Application of superpixel segmentation and morphological projector for structural changes detection in remote sensing images

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Abstract. Detection of structural changes in images is one of the important tasks of remote sensing (RS) data thematic analysis. The effective way to solve it is applying the Pyt'ev’s morphological projector to the pair of images of the same scene acquired on different dates. The main advantage of this method is its invariance to global brightness transformations, which in the case of RS images correspond to different parameters of the atmosphere or the different values of the brightness-contrast ratio of the scene. However, the classical Pyt'ev’s morphological projector and its regularized versions do not take into account the spatial connectivity of image samples. As a result, they ignore the textural features of images. In this article, we suggest the algorithm of structural changes detection based on superpixel segmentation and Pyt'ev’s morphological projector that takes into account local characteristics of the image pixels. In the experimental research, we analyzed the accuracies of the proposed and classical Pyt'ev’s structural change detection methods using simulated and real RS images. The comparison of two algorithms showed that the proposed method is more robust to the additive white Gaussian noise (AWGN) at different values of signal-to-noise (SNR) ratio. Additionally, the experiments with nonlinear brightness distortions (vignetting) of one of the pair of images demonstrated that the proposed method has lower false positive rates than the classical one.

1. Introduction

Detection of the structural changes in images is an important image processing task. It consists of analyzing a pair of multi-temporal images of the same scene in order to detect the changes in the shape and position of the objects in the scene as well as their appearance or disappearance. In other words, structural changes are changes in the geometric properties of a scene that are not modeled by additive noises and global intensity transformations [1]. The result of the change detection operation may be represented as an image, in which each pixel contains a probability estimate of its change [2], or as a binary image (map of changes) [3].

In Earth remote sensing (ERS) images the presence of structural changes indicate the landscape changes caused by anthropogenic activity, climatic or ecological processes. This fact makes a change detection task very significant for applications of the complex analysis of the examined areas.
There are a large number of techniques for change detection in ERS images [4-12]. Since in practice it is desirable to provide the invariance of the change detection algorithm to various global intensity transformations and additive noise and the Pyt'ev's morphology [13] provides a mathematical formalization for comparing images by their form, the algorithms based on the Pyt'ev’s morphology are of particular interest.

Recent studies [1, 5, 14, 15] show that the major drawbacks of existing structural change detection methods based on the Pyt'ev’s morphology are the reduced performance dealing with the high level of additive noise and with the global nonlinear transformations of image intensity as well as the complexity of automatically estimation of the optimal change detection threshold. Obviously, the cause of the problems lies in ignoring the spatial relationships in the image by the classical Pyt'ev’s morphological projector.

In this paper, we propose the algorithm of structural change detection based on superpixel segmentation and the Pyt'ev’s morphological projector that overcomes the described limitations. We also suggest an efficient threshold selection algorithm for change detection. The experimental results show that our scheme outperforms the classical scheme based on the Pyt'ev’s projector and provides the less error of false detection in case of nonlinear global intensity transformations (by the example of vignetting) or noise distortions of the original images.

The rest of this paper contains the description of the classical and proposed change detection algorithms based on the Pyt'ev’s morphological projector and gives their comparative analysis on simulated and real ERS images.

2. Classical structural change detection algorithm based on the Pyt'ev’s projector

Let $f$ be the image defined on a set of pixels $X \subset \mathbb{R}^2$ and $f(x)$ be an intensity that is a function of the image pixel coordinates $f : X \rightarrow \mathbb{R}$.

The input data of the classical structural change detection algorithm based on the Pyt'ev’s projector [16] is a pair of images $f$ and $g$ of the same scene acquired on different dates. The images $f$ and $g$ are supposed to have the same size $N \times M$. The output data is an image of changes $R_e$ in which each pixel value is 1, if the structural change in the pixel was detected, and 0, if there is no structural change in it.

The change detection algorithm can be described as follows [16].

