# Tartalomjegyzék

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# A lokális hasonlósági mérték továbbfejlesztése távérzékelt képek változásainak becsléséhez*

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**Kivonat** A különböző szenzorokból, nagy időkülönbséggel készült távérzékelt képek közötti változás detekciója komoly kihívást jelent. Csak a pixelek fényességértéke nem ad elegendő támpontot az összehasonlításra, ehhez a további tulajdonságok is kellenek. A lokális hasonlósági mértékek, mint a kölcsönös információ, Kullback-Leibler távolság, vagy a "Cluster Reward" algoritmus alkalmasak a változások kiemelésére. A dolgozatban egy továbbfejlesztett lokális hasonlósági mértéket javasolunk, ahol a hisztogram készítésekor helyfüggő súlyozást alkalmazunk. Ebben a pixelek súlyozása egy exponenciális függvényt követ a kiértékelt ablak közepétől kifelé haladva. Ezzel az eljárással tudjuk a közeli és távoli környezet hatását kiegyensúlyozottan kezelni. A módszer hatékonyan kiváltja a nehezebben kezelhető és paraméterezhető több-skálájú megoldások alkalmazását. Az eljárás hatékonyságát eredményesen igazoltuk távérzékelt képek sorozatán.

**Abstract.** Detecting changes in remote sensing images taken at different times is challenging when images' data come from different sensors. The performance of change detection algorithms based on radiometric values alone is not satisfactory and need the fusion of other features. Local similarity measures such as Mutual Information, Kullback-Leibler Divergence, and Cluster Reward Algorithm can be used for enhancing change detection. In the paper, we propose an improved local similarity measure using weighted local histogram. Each pixel contributes to the calculation of the histogram according to its weight only. The weight assigned to each pixel in the histogram estimation window follows an exponential function of its distance from the center of the window and the corresponding pixel value in an initial change map image which is derived from other micro-structure or radiometric information. The proposed improved similarity measure benefits from the good detection ability of small estimation window and the good estimation accuracy of large estimation window; hence it can replace the time-consuming multi-scale selection approaches for statistics based similarity measures in remote sensing. The efficiency of this useful improvement has been validated on change detection in remote sensing image series.

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## 1 Introduction

Detecting regions of changes in series of images taken at different times is a challenging task when the time series data come from different sensors. In such case, the performance of change detection algorithms based on radiometric values alone is not satisfactory and need the fusion of other features. The change detection algorithms in the literature may follow either the *Post-Classification Comparison (PCC)* or the *direct* approach. *PCC* methods, such as in [1], [2], and [3], segment first the input images into various classes, like forest, meadow, river etc. Then, changes are obtained as regions with different class labels in the different layers. On the other hand *direct* methods, such as in [4], [5], [6], [7], [8], [9], and [10], derive a similarity-feature map between the multitemporal input images and then they cluster the feature map to separate changed and unchanged areas.

The definition of change is parallel to the definition of similarity; locations of image time series data that come from different sensors or different lighting and weather conditions can be compared if we can find robust local similarity measures. Inglada and Giros [11] showed that different local similarity measures such as Mutual Information (MI), Kullback-Leibler Divergence (KLD) and Cluster Reward Algorithm (CRA), can be successfully used for fine registration of remote sensing images. Through intensive simulation for performance comparison of different similarity measures, Alberga [7] proved that these local similarity measures are possible tools for change detection applications in multi-sensor images. However, as pointed out in [6], the local statistics in the two images are very different when the two image modalities are different and the change in the similarity measure value can't be independent of the changes within the image itself. To overcome this problem, the authors of [6] proposed a method to estimate the local statistics of the first image through the point of view of the second one. They assume that some dependence exists between the two images in unchanged areas. This dependence is modeled using copula theory and used to perform an estimation of the local statistics that would have been observed if the acquisition conditions of the first image had been similar to the ones of the second image. The problem, however, in the *direct* approach based methods such as in [6], [11], is the choice of the threshold value for change/no-change classification. The choice of the threshold value affect significantly the change map. This problem can be handled using automatic selection of the threshold using approaches similar to the one proposed in [12].

In [3], following *Post-Classification Comparison (PCC)* approach, we have proposed image segmentation and change detection method based on multi-layer fused model MRF. In this method, we add local similarity measures to the stacking of the layers' pixel/micro-structure information; In particular we have proposed to use *CRA* similarity measure in the multi-layer fusion calculated between layer pairs in the series. It was verified through experimental results that the addition of these local similarity measures to other radiometric values could enable better segmentation for regions where radiometric values are dubious;

change detection map is then calculated from the difference in the label map of single layers and accordingly independent of any threshold.

