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Change Detection in VHR Images Based on Sparse Representation of Morphological Attribute Profile

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Abstract

Change information of the earth's surface is becoming more and more important in monitoring the local, regional and global resources and environment. For this reason , Change Detection has an increasing importance in the field of remote sensing. The image acquired by periodical passes of remote sensing satellites over the same areas permit a regular analysis of the changes that occurred on the ground. In this paper a new approach to change detection in very high resolution remote sensing images based on sparse representation of morphological attribute profile is presented. Attribute profiles allows the extraction of geometrical features related to the structure within the scene at different scales. The temporal changes are detected by comparing the geometrical features extracted from the image on each date. Morphological operators have been used in order to decrease the complexity of the image and extract spatial information. The operators are based on mathematical morphology, which is a theory for the analysis of spatial structures based on set theory.

Keywords— *Change Detection, sparse representation, morphological attribute profile, remote sensing , very high rersolution imahges.*

INTRODUCTION

Human development and natural forces continuously alter landscapes. The analysis of these variations is necessary in many tasks such as monitoring land use, risk assessment, and the analysis of worldwide population growth and development. For this reason, change detection (CD) has an increasing importance in the field of remote sensing. The images acquired by periodical passes of remote sensing satellites over the same areas permit a regular analysis of the changes that occurred on the ground.

In this context, we need to define strategies that are able to exploit all the available geometrical information for the analysis of multitemporal acquisitions. In the literature, various techniques have been proposed for CD 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 object that are heterogeneous in size, taking into account their spatial scale[3] . 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. Recently, sparse representation have become a widely popular approach in the context of remote sensing data processing [4].

In Section II, the overview of the characteristics of morphological attribute profile is discussed. The next section describes and sparse representation classification method of morphological APs. The proposed approach is then described in Section III. The Section IV presents the simulation results. Finally, Section V draw the conclusion of this paper.

MORPHOLOGICAL APs

The APs and DAPs are a generalization of the conventional morphological profiles (MPs) and differential MPs [5], 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, and standard deviation). This permits obtaining a richer description of the regions in the scene since the filtering is performed according to measures of their spatial, spectral, textural, and other 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 AP is based on the concept of granulometry, in case of opening operation, and antigranulometry, in case of closing operation. Let us consider a family of increasing criteria $T = \{T_\lambda : \lambda = 0, . . . , l\}$, with T_0 = true $\forall X \subseteq E$, where E is a subset of the image domain R^n or Z^n (usually $n = 2$, i.e., 2-D images), X is a connected region in the image, and λ is a set of scalar values used as reference in the filtering procedure. Considering a gray-scale image f (with single tone value), which is a mapping from E to R or Z, the *attribute closing profile* can be defined mathematically as

$$\Pi_\varphi^T(f) = \{\Pi_{\varphi\ \lambda}^T : \Pi_{\varphi\ \lambda}^T = \varphi^T{}_\lambda(f)\ \forall \lambda \in [0, . . . , l]\} \quad (1)$$

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

$$\Pi_\gamma^T(f) = \{\Pi_{\gamma\ \lambda}^T : \Pi_{\gamma\ \lambda}^T = \gamma^T{}_\lambda(f)\ \forall \lambda \in [0, . . . , l]\} \quad (2)$$

where $\gamma^{T\lambda}(f)$ denotes the morphological attributes opening. An *AP* is the concatenation of closing and opening profiles . By performing the derivative of the AP, we obtain the *DAP* that represents the residual of the progressive filtering.

