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# Change Detection in VHR Images Based on Morphological Attribute Profiles

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**Abstract**

A new approach to change detection (CD) in very high resolution remote sensing images based on morphological attribute profiles (APs) is presented. A multi-resolution contextual transformation performed by APs allows the extraction of geometrical features related to the structures within the scene at different scales. The temporal changes are detected by comparing the geometrical features extracted from the image of each date. The experiments performed on panchromatic QuickBird images related to an urban area show the effectiveness of the proposed technique in detecting changes on the basis of the spatial morphology by preserving geometrical detail.

**Index Terms**

Change detection, very high resolution images, morphological attribute profiles, remote sensing.

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# I. INTRODUCTION

Change detection is becoming one of the most important application in remote sensing. The analysis of the changes occurred on the ground is widely exploited in different application domains pertaining human activities, such as urban planning (e.g., human settlements) and environmental monitoring (e.g., deforestation). The new generation of satellite sensors has increased the availability of images with very high geometrical resolution (VHR). VHR images, which are characterized by sub-metric spatial resolutions, allow us to recognize different kinds of complex structures within a scene, such as buildings, trees, etc. In contrast to decametric geometrical resolution images, in which each pixel represents one or more objects on the ground, an object in VHR images is composed of many spatially correlated pixels. Thus, the spatial information becomes very important, especially when only panchromatic images are available, since the spectral information in these images is very limited.

In this context, we need to define strategies able to exploit all the available geometrical information for the analysis of multitemporal acquisitions. In the literature, various techniques have been proposed for change detection on VHR images. The properties of these images make pixel-based approaches ineffective. Therefore, it is necessary to develop context-based methods that can handle the information of a pixel considering its spatial neighborhood system in order to generate spatially accurate maps of the changes. Starting from this idea, the studies carried out in recent years have introduced methods based on multilevel analysis, in which an image decomposition at different levels of resolution can be used to identify objects heterogeneous in size taking into account their spatial scale [1]. However, the structural complexity of images due to the increased resolution of VHR images, often results in the presence of a high level of details which is not significant for an analysis of changes.

Morphological operators have been used in the literature in order to (i) decrease the complexity of images and (ii) to extract spatial information. These operators are based on Mathematical Morphology (MM), which is a theory for the analysis of spatial structures, based on set theory, lattice algebra and integral geometry. In image processing, MM allows for investigation of spatial features (e.g., geometry, shape, edges) of the objects in the scene by using specific morphological filters that perform a contextual image transformation. Morphological filters have been included in techniques for exploiting structural information in segmentation [2] and classification [3] tasks. Moreover, their effectiveness has also been proved in CD applications [4]. The outcome of the contextual image transformation depends on how the structures that are present in the image interact with the filter. Since in VHR images the shapes and contours of the regions are significant features, a proper filtering technique should simultaneously attenuate unimportant details (e.g., image simplification) and preserve the geometrical characteristics of the relevant regions. This property can be achieved by morphological connected filters, such as filters by reconstruction. However, since the contextual transformation is based on a sliding window (i.e., Structuring Element, SE), these filters are not suited to model other features other than the size of the objects. Morphological attribute filters are introduced in [5] for the analysis of VHR images as an extension of the common morphological filters by reconstruction based on SEs. In this case the context transformation is based on an attribute of the regions. A flexible analysis of the scene can be obtained by computing profiles with morphological attribute filters (which are called morphological Attribute Profiles, APs), leading to a richer modeling of the spatial information [5]. APs are obtained by the sequential application of progressively coarser attribute thinning and thickening transformations, which are operators defined in the mathematical morphology framework. Computing the derivative of an attribute profile, we obtain the correspondent Differential Attribute Profile (DAP), which represents the residuals between progressively more severe filters.