Another problem that significantly affects the performance as well as the computational load of all the above mentioned methods is the size of the window used for the estimation of the joint and marginal probability density functions (pdfs). Large window size provide better estimates for the joint and marginal pdfs; however, using large window size is not good for detecting small changes; Inglada and Mercier [13] argued that histograms need large window size to be correctly estimated and thus should not be used for local pdfs estimation. They first proposed a computationally efficient method for KLD calculation based on cumulants higher order statistics; then they propose to generate multi-scale change profile where multi-channel images are produced using different window sizes; the best change scale is selected either using principal component analysis on the multi-channel image or by choosing the one with highest KLD value. However, even higher order moments require amount of large data to be correctly estimated and do not give good performance for small changes.

In this paper, we propose a method for improved local similarity measure calculation based on weighted histogram where each pixel contributes to the calculation of the local histogram according to its weight only. The weight of each pixel is chosen based on its distance from the center of the histogram estimation window and the corresponding pixel value in an initial change map image which is derived from other micro-structure or radiometric information. In this paper, each pixel in the initial change map image is calculated from the maximum change ratio of the variances of the corresponding windows in the two images evaluated for different window sizes. The proposed method is validated for change detection application using $CRA$ similarity measure; however, the applications is not limited to $CRA$ similarity measure. The proposed weighted histogram method is useful in the calculation of any local similarity measure based on local histogram calculation such as MI and KLD which are used in different applications such as image registration as well as change detection.

## 2 Improved Local Similarity Measure Estimation

According to [11], given two images I and J, a similarity measure is any scalar strictly positive function $f(I; J; c)$ that quantifies how similar are the images according to the criterion $c$. $f$ has an absolute maximum when I and J are identical. The selection of the similarity criterion, and hence the definition of the function $f$, can vary according to the type of images under analysis, the application (e.g., image registration or change detection) and the parameters used to define it (radiometric values, features characteristics, etc.). Local similarity measure is estimated for each pixel in the image using $N \times N$ neighborhood window.

Let I and J denote two co-registered images acquired from different sensors at two different dates. For each pixel $s$, let $X_I^N(s)$ and $X_J^N(s)$ denote two co-located sample sets in the neighborhood of $s$ within window size $N \times N$ with $s$

at the center of the window. The $CRA$ similarity measure at pixel $s$ is calculated as follows [11]:

$$CRA(I,J,s) = \frac{\sum_{i,j} p_{IJ}^2(i,j) - \sum_i p_I^2(i) \cdot \sum_j p_J^2(j)}{\sqrt{\sum_i p_I^2(i) \cdot \sum_j p_J^2(j)} - \sum_i p_I^2(i) \cdot \sum_j p_J^2(j)}, \tag{1}$$

where $i$ and $j$ refer to the intensity values of I and J respectively; $p_{IJ}(i,j) = p(I(s) = i, J(s) = j)$ and $p_I(i) = p(I(s) = i)$, $p_J(j) = p(J(s) = j)$ are respectively the joint and marginal probabilities calculated from the local windows $X_I^N(s)$ and $X_J^N(s)$. For $CRA$ similarity measure, joint histogram estimation noise has weak influence on the $CRA$ values and thus smaller window size can be used [7], which in turn enables better detection of changes in small areas.

The size of the window N used for the estimation of the joint and marginal pdfs significantly affect the detected change map. Large window size gives better estimates for joint and marginal pdfs, however, it can not be used for detecting small changes. In fact small changes will be lost using large window size. On the other hand, the local statistics in the two images are very different when the two image modalities are different and the change in the similarity measure value can't be independent from the changes within the image itself. The effect of this problem is specially clear when small size estimation window is used and is reduced considerably when using large histogram estimation window.

To handle these problems, we here propose to use fixed large estimation window for the calculation of the histograms, however each pixel within this window is assigned a weight $w_s$; each pixel contributes to the calculation of the local histogram according to its weight only. The weights follows exponential function of two parameters: $d_s$ the distance from the center of the estimation window, and $v_s$ the corresponding pixel value in an Initial Change Map (ICM) image. The ICM image is derived based on some other micro-structure or statistical feature of interest as will be explained later in the sequel.