1. Calculate the projection $P_f g$ of the image $g$ on the form of the image $f$ by (1) and similarly the projection $P_g f$ of the image $f$ on the form of the image $g$.

$$
P_f g = \sum_{i \in X} \sum_{x' \in \chi_i'} \chi'_i(x') \chi_i'(x')
$$

where $\chi'_i(x)$ is the indicator function of the pixels with the intensity values $f(x)=i$ i.e.:

$$
\chi'_i(x) = \begin{cases} 
1, & \text{if } f(x) = i \\
0, & \text{otherwise}
\end{cases}
$$

2. Calculate the difference images $R_{fg} = |P_f g - g|$ and $R_{gf} = |P_g f - f|$.

3. Calculate the common difference image $R = \max(R_{fg}, R_{gf})$.

4. Process the image $R$ with the threshold value $T$ to get the resulting difference image $R_t$:

$$
R_t = \begin{cases} 
1, & R \geq T \\
0, & \text{otherwise}
\end{cases}
$$

It is obvious that the classical change detection algorithm based on the Pyt'ev’s morphological projector considers the image structure as the regions with the same intensity and detects changes in
those regions where the intensity value in the first image corresponds to the several intensity values in the second image.

3. Structural change detection algorithm based on the Pyt'ev's projector and superpixel segmentation

In the Pyt'ev's morphological projector (1) the characteristic functions $\chi_i(x)$ of the subsets of pixels with the same intensity $f(x)=i$ represent the image structure or image form. However, this method of specifying the structure does not take into account the spatial relationships in the image.

In this article, we propose to use a superpixel representation of the images in order to describe image structure. This approach allows taking into account the local spatial correlation relationships of the image pixels.

A superpixel stands for a spatially connected and intensity-homogeneous set of the image pixels $S_j$ where $j=1,...,N$ is the superpixel number. Thus, the intensities of any pair of pixels $x_1$ and $x_2$ belonging to the same superpixel differ from each other by no more than $2\varepsilon$ i.e. the inequality (4) is valid:

$$|f(x_2) - f(x_1)| \leq 2\varepsilon.$$  \hspace{1cm} (4)

We propose to define the image structure as a set of characteristic functions $\chi_i(x)$ determined by the set of image superpixels $S\equiv\{S_j\}_{j=1,...,N}$:

$$\chi_i(x) = \begin{cases} 1, & \text{if } x \in S_j, \\ 0, & \text{otherwise} \end{cases}, \quad \forall i \neq j, \quad S_j \cap S_i = \emptyset, \quad \bigcup_j S_j = X.$$  \hspace{1cm} (5)

Then the following modified Pyt'ev's projector can be applied to detect structural changes:

$$\hat{P}_j g = \sum_{x \in S_j} g(x') \chi_i(x') \sum_{x \in S_j} \chi_i(x') \chi_i(x).$$  \hspace{1cm} (6)

The morphological projector $\hat{P}_j g$ presents an averaging of the intensity values of the image $g$ within the spatially connected regions of the image $f$ with homogeneous intensity values. The projector $\hat{P}_g f$ is calculated in a similar way and presents an averaging of the intensity values of the image $f$ within the spatially connected and intensity homogeneous regions of the image $g$.

The proposed algorithm for structural change detection can be described by the following sequence of steps.
1. Separate superpixel segmentation of multi-temporal images $f$ and $g$.
2. Computation of the projections $\hat{P}_j g$ and $\hat{P}_g f$.
3. Computation of the difference images $R_{fg} = |\hat{P}_j g - \hat{P}_g f|$ and $R_{gf} = |\hat{P}_g f - \hat{P}_j g|$.
4. Computation of the common difference image $R = \max(R_{fg}, R_{gf})$.
5. Estimation of the optimal threshold value $T$.
6. Thresholding the image $R$ with the threshold $T$ to get the resulting difference image $R_T$ by (3).

Superpixel segmentation, as well as threshold estimation, can be performed in different ways. In this paper, we use the threshold segmentation algorithm described in [17] to obtain superpixels. The advantage of this algorithm is simple and efficient implementation.