In this letter, we define a new approach to change detection based on APs, which is able to characterize spatial features related to the regions within the scene by performing a multi-resolution level filtering of the multitemporal images. This property allows us to define an approach capable of detecting changes in the geometrical and morphological properties of objects in multitemporal acquisitions. Furthermore, by using APs it is possible to exploit the spatial contextual relations and preserve the geometrical information in VHR images. This is done by considering the physical structural meaning of the objects in order to obtain accurate and spatially precise maps of the changes. The proposed technique is particularly effective when only panchromatic multitemporal images are available and thus geometrical information is fundamental for an effective change detection. This technique is tested on panchromatic multitemporal images of a urban area that has been damaged by earthquakes.

## II. Morphological Attribute Profiles

In this section, the concepts of attribute profiles (APs) and differential attribute profiles (DAPs) are briefly recalled. These non linear morphological operators are defined as the sequential application of morphological attribute filters. The APs and DAPs are a generalization of the conventional Morphological Profiles (MPs) and Differential Morphological Profiles (DMPs) [2], whose contextual image transformation is achieved by probing the image using SEs. In contrast, the APs perform a contextual analysis of the image considering measures computed on the regions (e.g., area, length of diagonal of the bounding box, standard deviation). This permits to obtain a richer description of the regions in the scene since the filtering is performed according to measures of their spatial, spectral, textural, etc. characteristics. Moreover, the fact that APs are based on the max-tree representation [6] renders them computationally more efficient with respect to MPs.

The definition of an attribute profile is based on the concept of granulometry, in case of opening operation, and anti-granulometry, in case of closing operation. Let us consider a family of increasing criteria [5], $T = \{T_\lambda : \lambda = 0, ..., l\}$, with $T_0 = true\ \forall X \subseteq E$, where $E$ is a subset of the image domain $\mathbb{R}^n$ or $\mathbb{Z}^n$ (usually $n = 2$, i.e., 2D images), $X$ is a connected region in the image, and $\lambda$ is a set of scalar values used as reference in the filtering procedure. Considering a greyscale image $f$ (with single tone value), which is a mapping from $E$ to $\mathbb{R}$ or $\mathbb{Z}$, the *attribute closing profile* can be defined mathematically as:

$$\Pi_{\phi^T}(f) = \left\{ \Pi_{\phi^{T_\lambda}} : \Pi_{\phi^{T_\lambda}} = \phi^{T_\lambda}(f),\ \forall \lambda \in [0, ..., l] \right\} \tag{1}$$

where $\phi^{T\lambda}(f)$ denotes the morphological attributes closing for an increasing criterion $T$. By duality, the *attribute opening profile* can be defined as:

$$\Pi_{\gamma^T}(f) = \left\{ \Pi_{\gamma^{T_\lambda}} : \Pi_{\gamma^{T_\lambda}} = \gamma^{T_\lambda}(f),\ \forall \lambda \in [0, ..., l] \right\} \tag{2}$$

where $\gamma^{T\lambda}(f)$ denotes the morphological attributes opening. An *attribute profile* is the concatenation of closing and opening profiles and is defined as follows:

By performing the derivative of the AP we obtain the *differential attribute profile* (DAP) that represents the residual of the progressive filtering and is defined as follows: If the considered criteria are non-increasing, $\phi^{T\lambda}(f)$ and $\gamma^{T\lambda}(f)$ denote an attribute thickening and thinning, respectively. Thus, analogously to opening and closing, we can obtain an AP composed by

$$\Pi(f) = \Pi_i : \begin{cases} \Pi_i = \Pi_{\phi^{T_\lambda}}, \ \ with \ \lambda = (l - i + 1) & \forall i \in [1, l] \\ \Pi_i = \Pi_{\gamma^{T_\lambda}}, \ \ with \ \lambda = (i - l - 1) & \forall i \in [l+1, 2l+1] \end{cases} \tag{3}$$

$$\Delta(f) = \Delta_i : \begin{cases} \Delta_i = \Delta_{\phi^{T_\lambda}}, \quad with \ \lambda = (l - i + 1) & \forall i \in [1, l] \\ \Delta_i = \Delta_{\gamma^{T_\lambda}}, \quad with \ \lambda = (i - l) & \forall i \in [l+1, 2l] \end{cases} \tag{4}$$

attribute thinning and attribute thickening profiles. The definition of the attribute opening profile also includes the definition of the morphological opening profile by reconstruction, since openings by reconstruction are a particular set of attribute openings.

