# A New Change Detector in Heterogeneous Remote Sensing Imagery

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Abstract—Multimodal change detection in satellite images is a challenging and complex problem mainly because the local statistics of the images to be compared can be very different. In this paper, we present a novel, reliable and simple change detection operator which is first based on a imaging modality-invariant operator that detects the common specific high-frequency pattern of each structural region existing in the two heterogeneous satellite images. The resultant similarity map is then filtered out by a superpixel-based spatially adaptive filter which increases its reliability against noise. Second, in order to achieve more robustness, changes are then identified, from this similarity map, by combining the results of different automatic thresholding algorithms with a weighted spatially regularized multi-criteria decision analysis. Experimental results involving a mixture of different types of imaging modalities confirm the robustness of the proposed approach.

*Keywords*— Change detection, Data fusion, High-frequencybased operator, Multitemporal multimodal images, Spatialtemporal-based CD operator, Thresholding algorithms.

# I. INTRODUCTION

In remote sensing, multi-modal Change Detection (CD) is a process whose purpose is to analyze two (or possibly several) images generated by different sensors (or from different spectral bands) of the same geographical area, at different times, in order to identify any land cover changes that may have occurred between them. It is a recent and challenging problem which generalize the classical *mono-modal* CD problem since it requires less restrictive condition about the origin of the data. On the other hand, this technique has to be flexible enough to adapt itself to any existing heterogeneous data types.

Multi-modal CD has recently attracted widespread interest as it is particularly useful for dealing with the huge amount of heterogeneous data we can now get from existing Earth observing satellites or extracted from various archives.

Classical applications such as environmental monitoring, deforestation, urban planning, land or natural disaster/damage monitoring and management to name a few can be solved [1]. Moreover, since multi-modal CD is adaptable to heterogeneous data with different statistics, this multi-modal technique turns out also more robust to natural variations in environmental variables such as soil moisture or phenological states (such as flowering, maturing, drying, senescence, harvesting, etc.) or shading effects that cannot be avoided and well taken into account and corrected in the preprocessing step of a classical mono-modal CD approach. Finally, let us also stress that this multi-modal approach may be useful and sometimes indispensable in some emergency cases (*e.g.*, an optical image of a given area is provided by an available remote sensing image archive data and only a new SAR image can be acquired for technical reasons, lack of time, availability or atmospheric conditions in an emergency situation for the same area) or in some specific cases, such as forest monitoring in tropical or boreal areas for which SAR, thanks to its ability to penetrate heavy clouds and fog, is often used as a complement to optical data (this complementarity between SAR and optical sensors can also be exploited in the case of frequently snow-covered regions of high altitudes since SAR is also able to penetrate a thin snow layer).

Up to now, relatively few research works have been developed in heterogeneous CD. However, we can mention the statistical approach proposed in [2] in which the dependence between the two satellite images, in unchanged areas, is modeled by a quantile regression applied according to the copula theory and Kullkack-Leibler-based comparisons on local statistical measures to generate a similarity map which is then finally analyzed by thresholding, in order to detect between change and no change areas. An interesting twostep multivariate statistical approach has also been proposed in [3], [4] whose the first step aims at estimating a physical model, based on a mixture of multi-dimensional distributions (both taking into the noise model, the relationships between the sensor responses to the objects and their physical properties), with the expectation-maximization (EM) algorithm [5]. Then, a statistical test based on this model allows to estimate the changes. In the same spirit, the authors in [6] also propose to first estimate a multi-dimensional distribution mixture estimation based, in their application, on a new family of multivariate distributions with different shape parameters especially well suited for detecting changes in SAR images acquired by different sensors having different numbers of looks. Finally, [7] propose to use a technique closed to the coregistration and based on the use of a combination of different invariant similarity measures (such as correlation ratio, mutual information, etc.) in order to estimate the correspondence between the same points in the two images and finally to detect eventual changes existing between the two data acquisitions.

In this work, we propose a new, simple and effective change

detector which first allows us to generate a robust similarity feature map, especially well suited to estimate the differences existing in the land cover change between heterogeneous images coming from different sensors (and thus exhibiting different image statistics). The proposed change detector can also be viewed as a local similarity measure which proves to be fairly invariant to the different types of modalities involved in remote sensing imagery. Once a similarity feature map is estimated by this modality-invariant change detector, changed and unchanged areas are then finally identified by fusing the results of different automatic thresholding algorithms.