4. Algorithm for estimation of the optimal threshold of changes

In our research, we figured out that the classical threshold estimation algorithms such as the Otsu method [18], histogram quantile, and clustering into two clusters [19] are not effective for automatically determining the threshold in the difference image $R$ because the histogram of the image
$R$ is not bimodal. For this reason, we developed the algorithm for estimating the optimal threshold $T$ that is described in detail below.

1. For the source images $f$ and $g$ the sets of boundary pixels of superpixels $\overline{X}_f \subset X$ ($\overline{X}_g \subset X$) are defined independently such that for each pixel $x \in \overline{X}_f$ ($x \in \overline{X}_g$) at least one of the neighboring pixels belongs to another superpixel. The resulting set of boundary pixels is formed by the union of these two sets of boundary pixels: $\overline{X} = \overline{X}_f \cup \overline{X}_g$. We propose such pixel selection due to the fact that changes of the scene are most likely reflected on the boundaries of the superpixels of both images. Thus, in order to reduce the effect of unchanged pixels on the result, we skip the inner regions of the superpixels.

2. For a set of boundary pixels $\overline{X}$ the values of the difference image $R$ are clustered into three clusters: $\Omega_1$ is the unchanged samples cluster, $\Omega_2$ is the “doubtful” sample cluster, $\Omega_3$ is the changed sample cluster. As a result, for any pixels $x \in \Omega_1$, $y \in \Omega_2$, $z \in \Omega_3$ the corresponding $R$ values have to satisfy the inequality: $R(x) < R(y) < R(z)$ i.e. clustering determines the division of possible difference value range $[R_{\text{min}}, R_{\text{max}}]$ into three intervals $[R_{\text{min}}, r_1], [r_1, r_2]$ and $(r_2, R_{\text{max}}]$ where $r_1 = \max \{R(x) \}$ and $r_2 = \max \{R(x) \}$.

3. For the cluster $\Omega_2$, whose elements belong to the range $[r_1, r_2]$, a histogram of the difference image values $H(r) = v$ is calculated where $v$ is the number of boundary pixels such that $R(x) = r$.

4. The threshold $T$ is defined as the first local minimum of the histogram $H(r)$: $T = \min \{r \} \{r = r_1 + 1, \ldots, r_2 - 1: H(r) < H(r-1) \land H(r) < H(r+1) \}$ or as $T = r_2$ if the histogram $H(r)$ is a monotonic function on the segment $[r_1, r_2]$.

The algorithm described above stems from the fact that the distribution of intensity values of the difference image can be described by a mixture of the Rice and the Rayleigh distributions and the Rayleigh distribution corresponds to the differences of the image pixels without changes [20]. The probability density function of the Rayleigh distribution is monotonously decreasing after the mode value whereas the probability density function of the Rice distribution is not monotonously decreasing after the mode because the Rice probability density function is the product of a unimodal function and a Bessel shifted function of the first kind of order zero. The Bessel function is not monotonically decreasing and has a local maximum and minimum. Thus, the total distribution of the image intensity should have the first local minimum at the intersection point of the distribution graphs, and this intersection point corresponds to the optimal threshold value.

In practice, the image histogram is only an estimate of the analytical density distribution and may contain unnecessary local minimums. Thus, we propose to use clustering of the $R$ values into three clusters to obtain the interval of the potential threshold location. The obtained clusters correspond to $R$ values of unchanged points, “doubtful” points and changed points. Taking into account the intended nature of the distribution of the difference image values for points without changes and points with changes the threshold is searched in the area of “doubtful” points.

5. Algorithm validation

In this paper, the quality of change detection is measured by the true positive rate $R_{TP}$ characterizing the rate of correctly detected changed pixels by (7) and the false positive rate $R_{FP}$ characterizing the rate of falsely detected unchanged pixels by (8) [21].

$$R_{TP} = \frac{N_{\text{me2}}}{N_{R_2}},$$

where $R_2$ is the structurally changed region of the image; $N_{R_2}$ is the total number of pixels in the region $R_2$; $N_{\text{me2}}$ is the number of correctly detected structurally changed pixels in the region $R_2$. 

$$R_{FP} = \frac{N_{\text{me2}}}{N_{R_2}},$$
where $R_i$ is the unchanged region of the image, $N_{R_i}$ is the total number of pixels in the region $R_i$, and $N_{mex}$ is the number of falsely detected unchanged pixels in the region $R_i$.

