Change Detection Using an Effective Object-based Approach

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Abstract. Change detection in imagery is quite useful generally but it has particular value in the remote sensing context. The conventional change detection methods based on pixel, which are appropriate to the low/middle resolution images, could not model the high-resolution imagery very well. In this case the object-based change detection techniques become effective. The main advantage of the object-based approaches is that the digital image is no longer considered as a grid of pixels, but as a group of regions, called image objects. In this research, an effective change detection method based on image segmentation is performed. The proposed method involves filtering bands of a multispectral image with a bilateral filter, and obtaining the changed objects by means a method based on a region growing approach. For the analysis of the quality of the resulting segmentation, a measure of intrasegment homogeneity (variance indicator) and one of intersegment heterogeneity (Moran index) have been used. The changed segments are placed into the multitemporal images to identify the nature of change (from-to). In urban expansion areas, the results are promising and show that object-oriented systems facilitate the interpretation of change detection results derived from commercial satellite data.

Keywords. Change detection, filtering, region-growing algorithm, segmentation quality evaluation, from-to information, urban expansion areas.

1. Introduction

Updating land cover maps and the management of natural resources need information about the earth’s surface changes. This may be obtained by visiting sites on the ground and/or extracting it from remotely sensed data. Change detection and classification are now typically aimed at providing updated thematic maps that are very rich in detail; the extraction of specific land coverage information is often required for the updating of Geographical Information Systems.

Change detection in imagery is quite useful generally but it has particular value in the remote sensing context. Multitemporal images allow one to follow the evolution in time of a given region of interest by means of change detection techniques, and therefore represent valuable tools. A variety of digital change detection techniques [1] [2] has been developed in the past decades, like result of the many researchers studies. Basically, the different algorithms can be grouped into the following categories: algebra, change vector analysis, transformation, classification, and hybrid methods. However, the conventional change detection methods based on pixel, which are appropriate to the low/middle resolution images, could not model the high-resolution imagery very well. In this case the pixels are not spatially independent, resulting in the conventional change detection techniques becoming ineffective [3].

The main advantage of the object-based approaches is that the digital image is no longer considered as a grid of pixels, but as a group of regions, called image objects. Using this kind of representation, one can tackle the problem of using local criteria for change detection, as these features can be computed within the boundaries of an image object. This can be usually performed as a
processing step for many image interpretation applications, for example, in some change detection methodologies. In these cases, the aim of change detection is to find objects in pairs of co-registered images that correspond to real changes on the ground.

On the other hand, in many landscape studies one main objective is to obtain homogeneous landscape units or region, on which one can assess the superficial changes observed through established time. In these cases, the object-oriented strategy is a best way to perform change analysis [4]. Also in the analysis of the change detection of man-made objects on high-resolution images or urban data updating, the object-based methods are specially recommended with many successful case studies reported [5].

The critical challenge of the object-oriented method is the object detection and segmentation, which is normally defined as the subdivision of an image into homogeneous groups such that each region is homogenous but the union of no two adjacent regions is heterogeneous [6]. In remote sensing, it is often viewed as an aid to landscape change detection and land use/cover classification.

In this research, an effective change detection method based on image segmentation is performed. The proposed method involves filtering bands of a multispectral image with a bilateral filter [7], and obtaining the changed objects by means a region growing approach [8]. For the measurement of the quality of the resulting segmentation, a measure of intrasegment homogeneity (variance indicator) and one of intersegment heterogeneity (Moran index) have been used. To establish a comprehensive change analysis methodology it is further necessary to extend the presented detection approach by adding the change assessment capabilities, i.e. the possibility to indicate what kind of change has occurred. With this objective, the segments are placed into the multitemporal images to identify the nature of change (from-to) and extracted to update the thematic maps. In urban expansion areas, the results are promising and show that object-oriented systems facilitate the interpretation of change detection results derived from commercial satellite data.

2. Methods

From the point of view of the observed phenomena, one can distinguish two types of changes whose nature is rather different: the abrupt changes and the progressive changes, which can eventually be periodic. From the data point of view, one can have: 1) Image pairs before and after the event (the applications are mainly the abrupt changes), and 2) Multi-temporal image series.

