Earth Observation Laboratory
PhD Program in GeoInformation
DISP - Tor Vergata University

Change Detection Algorithms: State of the Art

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Fabio Pacifici
f.pacifici@disp.uniroma2.it

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Abstract

Detecting temporal changes by observing surfaces at different times is one of the most important applications of satellite sensors because they can provide multidate imagery at short interval on global scale. A lot of experience has already been accumulated in exploring change detection techniques for medium/high spatial resolutions, but very few can be found for the new generation of very high spatial resolution satellite sensors such as IKONOS or QUICKBIRD. The advent of these new optical imagery has greatly increased our ability to monitor land cover changes from space, in fact, this high spatial resolution imagery better resolves the details of changes and makes it possible to overcome the *mixed pixel* problem inherent with more moderate resolution satellite sensors. At the same time, they present a new challenge over other satellite systems, in that a relatively large amount of data must be analyzed and corrected for registration and classification errors to identify land cover changes.

This report is a review of change detection techniques published in the past decade.

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1   Introduction

In the past few years, there has been a growing interest in the development of change detection techniques for the analysis of multitemporal remote sensing imagery. This interest stems from the wide range of applications in which change detection methods can be used, like environmental monitoring, agricultural surveys, urban studies and forest monitoring. Changes in land cover and land use in urban areas are dynamic processes, such that transitions occur at varying rates and in different locations within the constraints of, or in response to, social, economic and environmental factors. For many public and private institutions, the knowledge of the dynamics of either natural resources or man-made structures is a valuable source of information in decision making. Regional planners and decision makers engaged in a map updating operation for a changing metropolitan or county area require up-to-date information on the nature and impact of urban expansion or transition to more intensive usage. Map updating is an intensive task requiring timely and accurate information from multiple sources of data especially for detailed mapping of complex urban scenes [1][2]. The primary method of updating land cover and land use maps has been, and in some case still is, through human interpretation. In this process, the full range of human interpretation capabilities can be employed, including the interpreter's own knowledge of the area. However, it is time consuming, subject to errors of omission and the abilities of the interpreter vary greatly. Also, there are limits to the ability of humans to absorb and process large volumes of information. Computer assisted methods offer approaches to detection and identification of land cover and land use change.

In this context, satellite and airborne remote sensing sensors have proved particularly useful in addressing computer assisted change detection applications related to environmental monitoring, agricultural surveys and urban studies [3][4]. In particular, recent advances in remote sensing technology suggest that satellite based earth observation has great potential for providing and updating spatial information in a timely and cost effective manner. Moreover, the availability of remote sensing data is guaranteed for decades to come, making earth observation a powerful long term change detection instrument [5]. This kind of change analysis, however, has the following problems [6][7]:

- a huge volume of data must be processed for detecting only few change areas;
- many types of satellite sensors are available, but their spectral bands are not always identical in center wavelength and band width;
- noise due to differences in light conditions, atmospheric conditions, sensor calibration and ground moisture at the two acquisition dates considered causes apparent changes;
- each image has own geometrical distortion and problems of alignment of multitemporal images (*registration noise*).

Concerning this last issue, two images should be registered so that pixels with the same coordinates in the images may be associated with the same area on the ground. This is a very critical step in very high resolution satellite and airborne imagery, especially when the angle of acquisition varies greatly, rendering change detection results unreliable.

2   Supervised and Unsupervised techniques

In the remote sensing literature, two main approaches to the change detection problem have been proposed: unsupervised and supervised. The former performs change detection by transforming the two multispectral images considered to a single band or multiband image in which the areas of land cover or land use change can be successively detected. The latter is based on supervised classification methods, which require the availability of a suitable training set for the learning process of the classifiers. Although the supervised approach exhibits some advantages over the unsupervised one as:

- the capability to explicitly recognize the kinds of land cover or land use transitions that have occurred;
- the robustness to the different atmospheric and light conditions at the two acquisition times;
- the ability to process multisensor and/or multisource images;

the generation of an appropriate training set is usually a difficult and expensive task [8].