The remainder of this paper is organized as follows: section II presents the different stages of the proposed change detection method. Section III shows a variety of experimentation and comparisons with other existing state-of- the-art multi-modal change detection methods recently proposed in the literature.

### II. PROPOSED MULTIMODAL CHANGE DETECTION MODEL

The proposed model is based on a four-step procedure, namely;

#### A. Similarity Map Estimation

Let us consider two (previously co-registered) bi-temporal remote sensing (N pixel size) images,  $y^{t_1}$  and  $y^{t_2}$  acquired at two times (before and after a given event), in the same geographical area, from different sensors (or from the same sensor but with different spectral bands).

In the classical mono-modal (or homogeneous) CD case, the two coregistred temporal images at two different times are usually first compared pixel by pixel in order to generate a *difference image* by differencing (with a simple subtraction or a temporal gradient operator) or (log-)rationing (*i.e.*, with a log temporal gradient). This latter *difference image* is such that the pixels associated with land-cover changes present gray-level values significantly larger from those of pixels associated with unchanged areas. A binary segmentation is then finally achieved on this temporal gradient image to distinguish between the changed and no changed areas.

In the heterogeneous or multi-modal case, this temporal gradient is not effective. Indeed, the gray or color value of each pixel is not a useful information since the texture of a same region, before and after a given event, may be different according to a given imaging modality and, consequently, the mean value of a same region may also be different. Conversely, two distinct regions, at two different times, may be locally coded with the same value since two different textures may have the same mean or similar local intensity/color value. Consequently, the classical temporal (or log temporal) gradient operator is thus irrelevant in the heterogeneous case for estimating an accurate *difference image* which will be subsequently used for identifying land cover change.

Nevertheless, for the same region, represented by two different

textures (or two different imaging modalities), there is a feature, which remains relatively invariant between different types of imaging and thus that can be herein efficiently exploited. This feature is the magnitude and orientation of the spatial edges and/or contours existing in the considered region. Indeed, each specific homogeneous region generally exhibits a unique geometric high-frequency pattern. For example an urban region exhibits a specific directional edge or gradient magnitude distribution (due to the presence of rectangular regions defined by the roads/streets, building roofs, parking lots, electric field lines etc.) which is, more or less, well preserved in the two imaging modalities in the high spatial frequencies of the texture pattern. It is also the case of an agricultural region where the intrinsic regular location of crops produces edges and contours which are also fairly well conserved in the two kinds of imagery. This remains true for the other homogeneous regions in satellite image, even for the water region where the absence or the presence of waves (or wavelets at a finer spatial scale) can be detected and localized in the two different heterogeneous modalities by a high-frequency filter or a simple edge detection algorithm for texture.

Consequently, since the edge at different spatial scales or more precisely, the specific high-frequency pattern of each textural region is fairly well preserved in spite of the difference in the modality between the two heterogeneous temporal images, we propose to base the estimation of our *difference image*  $y^D$  by a temporal gradient applied on a local spatial gradient (see Figure 3). In our case, this spatial temporal and spatial finite difference approximation (in the  $L_1$  norm). More precisely, the similarity map  $y^D$  is computed by estimating at each pixel site *s* by:

$$y_{s}^{D} = \sum_{\langle s,t \rangle \in W_{n}} \left| |\mathbf{y}_{s}^{t_{1}} - \mathbf{y}_{t}^{t_{1}}|_{1} - |\mathbf{y}_{s}^{t_{2}} - \mathbf{y}_{t}^{t_{2}}|_{1} \right|$$
(1)

where the summation is done over all pairs of pixels  $\langle s, t \rangle$ contained in a  $N_n \times N_n$  squared window  $W_n$  including the central pixel located at site s. This summation allows us both to render this temporal-spatial gradient operator invariant to rotation and also less sensitive to noise (due to the averaging process). In addition, since we want to compute a spatial gradient for a (possible) texture region, the difference  $\mathbf{y}_s^{t_1} - \mathbf{y}_t^{t_1}$ is achieved by considering  $y_s$  as being a vector obtained by gathering together all the grey (or color) values contained in a  $N_t \times N_t$  squared window  $W_t$  centered on pixel s. Finally this temporal-spatial local finite differences between these two (feature) vectors are computed in the  $L_1$  norm sense. Let us note that, instead of gathering the pixel values in the vector  $\mathbf{y}_s$ , we could also compute local statistics estimated from the values contained around s. In our application,  $N_n = 7$  and  $N_t = 3.$ 