In the L*a*b* color space, let $L_s$ denotes the luminance value at pixel s. For each pixel $s$, the proposed weighted marginal histograms $p_I(i, w_s)$ and $p_J(j, w_s)$ are estimated from the local neighborhood windows $X_I^N(s)$ and $X_J^N(s)$ respectively as follows:

$$\begin{aligned} p_I(i, w_s) &= \frac{\sum_s w_s \delta(L_s - i)}{\sum_s w_s}, s \in X_I^N(s) \\ p_J(j, w_s) &= \frac{\sum_s w_s \delta(L_s - j)}{\sum_s w_s}, s \in X_J^N(s) \end{aligned} \tag{2}$$

where $\delta(L_s - i)$ is the delta function and equals one if $L_s = i$; and zero otherwise. The weight $w_s$ given to each pixel in the estimation window is defined as:

$$w_s = e^{-K d_s / v_s}, \tag{3}$$

where $K$ is a positive constant proportional to the size of the window.

Note that the use of weights in the calculation of the histograms enables us to change the shape of the estimation window which might be not square, for example, the weight can be chosen to be high in pixels that satisfy some other radiometric, textural, or statistical criteria.

The $CRA$ similarity measure using the proposed weighted pdfs can then be rewritten as follows:

$$CRA(I,J,s) = \frac{\sum_{i,j} p_{IJ}^2(i,j,w_s) - \sum_i p_I^2(i,w_s)\sum_j p_J^2(j,w_s)}{\sqrt{\sum_i p_I^2(i,w_s)\sum_j p_J^2(j,w_s)} - \sum_i p_I^2(i,w_s)\sum_j p_J^2(j,w_s)}. \quad (4)$$

Different joint features of the two images I and J can be used to generate the ICM for different applications. In this paper we propose a method based on the change ratio of the local variances in the two images for the calculation of ICM as explained in the following four steps.

1. Registration of the two images.
2. For a set of L increasing values for the size of the histogram estimation window $N = N_1, \ldots, N_L$, the following variance change ratio $VR_N(I,J,s)$ is calculated for each pixel $s$ in the image:

$$VR_N(I,J,s) = 1 - min(\sigma_I^2/\sigma_J^2, \sigma_J^2/\sigma_I^2), \quad (5)$$

where $\sigma_I^2$ and $\sigma_J^2$ are respectively the variances of $X_I^N(s)$ and $X_J^N(s)$ the local neighborhood windows of $s$ in images I and J.
3. The value of pixel $s$ in the Variance Change Ratio (VCR) image is set to be the maximum variance change ratio, that is $VCR(s) = max(VR_N(I,J,s)), N = N_1, N_2, \cdots, N_L$.
4. The VCR image is then segmented into M classes using linear discriminant analysis [14]. In our presentation here we choose M=3, changed $\omega_c$, unchanged $\omega_u$ and possibly changed $\omega_{pc}$ classes, however extension to multi-class segmentation for multi-valued ICM is straight forward. The result of this step is the ICM image defined at pixel $s$ as:

$$\begin{aligned} v_s &= w_h, \quad \text{if} \quad s \in \omega_c, \\ v_s &= w_l, \quad \text{if} \quad s \in \omega_u, \\ v_s &= w_m, \quad \text{if} \quad s \in \omega_{pc}, \end{aligned} \quad (6)$$

where $w_h$, $w_m$ and $w_l$ are three positive high, medium, and low values such as 3, 2 and 1 respectively.

## 3 Change Detection Algorithm

In this paper we use the improved $CRA$ similarity measure (Eq. 4) for change detection in remote sensing images. The steps of the proposed change detection method with improved local similarity measure are as follows.

1. Selection and registration of the two images.

2. Calculation of the initial change map based on some micro-structural/radiometric joint feature of the two images.
3. Calculation of the weighted histograms. The weight given to each pixel in the histogram estimation window is defined as exponential function of the distance from the center of the window and the corresponding value in the initial change map image.
4. For each pixel in the image, the improved local similarity measure $CRA(I, J, s)$ image can then be calculated using the weighted histograms (Eq. (4)).
5. The $CRA(I, J, s)$ similarity measure image is then segmented into change/no-change classes using either manual threshold or using the method in [14] to obtain the final change map.