## III. Proposed CD Technique based on Morphological Attribute Profiles

Let $X_1$ and $X_2$ be two co-registered panchromatic images acquired on the same area at the time $t_1$ and $t_2$ respectively, and $\Omega = \{w_c, w_u\}$ be the set of the classes associated with changed $(w_c)$ and unchanged $(w_u)$ pixels. In the proposed technique the detection of changes is achieved by comparing pixel-by-pixel the behavior of the attribute profiles computed on the image of each date. Even if a pixel-wise comparison is performed, by considering APs it is possible to analyze the changes according to their spatial characteristics. The basic assumption is that pixels belonging to unchanged areas, having similar spatial characteristics, result in similar profiles, whereas pixels belonging to changed areas exhibit profiles with significant differences at the considered acquisition dates due to a variation in their geometry.

The proposed change detection technique is based on three main steps (see Figure 1): 1) Application of the APs to each image; 2) Region extraction and reliable level selection by analyzing the DAPs; 3) Comparison of the APs and generation of the change-detection map. These steps are detailed in the next subsection.

### A. Computation of the Morphological Attribute Profiles

The purpose of the first step is to compute on each image the AP and the corresponding DAP. This requires the extraction of the closing and opening attribute profiles for each image. The application of the attribute profile performs intrinsically a multi-resolution analysis according to

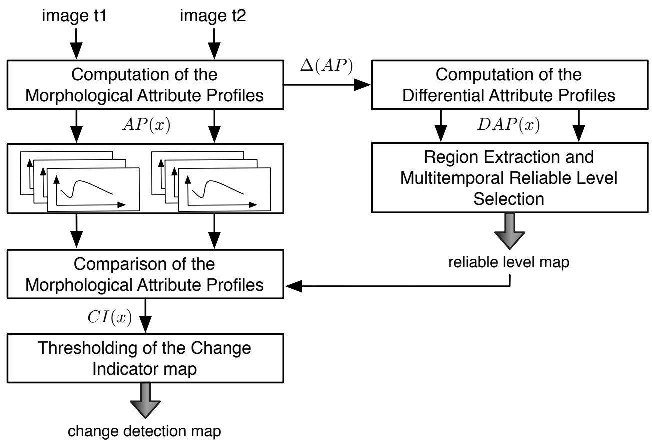



Figure 1. General scheme of the proposed technique

the defined set of scalar values $\lambda$, which are used as reference for the increasing criterion $T$ in the filtering procedure. The criterion $T$ depends on the selected attribute, and the vector of threshold values $\lambda$ has to be selected taking into account the significant range of variation of the given attribute for all regions presented in the image. The behavior of the APs is characterized by a monotonous decreasing trend of gray levels from the components of closing to opening, where the closing profile shows dark regions, and the opening profile points out the bright ones. Since the DAPs are generated by computing the derivative of APs, they show peaks in correspondence of changes in the values of APs. A DAP is calculated as the difference between a given level of the relative AP and its previous level.

## *B. Region Extraction and Reliable Level Selection*

The second step aims to extract spatial features related to the structures within the scene and to identify the reliable level in which each region is adequately represented from a perceptual point of view. This is achieved by analyzing the multilevel behavior of the DAP that shows at each level the residual, i.e., the set of all the filtered regions that do not fulfill the evaluation criteria between adjacent AP levels. The spatial features of a given region are the *standard deviation* and *spatial size* [7]. The method is based on the observation that meaningful regions are homogeneous. Assuming that a single pixel is the most homogeneous region, the joint use of the mentioned parameters ensures that a selected region labeled as meaningful will be spectrally homogeneous and as large as possible. Thus, for each region that belongs to each date, the reliable level, $R$, is computed according to the following criterion:

$$\begin{aligned} &R = \hat{n} : max\big\{M(n)\big\} \\ &with\ M(n) = D\big(n, parent(n)\big) \cdot C(n) \end{aligned} \tag{5}$$