# B. Superpixel-Based Filtering Step

Once the similarity map  $y^D$  is estimated thanks to our above-presented rotation-invariant temporal-spatial gradient operator for texture (see Eq. (1)), we decide to filter  $y^D$  with an original superpixel-based filtering strategy in order to make  $y^D$  less noisy and thus to make its subsequent binarization (see Section II-C) more robust.

A superpixel is a perceptually meaningful collection of pixels, obtained from some low-level grouping process. Fundamentally, it is the result of an oversegmentation in which the pixels inside of each superpixel form a consistent, perceptually meaningful, unit or atomic region e.g., in terms of color, texture, intensity and so on. In addition to estimate a set of homogeneous regions (of nearly similar size) allowing to preserve the important structures in the image, this lowlevel process is also representationally and computationally efficient. By replacing the rigid structure of the pixel grid, it reduces the complexity of images from hundreds of thousands of pixels to only a few hundred superpixels. Recently, an interesting superpixel algorithm called simple linear iterative clustering (SLIC) [8] has been proposed, which, compared to the state-of-the-art superpixel methods, turns out to be superior for both efficiency and boundary preservation. SLIC is a two step procedure which first estimates superpixels by grouping pixels with a local k-means clustering method and second, exploit a connected components algorithm to remove the generated small isolated regions by merging them into the nearest large superpixels.

In our application, SLIC is applied on  $y^{t_1}$  and  $y^{t_2}$  in order to detect the different consistent structural regions (land uses) existing in these images. The intersection between these two SLIC segmented images allows us to define a third oversegmented map  $y^{S}$  (with thus smaller superpixels) in which the set of pixels inside each new superpixel has the appealing property to both exhibit homogeneous structural regions (in terms of land uses) in the before and after images (see Figure 3). At this stage, a possible strategy is to exploit the collection of superpixels belonging to  $y^S$  (and  $\{y^{t_1}, y^{t_2}\}$  or  $y^D$ ) to individually classify each superpixel into *changed* or no-changed class. Another strategy, used in this work, is to average each pixel value of  $y^D$ , inside each superpixel of  $y^{S}$ , between them. Conceptually, this later strategy can be interpreted as a segmentation-based spatially adaptive filter which averages the values given by our CD operator (see Eq. (1)) within each individual homogeneous changed or nochanged small region previously estimated.

#### C. Binarization of the Filtered Similarity Map

In this step, three (T = 3) different unsupervised thresholding algorithms are applied on the previously estimated filtered similarity map  $y^D$  (namely [9], [10], [11]) to automatically identify the *changed* vs *no-changed* areas. The results of these T = 3 binarizations will be then fused together (see Section II-D) to further increase the robustness and reliability of our final classification/detection scheme.

## D. Weighted Fusion of Binarization Results

Let us stress that the similarity map  $y^D$  to be binarized may have different statistics according to the different types of mixture of (possible) imaging modalities involved in our heterogeneous CD problem. Because of this variability, it is difficult to find a binarizer that is reliable in all cases. An alternative consists in designing a self-adjusting weightedcriteria binarization process which selects and appropriately combines the different binary results or equivalently, which self-adjusts each criterion's influence in the final binarization process. Experimentally, this strategy turned out to be robust in our application because each binarizer is optimal for a specific imaging modality.

This strategy, based on the concept of combining classifiers (in our case binarizers), has already been used in [12]. Let us mention that, in this context, Dietterich [13] have provided an accessible and informal reasoning, from statistical, computational and representational viewpoints, of why combination of classifiers (also called a committee machine, ensemble classifiers, or mixture of experts in machine learning) can improve results. In our application, this binary fusion process is a two-step procedure, namely:

1) Weighting of Each Binarization: In our multi-criteria binarization process, we first estimate, for each binarization map, a confidence measure which will be then used as weighting parameter in our final weighted-criteria fusion process. This confidence factor aims at measuring the quality of each binary clustering of  $y^D$ . To this end, a commendable goal in clustering consists in minimizing the within-class variation or inertia (or within-class variance) in order to have homogeneous clusters, while maximizing the between-class inertia (*i.e.*, the separation between the two clusters) so that these clusters are as different as possible. This is achieved by estimating the inertia ratio (used in the linear discriminant analysis of Fisher [14]) which is the ratio of between-class and within-class variation:

$$\rho = \frac{\sum_{c=1}^{C} P_c \sum_{j=1}^{n_c} (y_{c\,j} - \overline{m}_c)^2}{\sum_{c=1}^{C} P_c (\overline{m_c} - \overline{m})^2}$$
(2)

where C = 2 refers to the two classes (or clusters *changed* and *no-changed* areas) and  $P_c$  to the probability (proportion) of the *c*-th class.  $n_c$  denotes the number of samples in the *c*-th class and  $y_{cj}$  represents the *j*-th sample (*i.e.* its grey level) in the *c*-th class.  $\overline{m_c}$  and  $\overline{m}$  refer respectively to the mean of the *c*-th class and the mean of all samples.

Since the inertia ratio (Eq. 2) is low for a good binarization result, a strategy to convert this inertia ratio into a confidence measure is to consider  $\rho^{-1}$ . Nevertheless, the different confidence measures obtained with this strategy are not very different and leads to very close weighting factors. Another possibility, adopted in this work, consists in considering  $\rho$ as a distance and to favour more heavily low distances with the procedure described in [15] in order to get dissimilar and reliable weighting factors.

2) Weighted Majority Vote Filter: In our application, this binary fusion process is simply achieved by using a weighted majority vote filter using a three dimensional window  $W \times$  $W \times T$  whose the first two dimensions are spatial and the third dimension indexes the different binary thresholded maps to be fused. In our application, this majority vote is achieved with a 3D window which is spatially centered on the pixel to be classified, and that collects the weighted (with the weights previously estimated in Section II-D.1) binary class labels of the different binary thresholded maps and finally by assigning to that central pixel, the class label that has the majority vote. This strategy has the advantage to ensure both the spatial regularization of the final fused (detection) map result and also to provide a reliable weighted decision fusion between results obtained by different thresholding techniques weighted by the confidence measures provided in Section II-D.1.

#### **III. EXPERIMENTAL RESULTS**

To validate our approach, we present in this section a series of tests conducted on different real heterogeneous datasets, chosen to reflect the three possible change detection conditions in multimodal case; Namely, two heterogeneous optical images, heterogeneous SAR images, one optical and one SAR images. This allows us to compare the performance of the proposed method with different state-of-the-art *multi-modal* change detection algorithms recently proposed in this field [3], [16] [4] [6] [2] in different CD conditions. We also compare the obtained results with other change detector traditionally proposed in *mono-modal* case and provided by the ORFEO Toolbox [17] on the first and second data set.

#### A. Dataset Description

• The first data set is a pair of satellite images (Gloucester, UK) (size  $2325 \times 4135$  pixels with a resolution of 7.3 meters) composed of one optical image given from a Google Earth VHR satellite (December 2006 before a flooding), and one SAR image captured by the TerraSAR-X satellite in July 2007 (after the flooding). The change mask was provided by a photo interpreter [4]. The optical image was re-sampled [4] to have the same resolution of the SAR image.

• The second dataset shows two Heterogeneous optical images acquired in Toulouse (Fr) area by different sensor specifications (size  $2000 \times 2000$  pixels with a resolution of 0.5 meter). The *before* image is acquired by the Pleiades sensor in May 2012 before the beginning of the construction work, and the *after* image is from a Google Earth VHR satellite in July 2013 after the construction of a building. The change mask was provided by a photo interpreter [4]. The Google Earth image was re-sampled [4] to have the same resolution of the Pleiades image.



Fig. 1. Optical VHR satellite/TSX data set. From lexicographic order; image  $t_1$ ,  $t_2$ , ground truth, filtered similarity map, final weighted binary fusion.

• The third data set [6] shows a pair of heterogeneous satellite images (size  $400 \times 800$  pixels and resolution of 10 meters) acquired over the Democratic Republic of the Congo before and after the eruption of the Nyiragongo volcano (January 2002). It consists of two SAR images captured by the RADARSAT satellite with different numbers of looks. The number of looks for the image before and after change is 3-looks and 5-looks. The change mask was provided by a photo interpreter [6].