Further the measures $R_{fp}$ and $R_{fp}$ are used to estimate the quality of pixels containing structural changes detection by a pair of multi-temporal images.

6. Experimental research

The aim of our experimental research was to investigate the quality of structural change detection for the classical algorithm based on the Pyt'ev’s projector and the proposed method based on the Pyt'ev’s projector and superpixel segmentation. We used the pairs of simulated and real ERS images with artificially generated changes. To assess the quality of change detection the measures $R_{tp}$ and $R_{fp}$ were calculated.

First of all, experiments were carried out on simulated images that contained a constant-intensity background and constant-intensity objects. An example of a pair of simulated multi-temporal images and masks of changes are shown in Figure 1.

![Figure 1](image.png)

**Figure 1.** The example of a pair of simulated multi-temporal images: a) unchanged simulated image, b) changed simulated image, c) mask of all changes, d) mask of structural changes.

The masks of changes 1(c), 1(d) and all subsequent masks were reversed for better perception i.e. the white areas correspond to the unchanged image areas and the black areas correspond to the changed ones. It should be noted that the masks 1(c) and 1(d) do not completely coincide since not all of the changes are structural.

The results of the structural changes detection in a simulated pair of images using the classical method and the proposed one are presented in Figure 2. Figure 2 shows that the results of the both considered methods fully coincided with the mask of structural changes presented in Figure 1(d), thus, the values of the quality measures of both methods for a pair of simulated images are $R_{tp} = 1$, $R_{fp} = 0$.

![Figure 2](image.png)

**Figure 2.** The result of the detection of structural changes: a) the classical projector, b) the proposed method.
Further, we tested the robustness of the methods to AWGN. For this purpose, we added AWGN with different signal-to-noise ratio values: $\text{SNR (dB)}$ 35, 30, 25, 20 to the source images. The results of this experiment for images 1(a)-1(b) using classical and proposed method are presented in Figure 3 and Figure 4, respectively.

![Figure 3. The performance of the classical structural change detection method on a simulated pair of multi-temporal images, containing AWGN at different values of $\text{SNR}$: a) $\text{SNR} = 35$, b) $\text{SNR} = 30$, c) $\text{SNR} = 25$, d) $\text{SNR} = 20$.]

Table 1 and Table 2 show the dependence of the quality measures $R_{TP}(\text{SNR})$ and $R_{FP}(\text{SNR})$ on the $\text{SNR}$ value for the classical and the proposed method, respectively.

The results of the experiment showed that the proposed method is robust to AWGN at $\text{SNR} \geq 30$ dB. At $\text{SNR} = 20$ dB the quality of detection by the proposed structural change method is still good: $R_{TP} = 0.958$ and $R_{FP} = 0.018$. The classical method is also resistant to AWGN at $\text{SNR} \geq 35$ dB. For the smaller SNR, the numbers of false detections for the classical and proposed methods level off. However, the number of correctly detected structural changes for the classical method decreases sharply at $\text{SNR} = 20$ dB and equals to $R_{TP} = 0.420$. Thus, the results of the study of robustness of the methods to AWGN showed that the proposed method outperforms the classical version of Pyt'ev’s projector since it is able to detect structural changes in images even at such low $\text{SNR}$ value as $\text{SNR} = 20$ dB.

![Figure 4. The performance of the proposed structural change detection method on a simulated pair of multi-temporal images, containing AWGN at different values of $\text{SNR}$: a) $\text{SNR} = 35$, b) $\text{SNR} = 30$, c) $\text{SNR} = 25$, d) $\text{SNR} = 20$.]