This study is focused on the problem of detecting abrupt changes between a pair of images, which may be summarizes as follows: Let I1, I2 be two images acquired at different dates t1, t2 where t1 < t2; we aim at producing a thematic map, which shows the areas where changes have taken place and the nature of change (from-to).

The rationale of the proposed approach is to extract regions from I1 by segmentation based on a region-growing algorithm (including objective segmentation evaluation), and then the obtained segments are placed in I2. Then unsupervised change detection analysis was used to detect changes in the pair of segmented images. Finally the changed segments are classified and labeled by a supervised Minimum Distance method.

It should be pointed that radiometric correction of original images isn’t necessary for all change detection methods. For those change detection algorithms based on feature, object comparison, radiometric correction is often unnecessary. In addition, it is unnecessary to conduct atmospheric correction before the change detection of post-classification comparison [9].

On the other hand, precise registration to the multi-temporal images is required by many change detection methods. Although geometrical registration of high accuracy is necessary to the pixel-based methods, it is unnecessary for object-oriented methods. In this cases, can be employed a “buf-
fer detection” algorithm [10] but at the present research has been done into how much registration accuracy error is tolerable for each kind of object.

A more detailed description of all the steps of the proposed approach is elaborated in the following paragraphs.

2.1. Scene study

For the present work there has been chosen a geographical area placed in the Madrid Community (Spain), which corresponds to a Mediterranean ecosystem forest principally composed by oaks, bushes and meadows. Two aerial images from June 2001 (I1) and June 2005 (I2) were used in this research. The visual comparison of the images points out some of the problems related to high resolution satellite imagery. Due to solar conditions at both acquisition times the objects are mismatched and form different shadows as is shown in Fig. 1.

![Figure 1: Multi-date RGB aerial imagery of the study area.](image)

Near-anniversary dates were selected in order to reduce the seasonality effect. In the scenes that represent partially degradation Mediterranean landscape, built-up structures and road infrastructures, industrial or residential areas coexist with extensions of natural Mediterranean forest. These aerial images have a spatial resolution of 0.5 m and cover an area of the order of 36.8 km² (384 x 384 pixels). The top left corner of these images are placed at 428446.43E/4474498.22N, (UTM geographic coordinates, h30).

2.2. Segmentation process

The minimized unit of object-level change detection approaches is the object, which is extracted by segmentation. This research proposes the segmentation of I1 (old image) based on a region-growing algorithm [8] with an initialization step where the image is filtered by means of a bilateral filter [7]. The main advantage of using bilateral filter is the growth of large and homogeneous regions.

The region growing algorithm starts by choosing a (or some) starting point or seed pixel. The most habitual way is to select these seeds by randomly choosing a set of pixels in the image, or by following a priori set direction of scan of the image. Once seeds have been generated, the region grows by successively adding neighboring pixels that are similar, according to a certain homogeneity criterion, increasing step by step the size of the region. In our approach the criterion is that the difference between the pixel and the average of the region is less than a user-specified value called similarity threshold. In order to compute this difference, the Euclidean Distance was used considering all bands in the image. This distance metric can be termed as similarity measure [11] and among all the image metrics, it is the most commonly used because it is inexpensive to compute compared with other distances [12], noise resistant (because it averages samples across all spectral bands), and reversible.
The growing process is continued until a pixel not sufficiently similar to be aggregated is found. It means that the pixel belongs to another object and the growing in this direction is finished. When there is not any neighboring pixel which is similar to the region, the segmentation of the region is complete. One unfortunate artifact of most image segmentation algorithms is that they tend to leave behind a significant number of small regions, that typically correspond either to transition pixels (such as edges along borders between regions), or to objects that are too small to be resolved at the spatial resolution of the image. This problem is known as over-segmentation and to overcome it, a region-merging algorithm will be applied.

The region merging algorithm used in this study includes two main stages. In the first stage all regions with area (number of pixels) smaller or equal than 5 (this parameter has been chosen after several experiments) will be eliminated by merging them with its most similar neighbor without taking into account the homogeneity criterion. This step is important to avoid very small regions caused by noise present in images. Again, the Euclidean Distance will be used as similarity measure but in this case the average of both regions will be used in order to compute it.

In the second stage all regions with area smaller than a user-specified value called population minimum will be eliminated by merging them with its most similar neighbor. The difference with the previous step is that the homogeneity criterion established in the region growing stage must be satisfied too.