2.1   Unsupervised Approach

Many unsupervised change detection algorithms process the multispectral images in order to generate a further image. The *Image Differencing* (IM) algorithm, for example, performs change detection by subtracting, on a pixel basis, the images acquired at two times to produce a new image. The computed difference image is such that the values of the pixels associated with land cover or land use changes present values significantly different from those of the pixels associated with unchanged areas. Changes are then identified by analyzing (e.g., thresholding) the difference image, since, under the hypothesis of few changes between the two times, changes can be detected in the tails of the probability density function of the pixel values in the difference image. Then, it follows that unchanged pixels present small gray level values, whereas changed pixels present rather large values. Other techniques, like *Normalized Difference Vegetation Index* (NDVI), make the same kind of comparison by using, instead of a spectral band, vegetation indices or other linear or nonlinear combinations of the original bands. Also the widely used *Change Vector Analysis* (CVA) technique exploits an analogous concept. In this case, however, the pixels at each time are represented by their vectors in the feature space. Then, for each couple of pixels, the spectral change vector is computed as the difference between the feature vectors at the two times. The statistical analysis of the magnitudes of the spectral change vectors allows one to detect the presence of changes, while their directions make it possible to distinguish among different kinds of transitions. The techniques based on the *Principal Component Analysis* (PCA) can be used to perform change detection by applying the principal component transformation separately to the feature space at single time or to the merged feature space at two times. Another technique similar to the above described ones is *Image Rationing* (IM). In this case, the comparison between spectral bands at two times is performed by computing the ratio, instead of the difference, between images. In unsupervised change detection, the separation between changed and unchanged classes is done on the magnitude of the resulting spectral change vectors by means of empirical or theoretical well founded

thresholding strategies. In [8], two automatic techniques based on the Bayes theory for the analysis of the difference image are proposed. One allows an automatic selection of the decision threshold that minimizes the overall change detection error probability under the assumption that pixels in the difference image are spatially independent. In the hypothesis of Gaussian distribution for changed and unchanged classes, the estimation of the parameters of the Gaussian model is carried out using the *Expectation Maximization* (EM) algorithm. The other technique analyzes the difference image using a *Markov Random Field* (MRF) approach that exploits the interpixel class dependency in the spatial domain by considering the spatial contextual information included in the neighborhood of each pixel to improve the accuracy of the final change detection map according to the use of a regularization term. This approach has been extended in [7] by adopting an adaptive semiparametric method that exploits the *Reduced Parzen Estimation* (RPE) technique to perform the estimation of the statistical terms associated with gray levels of changed and unchanged pixels in the difference image for a better modeling of the density functions. In [9], the multitemporal images are modeled as MRFs in order to search for an optimal image of changes by means of the *Maximum a Posteriori Probability* (MAP) decision criterion. The algorithm involves the simulated annealing energy minimization procedure. In [10], the authors investigate a methodology aimed to characterized and understand the spatial behavior of changes by decomposing the change intensity image into a tree of entities called Echelons. Such a tree architecture can determine connections between changes. In [11], objects are first extracted from each image to be analyzed and a site model is constructed containing image segmentation maps and extracted object features, then, Object-level Change Detection (OLCD) is accomplished by comparing objects extracted from a new image to objects recorded in the site model and the differences are highlighted. In [12] is introduced a new extensions to the previously published Multivariate Alteration Detection (MAD) method [13] called Iteratively Reweighted MAD (IR-MAD) for change detection in multi and hypervariate data, inspired by boosting methods often applied in data mining works. The MAD method is based on established technique of canonical correlation analysis. This MAD and the combined MAF/MAD (*Maximum Autocorrelation Factor)* transformations are invariant to linear scaling. Therefore, they are insensitive, for example, to differences in gain settings in a measuring device, or to linear radiometric and atmospheric correction schemes.

The above techniques mainly do not aim to identify explicitly what kinds of land cover or land use transitions have taken place in an area (e.g., the fact that a vegetated area has been urbanized). Then, these techniques are suitable for applications like, for example, detection of burned areas or detection of deforestation. However, they cannot be applied when the only information on the presence of change is not sufficient, like, for example, in the monitoring of the shifting cultivation or urban growth, where it is necessary to recognize the kinds of changes that have taken place in the area investigated. Only the CVA technique allows one to distinguish among different kinds of changes but, being not supervised, it does not explicitly identify the typologies of transitions. In [14] the authors present a consistent theoretical framework for proper representation, modeling and exploitation of the information present in the CVA technique, introducing a set of formal definitions and analyzing the distributions of changed and unchanged pixels in

the context of the polar domain. In addition, as already highlighted, the performances of unsupervised techniques are generally degraded by several factors like differences in illumination at two times, differences in atmospheric conditions and in sensor calibration that make difficult a direct comparison between raw images acquired at different times. To mitigate these problems, further processing is required by performing, for example, a radiometric calibration of the images.

