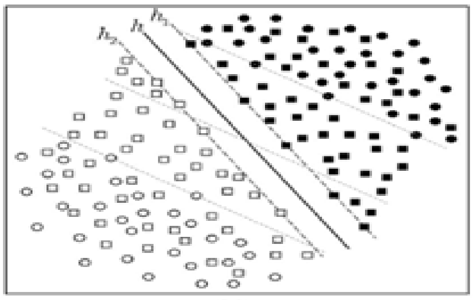
Hij = 1/PxQ Σ yip.. yjp , p=1 to PxQ

Where yip and yjp are the estimated labels of the pth pixels in the change-detection maps associated with solutions

Si and Sj, respectively. As yip and yjp can assume values in {−1, +1}, their product is equal to 1 if yip = yjp and to −1 otherwise. Accordingly, the value of the similarity measure Hij is equal to 1



(a) (b)



(c)

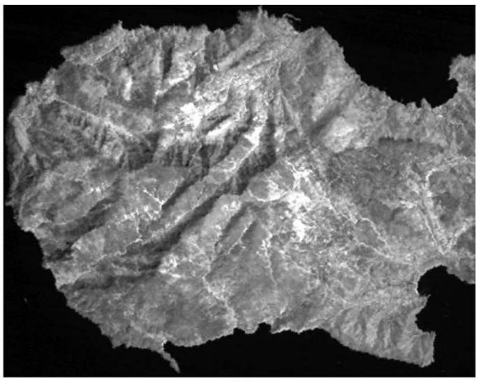
Fig 3 : Seperation hyperplane (solid line) and margin bounds (dashed lines) resulting at different stages of the S3VM algorithm for a simulated change-detection problem. Patterns in the pseudotraining set are shown as white and black circles. Corresponding semilabeled patterns are shown as white and black squares, respectively. Unlabeled patterns are represented as gray squares. Kernel space structure obtained at different iterations.

if the two considered solutions result in an identical change-detection map; otherwise, it is lower than 1.

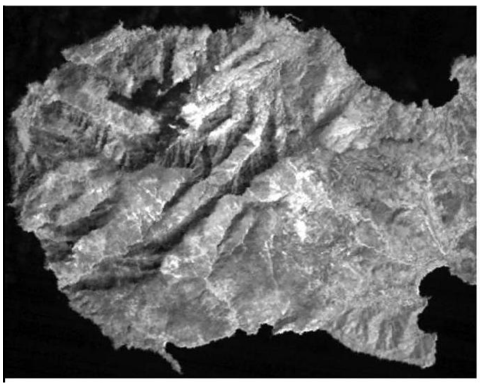
EXPERIMENTAL RESULTS

This data set is made up of two co registered multispectral images acquired by the TM sensor on the western part of Elba Island, Italy. Bands 4 and 7 were considered in the experimental analysis, as they proved to be the most effective for the detection of the burned areas.

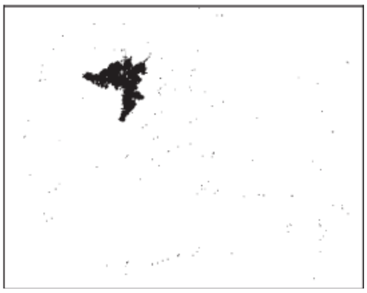
The proposed method sharply outperformed the standard CVA technique, increasing the value of the kappa coefficient from 0.654 to 0.841 and decreasing false alarms from 1681 to 380 and missed alarms from 390 to 375.



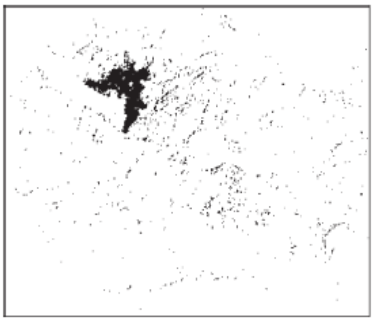
(a) August 1994



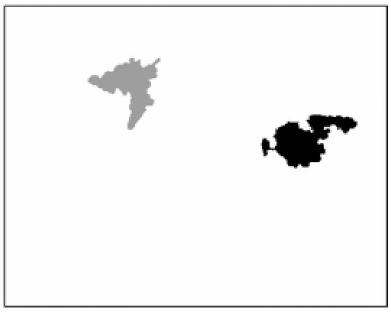
(b) September 1994



(c) Proposed technique



(d) Change-detection maps using the standard CVA.



(e) Reference map (gray spot)

DISCUSSION AND CONCLUSION

The proposed architecture properly exploits the information present in the original images. Most of the problems of earlier methods are overcome in the proposed technique.

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