It is critical to have a criterion that enables the quality of a segmentation to be evaluated. We consider that segmentation has two desirable properties: each of the resulting segments should be internally homogeneous and should be distinguishable from its neighborhood. Our segmentation quality evaluation combines a variance indicator that expresses the overall homogeneity of the regions and a spatial autocorrelation indicator that detects separability between regions. The intrasegment variance of the regions is calculated by the equation 1, where \( \sigma^2 \) is the variance and \( a_i \) is the area of region \( i \).

\[
\sigma^2 = \frac{\sum_{i=1}^{n} d_i \sigma_i}{\sum_{i=1}^{n} a_i}
\]

To assess the intersegment heterogeneity, it is used Moran’s I autocorrelation index, which measures the degree of spatial association as reflected in the data set as a whole. In this case, Moran’s I is expressed by equation 2, where \( n \) is the total number of regions, \( w_{ij} \) is a measure of the spatial proximity, \( y_i \) is the mean grey value of region \( R_i \), and \( y \) is the mean grey value of the image. Each weight \( w_{ij} \) is a measure of the spatial adjacency of regions \( R_i \) and \( R_j \). If regions \( R_i \) and \( R_j \) are adjacent, \( w_{ij} = 1 \). Otherwise, \( w_{ij} = 0 \).

\[
I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (y_i - \bar{y})}{(\sum_{i=1}^{n} (y_i - \bar{y})^2)(\sum_{i \neq j} w_{ij})}
\]

2.3. Object-Oriented change detection analysis

Change detection techniques can be broadly grouped into three general types: 1) Post Classification Comparison: the principle of this approach is to obtain two land-use maps independently for each date and comparing them, 2) Joint classification: it consists in producing the change map directly.
from a joint classification of both images, and 3) Simple detectors: it consists in producing an image of change likelihood (by differences, ratios or any other approach) and thresholding it in order to produce the change map [13]. Because of its simplicity and its low computation overhead, the methodology introduced in this study is based on this third strategy.

It should be noted that, at this point, we have two images where the segments obtained from I1 (old image) have been placed over I2 (recent image). Each object in the pair of images is represented by its mean and standard deviation value for all spectral bands considered.

In this context, considering a segment \( S \) in I1 and its corresponding segment \( S' \) in I2, \( S \) is considered as a changed segment if it satisfies the following two conditions: 1) comparison based on its means, which is performed by the difference, ratio or local correlation method, is less than a threshold value obtained by Otsu’s method [14], and 2) comparison based on its standard deviation, which is performed by the difference method, is less than a 10% of the maximum standard deviation.

2.3.1. Mean Difference

The Mean Difference change indicator \( S_D \) of a segment \( S \) is expressed by equation 3, where \( \bar{S} \) is the mean value of the segment in I1 and \( \bar{S}' \) is the mean value of the same segment placed in I2. It should be noted that the algorithm is robust to noise because the segment’s mean is computed from a set of pixel values instead of using a single pixel value.

\[
S_D = |\bar{S} - \bar{S}'| \tag{3}
\]

2.3.2. Mean Ratio

In this case, the Mean Ratio change indicator \( S_R \) of a segment \( S \) is similar to the previous one except that it uses a ratio instead of the difference. In order to have a bounded and normalized detector the expression given by equation 4 is used [13].

\[
S_R = 1 - \min \left( \frac{\bar{S}'}{\bar{S}}, \frac{\bar{S}}{\bar{S}'} \right) \tag{4}
\]

2.3.3. Local Correlation

It will be demonstrated that a piecewise correlation between two multispectral image data sets can provide valuable information regarding the location and characteristics of change [15]. The correlation information derived from the neighborhood of a segment contains valuable change information associated with a central segment and its contextual neighbors.