with $n$ the level in DAP, $D(\cdot)$ the standard deviation computed between the pixels belonging to a given region of $n$ and its *parent(n)* region (i.e., the region in the previous level), and $C(\cdot)$ the area of that region. In general, a given region augments after a number of filtering steps, reaching the level in which it will merge with the surrounding ones, losing partially (or completely) its physical structural meaning. Consequently, we are interested in identifying the level value that precedes this effect. This approach is applied to both the closing and opening profiles separately, obtaining for each date a map of the reliable levels for both the closing and opening profiles. In order to obtain a unique multilevel reliable map for both closing and opening operators, we compute the maximum between the obtained reliable maps. This permits us to maximize the differences between the profiles associated to the changed areas, since the comparison of the profiles is performed up to the selected level, emphasizing the difference in the behavior of the profiles due to the change.

### *C. Comparison of the Attribute Profiles and Generation of the Change Detection Map*

In the third step the comparison of the multitemporal AP for each pixel is performed. We expect that profiles of unchanged regions will show a similar behavior, whereas profiles related to the changed areas will be characterized by a different behavior. This is true if the information related to the spatial context is included. Let us consider for instance a single pixel belonging to an unchanged building. The multitemporal profiles show a similar trend up to the level in which the building structure is merged to an adjacent region, whereas considering the profiles of subsequent levels can give different results since the information of the building structure will be lost. Thus, the context information is included in the analysis taking into consideration for each pixel a different range of profile values based on the reliable level map defined at the previous step. In addition, a normalization is applied to the AP, which is aimed at reducing the effects of radiometric variations due to the different acquisition conditions. For both the opening and closing components, the comparison of the multitemporal AP for each pixel $p$ is performed by applying (6) and (7) taking into account the range of values up to the reliable level $R$. The result is a gray-scale map, called *change indicator* (CI).

$$CI(p)_\phi = \sum_{l=1}^{R} |\Pi_{\phi_{t1}^T}(p,l) - \Pi_{\phi_{t2}^T}(p,l)| \tag{6}$$

$$CI(p)_\gamma = \sum_{l=1}^{R} |\Pi_{\gamma_{t1}^T}(p,l) - \Pi_{\gamma_{t2}^T}(p,l)| \tag{7}$$

Each component gives a CI map that shows different changes. The CI obtained by comparing the opening profiles gives information related to the changes in dark regions, whereas the CI obtained by comparing the closing profiles shows changes related to bright regions. In order to fuse all the change information in a unique CI map, the max operation is performed between the CI of each component.

$$CI(p) = max\Big\{CI(p)_\phi, CI(p)_\gamma\Big\} \tag{8}$$

where the lower values are associated with the unchanged class $w_u$, whereas the higher values identify the changed class $w_c$. A manual or automatic thresholding procedure can be then applied to the above defined change indicator in order to obtain a binary change detection map.