SPARSE REPRESENTATION CLASSIFICATION

In sparse representation models, the idea is that all the test samples can be represented by a (sparse) linear combination of atoms from an overcomplete training dictionary. Let us assume that we have a training dictionary, which is denoted by$\mathbf{A} = \{\mathbf{x}_1, . . . , \mathbf{x}_n\} \in R^{n\times l}$, with n samples of l dimensions, comprising a total of c distinct classes, and that the dictionaryis organized as $\mathbf{A} = [\mathbf{A}_1, . . . ,\mathbf{A}_c]$, where $A_k = \{X_{k_1}, \ldots\ldots, X_{k_{n_k}}\}$

A typical scenario in supervised classification of remote sensing data is that, normally, we have a (limited) set of labeled training samples for each class, and then, we use part of this information to train a classifier, which is then tested with the remaining labeled samples. Let $\mathbf{x}_i$ be a test sample, which can be appropriately represented by a linear combination of the atoms (training samples) in the dictionary **A** as follows:

$$\mathbf{x}_i \approx \mathbf{x}_1\alpha_1 + \mathbf{x}_2\alpha_2 + \cdots + \mathbf{x}_n\alpha_n$$

$$= [\mathbf{x}_1\ \mathbf{x}_2 . . . \mathbf{x}_n][\alpha_1\ \alpha_2 . . . \alpha_n]^T = \mathbf{A}\boldsymbol{\alpha} + \epsilon \quad (3)$$

where $\boldsymbol{\alpha} = [\boldsymbol{\alpha}^T{}_1 , . . . , \boldsymbol{\alpha}^T{}_c]^T$ is an n-dimensional sparse vector (i.e., most elements of $\boldsymbol{\alpha}$ are zero), $\boldsymbol{\alpha}_i$ is the vector of regression coefficients associated with class i, and ϵ is the representation error. The central assumption in our approach is that $\mathbf{x}_i$ is well approximated by$\mathbf{A}_i\boldsymbol{\alpha}_i$, i.e., $\boldsymbol{\alpha}_j = 0$, for $j \neq i$. Under this condition, the classification of $\mathbf{x}_i$ amounts to detect the support of $\boldsymbol{\alpha}$.

In order to obtain a sparse representation for a test sample $\mathbf{x}_i$ (which hereinafter is assumed to be obtained using an EMAP representation), we need to obtain a sparse vector $\boldsymbol{\alpha}$ satisfying $\mathbf{x}i = \mathbf{A}\boldsymbol{\alpha} + \epsilon$. The sparse vector $\boldsymbol{\alpha}$ can be estimated by solving the following optimization problem:

$$\hat{\boldsymbol{\alpha}} = \text{argmin} \|\boldsymbol{\alpha}\|_0 \text{ subject to } \mathbf{x}_i = \mathbf{A}\boldsymbol{\alpha} \quad (4)$$

where $\|\boldsymbol{\alpha}\|_0$ denotes the ℓ_0-norm, which counts the nonzero components in the coefficient vector. Due to the presence of noise and a possible modeling error, the optimization (4) is often replaced by

$$\hat{\boldsymbol{\alpha}} = \text{argmin} \|\boldsymbol{\alpha}\|_0 \text{ subject to } \|\mathbf{x}_i - \mathbf{A}\boldsymbol{\alpha}\|_2 \leq \boldsymbol{\delta} \quad (5)$$

where δ is an error tolerance.

PROPOSED METHOD

Let X_1 and X_2 be two co-registered panchromatic images acquired on the same area at the times 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 APs 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 CD technique is based on three main steps (see Fig. 1): 1) application of the APs to each image; 2) region extraction and reliable level selection by analyzing the DAPs; and 3) comparison of the APs and generation of the CD map.

These steps are detailed in the next subsection.