## B. Results & Evaluation

In order to discuss and compare obtained results, a quantitative study is conducted by computing the classification rate accuracy that measure the percentage of the correct changed and unchanged pixels:

$$PCC = \frac{TP+TN}{TP+TN+FN+FP}$$
(3)

Where TP is the true positive value that corresponds to the number of pixels that are detected as the changed area in both the ground truth image and the obtained results. TN is the true negative value that corresponds to the pixel number belonging to the intersection of the unchanged area in both the reference image and the obtained results. FN represents the false negative value that refers to the number of the missed changed pixels in the obtained results and FP represents the false positive corresponding to the unchanged pixels wrongly classified as changed.

Table 1. Accuracy rate of change detection on the three heterogeneous datasets obtained by the proposed method and the state-of-the-art *multi-modal* change detectors (first upper part of each table) and *mono-modal* change detectors (second lower part of each table).

Optical VHR sat. / TSX	Accuracy				
Proposed method	0.932	Pleiades / other optical VHR sat.	Accuracy		
Prendes et al. [4], [18]	0.918	Proposed method	0.870	SAR 3-looks / SAR 5-looks	Accuracy
Prendes et al. [3]	0.854	Prendes et al. [16], [18]	0.844	Proposed method	0.808
Copulas [2], [3]	0.760	Correlation [16], [18]	0.679	Chatelain et al. [6]	0.749
Correlation [2], [3]	0.688	Mutual Inf. [16], [18]	0.759	Correlation [6]	0.713
Mutual Inf. [2], [3]	0.768	Pixel Dif. [17], [18]	0.708	Ratio edge [6]	0.737
Pixel Dif. [17], [3]	0.782	Pixel Ratio [17], [18]	0.661		
Pixel Ratio [17], [3]	0.813				



Fig. 2. Pleiades/other optical VHR satellite data set. From lexicographic order; image  $t_1$ ,  $t_2$ , ground truth, filtered similarity map, final weighted binary fusion.

A comparison with different state of the art approaches [3], [16] [4] [6] [2] is summarized in Table 1. We can see that the rate accuracy of our method outperforms to the other state-ofthe-art approaches and shows the strength of our method to process a wide variety of multi modal image change detection conditions (see Figures 1, 2, and 4). We can also notice that the performance of the mono-modal methods are closely dependent on the images satellite modality *i.e.*, is affected by the sensor type using different change detection conditions, contrary to the proposed method which performs well on different multi-modal change detection conditions without applying any image preprocessing as noise reduction, radiometric correction or normalization step of the two multitemporal heterogeneous satellite image inputs. Besides, in our approach, the time complexity for the similarity map estimation (image difference) from the two heteregeneous images, remains linear with a small constant in the number of pixels, since we need to compute a temporal gradient applied on a local spatial gradient from any pixel at site s to no more than  $N_n \times N_n$  pairs of pixels  $\langle s, t \rangle$  given in a squared window  $W_n$  and the number of iterations is constant.



Fig. 3. SAR 3-looks/SAR 5-looks data set. From lexicographic order; contour superpixel image on  $t_1$  and  $t_2$ , similarity map, filtered similarity map.

#### IV. CONCLUSION

In this paper, we have proposed a novel multi-modal change detection approach based first on an imaging modalityinvariant temporal-spatial textural gradient operator that detects the common specific high-frequency pattern of each structural region existing in the two heterogeneous satellite images in order to distinguish between the significant changed and no changed areas. The resultant similarity map is then filtered out by a SLIC-based spatially adaptive filter and finally binarized with a multi-criteria fusion system based on dif-



Fig. 4. SAR 3-looks/SAR 5-looks data set. From lexicographic order; image  $t_1, t_2$ , ground truth, filtered similarity map, final weighted binary fusion.

ferent binarization schemes. Experimental results demonstrate that the proposed change detection method consistently performs well, without any image preprocessing and outperforms some complex state-of-the-art multi modal change detection methods on different types of input satellite images (CD conditions), degraded with possibly different types of noise or different levels of noise, and showing different kinds of changes due to a major urban construction and/or changes due to different types of natural phenomenon.

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