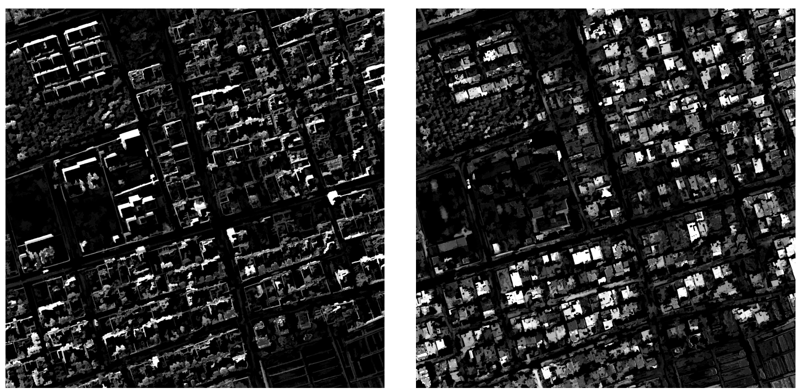
## IV. Experimental Results

The effectiveness of the proposed method is assessed on a data set that consists of multi-temporal panchromatic images acquired by the Quickbird satellite on the city of Bam (Iran) in September 2003 (Figure 2(a) and March 2004 (Figure 2(b)). A portion of 995x995 pixels of the images showing buildings is considered. After the earthquake occurred on 26th December 2003, most of the buildings were destroyed. An undamaged area characterized by some large buildings is located on the left side of the images. In order to perform a quantitative analysis of the obtained change detection results, a reference map was defined according to an accurate manual photo-interpretation of the images (Figure 5(c)). The map includes 59794 changed pixels and 112055 unchanged pixels.

Due to different acquisition seasons, the data set is affected by different illumination conditions that result in shadows differences. In order to focus our attention on changes associated with damages, the changes related to the shadows are masked after the change detection analysis and not considered during the statistical computation step. In our experiments, for both images 81-dimensional APs and consequently 80-dimensional DAPs were generated using the attribute

(a) (b)

Figure 2. Panchromatic multitemporal images of the city of Bam (Iran) acquired in (a) September 2003 and (b) March 2004.



(a) (b)

Figure 3. Change indicator maps obtained by: the closing (a) and opening (b) components.

*area* with a range of values between 0 - 2000, and a constant step increment of 50 pixels. These values are defined considering the geometry of the scene in order to perform an effective multi-resolution analysis. The result of the comparison of the APs performed by applying the relations in (6) and (7) is presented in Figure 3(a) and 3(b). For the considered data set, the CD map that refers to opening shows most of the changes occurred on bright regions mostly composed by buildings, whereas the CD map that corresponds to closing shows changes due to variation in dark regions.

Since this work aims at defining a strategy able to exploit the geometrical information also when only panchromatic images are available, the presented technique is compared to a multilevel parcel-based technique [8]. The considered multilevel parcel-based technique is based on hierarchical segmentation aimed to detect radiometric changes at different scales, where the

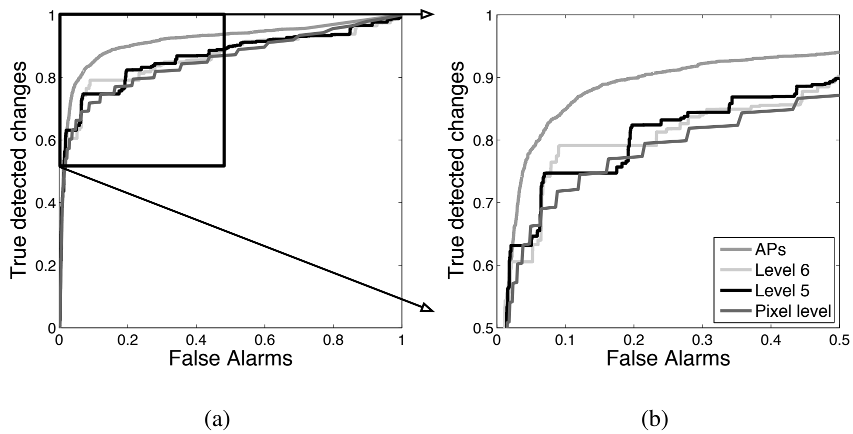



Figure 4. (a) ROC curves obtained by considering the reference single level parcel-based (the two best levels are shown: 5 and 6) and the proposed APs techniques. The performance of the pixel-level case is also shown. (b) Zoom of the area representing the best operating points.

multitemporal and spatial contexts are exploited by considering *parcels*, which are defined as homogeneous regions shared by both original images [9]. Parcels represent the local adaptive neighborhood of pixels. In the analysis we considered a six-level segmentation. Figure 4 shows the Receiver Operating Characteristic (ROC) curves obtained by the techniques considered in the reference [8]. For the parcel-based technique, each level is analyzed separately, whereas for the technique based on APs the final CI is considered. The ROC curves permit us to assess the effectiveness of the considered techniques by comparing two operating characteristics (detection rate, false alarms). Since the multilevel parcel-based technique was defined to be used on multispectral images, it is not accurate in the identification of the structures in a singular panchromatic image, decreasing the detection rate and increasing the false alarms. Figure 4 also reports the ROC curve obtained by using a simple pixel-level change detection in order to confirm the effectiveness of object-based techniques with respect to pixel-based ones.