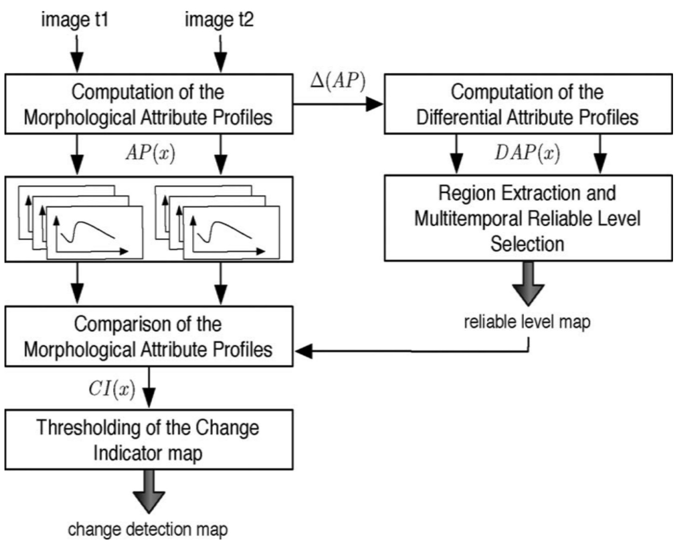


Figure 1: General scheme of the proposed technique.

A. Computation of the Morphological APs

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 APs for each image. The application of the AP performs intrinsically a multi-resolution analysis according to the defined set of scalar values λ, 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 λ 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:

$$R = \hat{n} : \max \{M(n)\} \text{ with } M(n) = D(n, \text{parent}(n)) \cdot C(n) \qquad (6)$$

with n as the level in DAP, $D(\cdot)$ as 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 $C(\cdot)$ as 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 APs and Generation of the CD 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 multi-temporal AP for each pixel p is performed by applying (7) and (8), taking into account the range of values up to the reliable level R. The result is a gray-scale map, called *change indicator* (CI)

$$\mathrm{CI}(p)_{\varphi} = \sum_{l=1}^{R} \left| \prod_{\varphi_{t1}^{T}}(p,l) - \prod_{\varphi_{t2}^{T}}(p,l) \right| \qquad (7)$$

$$\mathrm{CI}(p)_{\gamma} = \sum_{l=1}^{R} \left| \prod_{\gamma_{t1}^{T}}(p,l) - \prod_{\gamma_{t2}^{T}}(p,l) \right| \qquad (8)$$

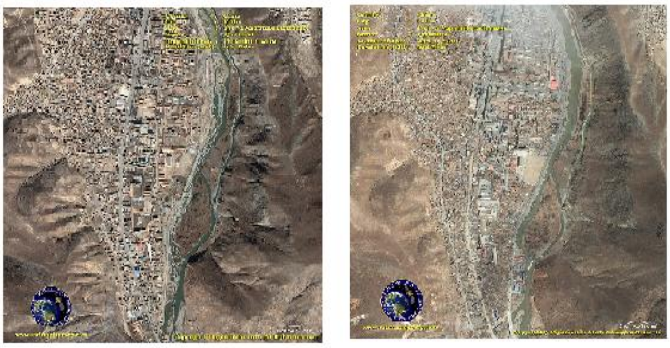
Each component gives a CI map that shows different changes. The CI obtained by comparing the opening profiles gives information related to the changes in dark regions, whereas the CI obtained by comparing the closing profiles shows changes related to bright regions. In order to fuse all the change information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

$$\mathrm{CI}(p) = \max\{\mathrm{CI}(p)_{\varphi}, \mathrm{CI}(p)_{\gamma}\} \qquad (9)$$

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 earlier defined CI in order to obtain a binary CD map.

SIMULATION 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 Yushu(China) in September 2004 [Figure 2(a)] and april 2010[Figure. 2(b)]. A portion of 995 × 995 pixels of the images showing buildings is considered. After the earthquake occurred on April 2010, most of the buildings were destroyed. An undamaged area characterized by some large buildings is located on the left side of the images



(a) (b)

Figure 2: Panchromatic multitemporal images of the city of Yushu (China) acquired in (a) September 2004 and (b) april 2010.

Due to different acquisition seasons, the data set is affected by different illumination conditions that result in shadow differences. In order to focus our attention on changes associated with damages, the changes related to the shadows are masked after the CD analysis and not considered during the statistical computation step. In our experiments, for both images, 81-D APs and, consequently, 80-D DAPs were generated using the attribute *area* with a range of values between 0 and 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 multiresolution analysis. For the considered data set, the CD map that refers to opening shows most of the changes that occurred on bright regions mostly composed by buildings, whereas the CD map that corresponds to closing shows changes due to variation in dark regions.