Table 1. The dependence of the quality measures on $\text{SNR}$ values for the classical method.

| $\text{SNR}$ | $R_{TP}$ | $R_{FP}$ |
|-------------|----------|----------|
| 35          | 1.000    | 0.002    |
| 30          | 0.990    | 0.013    |
| 25          | 0.752    | 0.013    |
| 20          | 0.420    | 0.018    |

The second experiment was devoted to the investigation of the robustness of the methods to such nonlinear distortion of image intensity as vignetting. Vignetting is a transformation that reduces the intensity of the image toward the periphery compared to the image centre. The distortion was
simulated by multiplying the image with structural changes 1(b) by a Gaussian weight function with values from 0 to 1 with a maximum in the centre of the image. Image 1(b) after vignetting and the results of the structural change detection by the classical and proposed methods are shown in Figure 5.

Table 2. The dependence of the quality measures on SNR values for the proposed method.

| SNR  | $R_{TP}$ | $R_{FP}$ |
|------|----------|----------|
| 35   | 1.000    | 0        |
| 30   | 1.000    | 0        |
| 25   | 0.998    | 0.002    |
| 20   | 0.958    | 0.018    |

Figure 5. The performance of the classical structural change detection method on a simulated pair of multi-temporal images after vignetting: a) changed image, b) the result of structural change detection by the classical method, c) the result of structural change detection by the proposed method.

Figure 5(b) shows that vignetting has a strong influence on the performance of the classical method, the quality measures for which are $R_{TP} = 0.874$ and $R_{FP} = 0.601$. Figure 1(c) illustrates the detection efficiency of the proposed method also decreases. The quality measures for the proposed method in such a case are $R_{TP} = 0.753$ and $R_{FP} = 0.149$ that represents a satisfactory detection quality because the false positive rate is in 4 times less than for the classical method and the false positive detection includes mostly the darkest corners of the image without damage of its central and most informative parts.

The experiments mentioned above were also conducted on ERS images containing artificially generated changes. To calculate $R_{TP}$ and $R_{FP}$ measures, we simulated the structural changes in the ERS images applying to the source image a “copy-move” operation. The examples of test images are shown in Figure 6. The result of structural change detection in a pair of such images is presented in Figure 7.

Figure 6. Example of the ERS data: a) the source ERS image, b) the ERS image after adding structural changes, c) the mask of structural changes.

Figure 7 shows that both methods provide a high quality of detection of structural changes in RS images. Note, that the classical method detects the changes clearly preserving their shape while the proposed method cannot clearly preserve the shape of changes because it uses the superpixels with an
irregular shape. However, the classical method has a crucial disadvantage such as a significantly larger amount of false detections that can be distributed throughout the image and are highly dependent on its content. It is also worth noting that there are much less false detections of the proposed method and they are concentrated mainly at the boundaries of structural changes (boundaries of objects) rather than being distributed throughout the image.

![Image](image_url)

**Figure 7.** The result of structural change detection in a pair of multi-temporal ERS images: a) the classical method, b) the proposed method.

7. Conclusions

In this paper, we propose the algorithm for structural change detection in ERS images and the algorithm for the optimal change detection threshold estimation by the histogram of the difference image. We also compared the performances of our method and the classical algorithm based on the Pyt'ev’s projector.

We found that the proposed algorithm effectively detects structural changes in a pair of multi-temporal images and outperforms the classical Pyt'ev’s version. A significant advantage of the proposed method over the classical implementation is noise resistance. Our method does not lose its ability to detect structural changes in images even at such low SNR value as $SNR = 20$ dB. In such a case the quality measures for the proposed method are $R_{tp} = 0.958$ and $R_{fp} = 0.018$ whereas $R_{tp} = 0.420$ for the classical method with the same $SNR$ value of the input image.

Another advantage of the proposed algorithm is its ability to preserve performance after applying nonlinear intensity distortions to the source images. That was verified by the example of vignetting. The performance of the classical method after such image transformation is low. At the same time, although vignetting reduces the performance of our method at strongly darkened edges of the image, the method generally provides a satisfactory detection quality by determining the structural changes in the rest of the image without errors.

The disadvantage of the proposed method lies in the fact that not all detected structural changes have clear boundaries since one of the stages of our scheme is splitting the source image into irregularly shaped segments.

8. References

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