Table I reports the quantitative results obtained by considering the reference single level and multilevel parcel-based techniques, where the latter is defined as the fusion of the single-level approach, and the proposed APs technique, in which both the components of closing and opening are considered. The thresholding of each level of resolution in the parcel-based case, and of the CI map in the APs case, is performed by considering the best operating point calculated by analyzing the relative ROC curve. A careful look at the results reported in the Table I points out the effectiveness of the proposed technique, which obtained the highest detection rate at the

Table I

CHANGE DETECTION RESULTS (IN NUMBER OF PIXELS) OBTAINED BY USING THE PIXEL-LEVEL, THE REFERENCE PARCEL-BASED (SINGLE LEVEL AND MULTILEVEL) AND THE PROPOSED APS TECHNIQUES

| **Method** | **Detected Changes** | **False Alarms** | **Missed Alarms** | **Overall Error** |
|---|---|---|---|---|
| Pixel level | 39609 | 5547 | 20185 | 25732 |
| L1 | 40906 | 5811 | 18888 | 24699 |
| L2 | 42367 | 6365 | 17427 | 23792 |
| L3 | 44351 | 10026 | 15435 | 25869 |
| L4 | 37790 | 5522 | 22004 | 27526 |
| L5 | 44668 | 7768 | 15126 | 22894 |
| L6 | 47206 | 10105 | 12565 | 22693 |
| Multilevel parcel-based | 45055 | 8473 | 14739 | 23212 |
| Proposed APs | 47346 | 6276 | 12448 | 18724 |

smallest overall error.

The change detection maps obtained by applying the multilevel parcel-based approach and the proposed technique are shown in Figure 5(b) and 5(a), respectively. The image decomposition performed by exploiting morphological attribute profiles using the attribute area permits to obtain a map that accurately shows the changed structures, preserving their geometrical information. These structures are more homogeneous and spatially precise with respect to those present in the change detection map obtained with the multilevel parcel-based approach. This is mainly caused by the limited effectiveness of the parcel-based approach when only a panchromatic image is available.

## V. DISCUSSION AND CONCLUSION

In this letter a novel technique for change detection in multitemporal VHR images based on the use of morphological attribute profiles has been presented. The sequential application of progressively coarser attribute opening/thinning and closing/thickening transformations to the

(a) (b) (c)

no-change change unlabled

Figure 5. Change detection maps of the city of Bam (Iran) obtained by using: (a) the proposed method based on APs; and (b) the reference multilevel parcel-based technique. (c) Reference map.

original images has permitted to built a multilevel attribute profile for each of them. Computing the derivative on the AP, we obtained the DAP, which shows the regions that have been filtered out at each level of the relative AP. The multilevel behavior of the DAP, permits the extraction of connected regions (i.e., objects in the scene of the image) at different levels of the profile. Then, for each pixel a region-based analysis has been performed in order to detect the most reliable level of resolution, for the APs comparison. The method has been applied to two panchromatic images of the city of Bam (Iran) by considering the *area* attribute and defining a family criteria $T$ (i.e., the values taken as reference in the filtering process) in order to perform an adaptive multi-resolution analysis. Moreover it is general and can be applied by using also different attributes.

The qualitative and quantitative analysis on the obtained results proved the effectiveness of the morphological attribute profiles in modeling the spatial context information by exploiting geometrical features. The comparison of the presented approach with multilevel parcel-based technique has shown the superiority of the presented method in detecting areas that changed their geometrical properties during the two acquisitions independently from spectral variations. This is due to the capability of this method to model the geometry of the objects.

As a final remark, it is worth noting that even if the proposed approach has been applied to panchromatic images, it can be easily extended to be used with multispectral images, using the concept of Extended Attribute Profiles [10].

## ACKNOWLEDGMENT

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