**Table 1.** Misclassified Pixels' Rates for Exp. 1

| Window size | Method [7] | Proposed Method |
|---|---|---|
| 15 | 1.1% | 0.8 % |
| 27 | 4 % | 1.4 % |
| 39 | 7 % | 3 % |

**Table 2.** Misclassified Pixels' Rates for Exp. 2

| Window size | Method [7] | Proposed Method |
|---|---|---|
| 21 | 17% | 10 % |
| 31 | 15 % | 7 % |

## 4 Experimental Results and Discussion

Experiments have been tested on aerial scanned images of Tiszadob area from years 2005, 2007; the spatial resolution is 0.5m/pixel, and all the images have been aligned as orthophoto. Image of 2005 is scanned on photo-films (Hasselblad 500 EL/M) before digital scan. The 2007 image has been originally scanned in digital form (Nikon D3X, with AF-S Nikkor 50 mm 1.4G lens). The data set of images is provided by the Hungarian Institute of Geodesy Cartography  Remote Sensing (FOMI). In the L*a*b* color space, only the Luminance component L is used in the following two experiments.

In the first experiment, we aim to show the effect of the choice of the size of the histogram estimation window and the effect of using weighted histogram on change detection map. So we make artificial changes to part of the 2007 image using part of the image itself. The changes are chosen to be squares of different

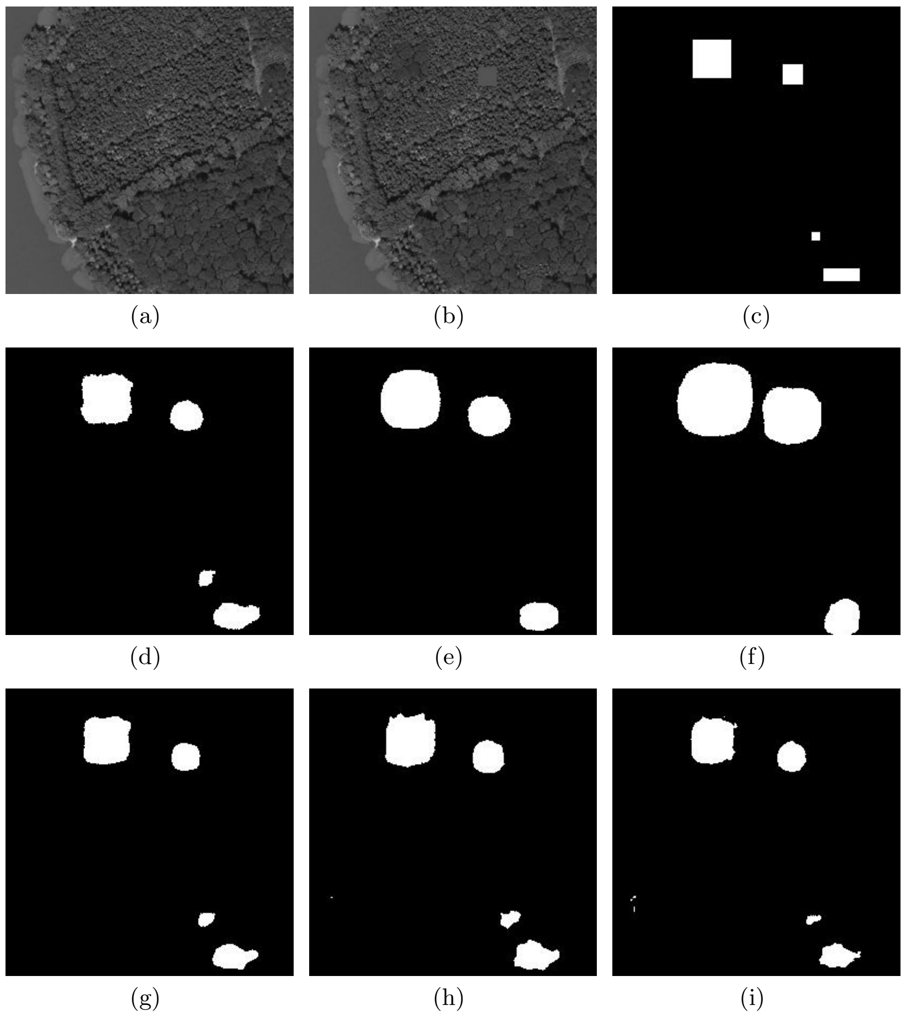
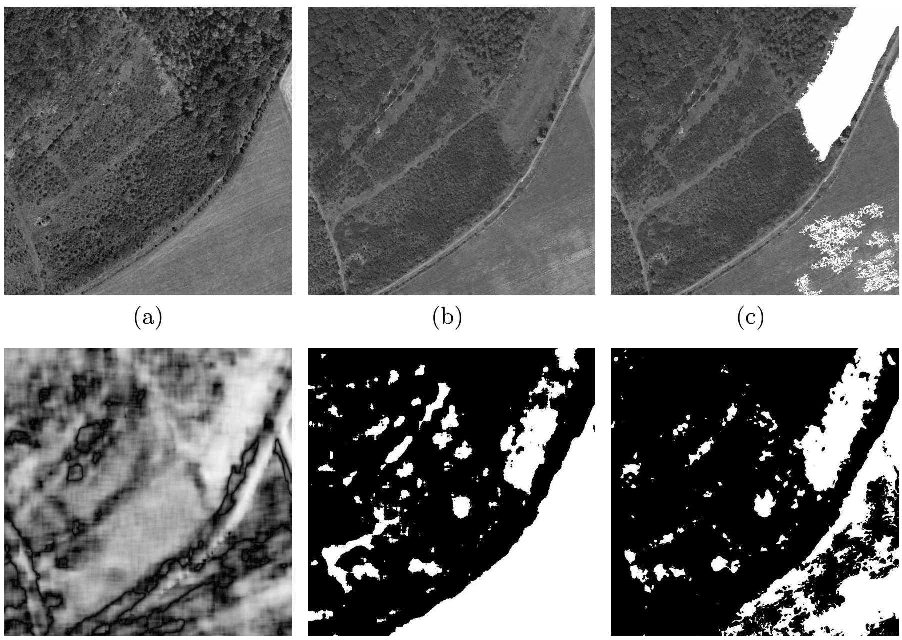