The Local Correlation change indicator \( S_{LC} \) of a segment \( S \) is expressed by equation 5, where \( N \) is the total number of neighbors of the segment \( S \) considering itself, \( S_i \) is the mean value of segment \( S_i, \bar{S}_N \) is the mean value of the neighborhood of \( S, \sigma_N \) is the standard deviation of the neighborhood of \( S, S' \) is the mean value of segment \( S', \bar{S}_N' \) is the mean value of the neighborhood of \( S' \) and \( \sigma_N' \) is the standard deviation in the neighborhood of \( S' \).

\[
S_{LC} = \frac{1}{N} \sum_{i=1}^{n} \left( S_i - \bar{S}_N \right) \frac{\left( S'_i - \bar{S}'_N \right)}{\sigma_N \sigma'_N} \tag{5}
\]
2.4. Classification process

Finally, the segments are classified and labeled by a minimum distance classifier because it works well when the values to be classified are completely different in nature, such as the attributes of the objects generated in the segmentation. This algorithm computes the Euclidean distance from the object to be classified to all objects in the training set and assigns it to the class of the most similar training object. In this investigation, the feature considered for classification is the change indicator obtained by means of the methods described above.

The reference samples constitute a total of 17939 pixels (12.16%), selected and identified according to the visual interpretation of the bi-temporal aerial imagery. It should be noted that only changed segments obtained after applying Otsu’s thresholding method are classified in one of the following change classes: bare land to paved parking, bare land to paved road, vegetation to built-up and vegetation to paved parking.

3. Results

The percentage of changed pixels per class and unchanged pixels is shown in Table 1. Generally, the results obtained for the three methods are similar from this point of view. Regardless of the method adopted for the change detection, it is observed that the main change is given for “Vegetation to Paved Parking” class since the most of the vegetation pixels have changed to Paved Parking pixels. On the other hand, the main difference between the Local Correlation method and the other two methods occurs for the “Bare land to Paved Road” class and this may indicate that this method has problems to detect changing pixels belonging to this class.

<table>
<thead>
<tr>
<th>Classes / Method</th>
<th>Mean Difference</th>
<th>Ratio of Means</th>
<th>Local Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bare land to Paved parking</td>
<td>4.9 % (7282)</td>
<td>6.7 % (10027)</td>
<td>0.7 % (1163)</td>
</tr>
<tr>
<td>Bare land to Paved road</td>
<td>6.4 % (9576)</td>
<td>4.6 % (6879)</td>
<td>5.3 % (7938)</td>
</tr>
<tr>
<td>Vegetation to Built-up</td>
<td>2.6 % (3856)</td>
<td>2.9 % (4384)</td>
<td>5.5 % (8158)</td>
</tr>
<tr>
<td>Vegetation to Paved Parking</td>
<td>24.5 % (36273)</td>
<td>28.5 % (42170)</td>
<td>22.2 % (32825)</td>
</tr>
<tr>
<td>Unchanged</td>
<td>61.47 % (90649)</td>
<td>56.9 % (83996)</td>
<td>66 % (97372)</td>
</tr>
</tbody>
</table>

In order to interpret the ideas presented above visually, the Fig. 2 is showed. In the first row, the two bi-temporal input images I1, I2 are shown after applying bilateral filter. The second row shows the segmentation selected for I1, which gets the best objective evaluation parameters described in section 2.2, and the result of placing these segments in I2. The consensus values obtained for these parameters, specifically the overall homogeneity of the segments is 79.3 and the spatial autocorrelation is 0.3, indicate that the resulting segments are homogenous and different from each other.

In the last three rows, the results obtained with the three change detection methods are shown. From left to right, image of change likelihood, change binary map after applying Otsu’s thresholding and changed segments classification (from-to). It should be noted that the image of change likelihood shows the most meaningfully changed segments with lighter values and unchanged segments with darker values.

Visually, the difference and ratio methods obtain very similar results and show a better behavior for identifying the nature of change (from-to), while the local correlation method is more efficient to detect meaningfully changes but has problems to detect changing pixels belonging to the class “Bare land to Paved Road” as mentioned above.
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Figure 2: Object-based change detection analysis.
4. Conclusions

This paper presents an object oriented change detection approach which includes three different methods for change extraction. The experimental results indicate that this methodology can be used without radiometric correction of the bi-temporal input images in order to obtain satisfactory results.

On the other hand, the local correlation used as change indicator can improve the detection of meaningfully changes compared with other typical methods based on differences and ratios.

The main limitation of this methodology based on segmenting the old image and place the segments obtained in the recent image is due to the fact that the segmentation of this second image is being guided. Therefore, in the future work, a new approach based on obtaining two segmentations independently for each image and comparing them will be studied.

References