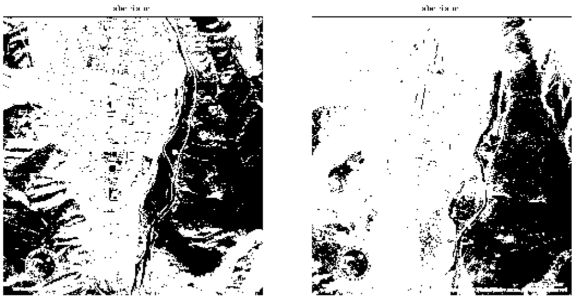


Figure 3: Dilated version of the input image

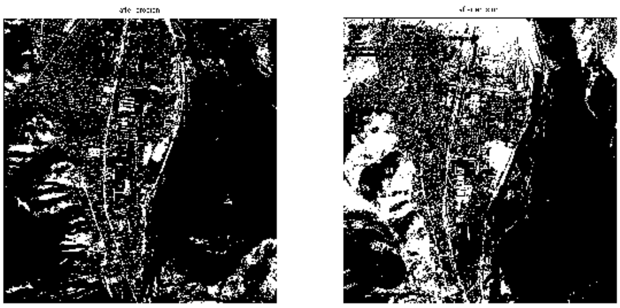


Figure 4 : Eroded version of the input image

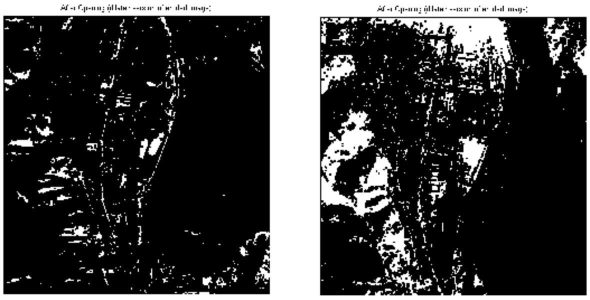


Figure 5: opening

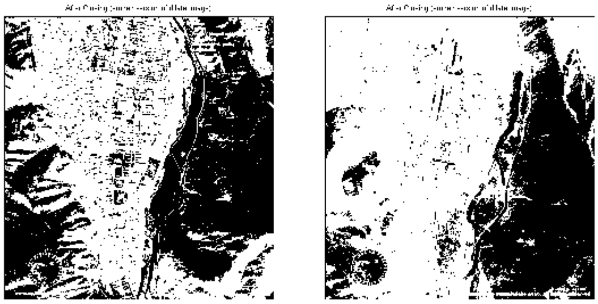


Figure 6 : Closing

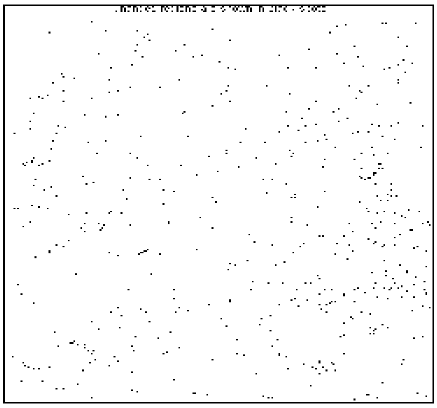


Figure 7: Change Detection map

CONCLUSION

This paper deals with an algorithm for change detection in VHR image based on sparse representation of morphological attribute profile. The sequential application of progressively coarser attribute opening/thinning and closing/thickening transformations to the original images has permitted building a multilevel AP 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.This poaper also combines the advantages of sparse representation and the rich structural information provided by EMAPs, can appropriately exploit state-of-the-art classification results. the inherent sparsity present in EMAPs in order to provide 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 AP comparison. The method has been applied to two panchromatic images of the city of yushu (china) by considering the *area* attribute and defining a family criterion *T* (i.e., the values taken as reference in the filtering process) in order to perform an adaptive multiresolution analysis. Moreover, it is general and can be applied by using also different attributes.

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