**Fig. 1.** Change detection results of Experiment 1. First raw: (a) original image; (b) modified image; (c) Ground Truth; Second raw (d). (e), and (f): change detection results using method [7] with N=15, 27, and 39 respectively. Third raw (d), (e), and (f): change detection results using proposed weighted histogram method with N=15, 27, and 39 respectively.



(a) (b) (c)

(d) (e) (f)

**Fig. 2.** Change detection results of Experiment 2. (a) Tiszadob image 2005; (b) Tiszadob image 2007; (c) Ground Truth (change mask in white); (d) variance change ratio image estimated with window sizes: N=21, 31, and 41. (e) change detection results with N=31 using method [7] and (f) change detection result using proposed weighted histogram, changed areas are shown in white.

sizes and different textures as shown in Fig. 1. The size of the changes from top to down are $36 \times 36$, $18 \times 18$, $7 \times 7$, and $33 \times 11$ respectively. We compare the performance of the proposed method with the method [7] (Eq. 1). Result Images are shown in Fig. 1. It can be seen that the use of weighted histogram gives better results than using either fixed small window or large window. Note that small changes were not well identified using large estimation window. The initial change map was derived using window sizes N=15, 27 and 39. The parameter K is chosen as positive real number proportional to the window size. In this experiment we used $K = 0.03N$. Table 1 shows the quantitative assessment results for different window sizes.

In the second experiment, we apply the proposed algorithm to the co-located parts of the real images of Tiszadob area from years 2005, 2007. We can see forest cut in the year 2007 on a very complex area. The initial change map was calculated using window sizes N=11, 21 and 31, and then segmented into three classes to produce the weights. Misclassified pixels' rates are shown in Table 2 for two window sizes (N=21 and 31). The original, classified, and ground truth images are shown in Fig. 2. These results show that the use of higher weights for pixels with high variance change ratio improve the change detection results in the forest cut area. In addition, as well known, in homogenous regions with very low variance such as the meadow area in Fig. 2, the error in similarity measure estimation (whether it is CRA, MI, or KLD) is very high; however the proposed weighted histograms also helped to improve classification results in the meadow area which was all classified as changed without the use of the weighted histogram.

## 5 Conclusion

We have proposed an improved local similarity measure based on weighted histogram estimation where each pixel in the histogram estimation window is given weight according to its distance from the center of the window and the corresponding pixel value in an initial change map derived from the maximum ratio of the local variances of the two images. The proposed method benefits from the good detection ability of small window and the good detection accuracy of large window and thus outperforms the fix window size cases. This paper shows that using weighted statistics can replace the time-consuming multi-scale selection approaches for statistics based similarity measures in remote sensing. The efficiency of this improvement has been validated on remote sensing image change detection applications. It should be noted that different features can be used to generate the initial change map to enhance detection of pixels that satisfy specific characteristics.

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