2.2   Supervised Approach

In order to overcome the limitations of an unsupervised approach, one can use techniques based on a supervised classification of multitemporal images. The simplest technique of this category is *Post Classification Comparison* (PCC) [15][16][17]. It performs change detection by comparing the classification maps obtained by classifying independently two remote sensing images of the same area acquired at different times. In this way, it is possible to detect changes and to understand the kinds of transitions that have taken place. Furthermore, the classification of multitemporal images avoids the need to normalize for atmospheric conditions, sensor differences, between the acquisitions. However, the performances of the PCC technique critically depends on the accuracies of the classification maps. In particular, the final change detection map exhibits an accuracy close to the product of the accuracies yielded at the two times [18]. This is due to the fact that PCC does not take into account the dependence existing between two images of the same area acquired at two different times, while *Direct Multidata Classification* (DMC) is able to overcome this problem [19]. In this technique, pixels are characterized by a vector obtained by stacking the feature vectors related to the images acquired at two times. Then, change detection is performed by considering each transition as a class and by training a classifier to recognize the transitions. Appropriate training sets are required: the training pixels at the two times should be related to the same points on the ground and should represent accurately the proportions of all the transitions in the whole images. Usually, in real applications, it is difficult to have training sets with such characteristics. The above mentioned methods are mainly pixel based, while [20] is a region based change detection algorithm, where the user requirement are explicitly introduced in the change detection chain by means of a cost function taking into account the user requirements. In general, the approach based on supervised classification is more flexible than that based on the comparison of multitemporal raw data. In addition to the already mentioned capability to explicitly recognize land cover transitions and to reduce the effects of different acquisition conditions at two times, it allows one to perform change detection also by using different sensors at two times. Modification of the classifier includes directly encoding contextual information, such as image texture or a priori probabilities from historical sources to weight class allocation.

Neural networks (NNs) and knowledge-based systems, have emerged as an important tool for classification. NNs are data driven self-adaptive methods since they can adjust themselves to the data without any explicit specification of functional or distributional form for the underlying model, moreover, they are universal functional approximators since they can approximate any function with arbitrary accuracy [21]. Due to this, NNs offer a compromise between the complexity, the data intensive knowledge-based

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systems and the parametric manipulation of imagery. Another typology of classifiers is the one based on *Support Vector Machines* (SVMs). Developed by Vapnik [22], SVMs are based on the structural risk minimization principle and their popularity within the remote sensing community is constantly on the increase, due to the their properties to analyzing hyperdimensional feature spaces [23][24].

3   Change Detection for SAR data

A special case in this review is the Synthetic Aperture Radars (SAR) imagery. In fact, SAR data has been less exploited than the optical one in the context of change detection. This is also due to the fact that SAR images suffer from the presence of the speckle noise that makes it difficult to analyze such imagery, and in particular to perform unsupervised discrimination between changed and unchanged classes. Despite the presence of speckle noise, the use of SAR sensors in change detection is potentially attractive from the operational viewpoint. The active microwave sensors present the advantage that (unlike optical ones) they are independent of atmospheric and sunlight conditions. This makes it possible to plan the monitoring of a region (by repeat pass imaging) with advance timing defined according to end-user requirements (e.g., seasonal and agricultural calendars). In the context of SAR image analysis, the problem of unsupervised change detection has been addressed focusing on different aspects, including image despeckling, choice of the comparison operator and optimal threshold selection. Because of the multiplicative nature of speckle noise, it appears more effective to use the ratio operator than the difference operator to compare two SAR temporal images [25]. In fact, the ratio method is quite sensitive to the presence of image speckle in the sense that speckle patterns, that are difficult to detect by a human eye in SAR images when the number of looks is large, will still be visible in ratio images. Another important reason for selecting the ratio method instead of the difference method is that the ratio method is very robust to calibration errors whereas the difference method is not. Radiometric errors are usually introduced in the imagery during SAR processing by assuming a flat Earth model, resulting in two errors:

- an error in the computation of the scattering element size due to errors in the true incidence angle of the electromagnetic signal onto the surface;
- an error in the antenna pattern removal due to errors in the true depression angle of the signal onto the reflecting surface.

Both errors are multiplicative factors to the total radar intensity. These factors are eliminated when computing the ratio image because calibration errors are exactly reproduced in repeat pass imagery. In contrast, in the difference method, radiometric errors directly modulate the difference of the radar intensities, typically yielding higher changes in very hilly terrain (e.g., slopes facing the radar) than in rather flat areas for the same type of surface, which is not a desired effect. In [26], intensity images are better suited for change detection purposes than correlation coefficient and phase difference between the copolarized channels. In particular, the authors used the ratio operator to compare the temporal images and a decision mechanism based on a desired value of the probability of false alarm. In [27] the authors present an approach

based on a closed loop process made up of three main steps: 1) a preprocessing based on a controlled adaptive iterative filtering that aims at reducing the speckle noise in a controlled way in order to maximize the discrimination capability between changed and unchanged pixels; 2) a comparison between multitemporal images carried out according to a standard log-ratio operator; 3) a thresholding procedure based on a reformulation of the Kittler-Illingworth threshold selection criteria. In [28], a wavelet based multiscale decomposition of the log-ratio image aims at achieving different levels of representation of the change signal, where each scale is characterized by a different trade off between speckle reduction and preservation of the geometrical details. In [29], a fuzzy version of the *Hidden Markov Chains* (fHMC) is presented: the simultaneously use of the Dirac and Lebesgue measures at the class chain level allows the coexistence of hard pixels, obtained with the classical HMC segmentation, and fuzzy pixels, obtained with the fuzzy measure, in the same image.

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