# Self-Adaptive Artificial Neural Network for Change-Detection of Land Cover: An Unsupervised Approach

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*Abstract:* - One of the main problems related to unsupervised change detection methods based on the “difference image” lies in the lack of efficient automatic techniques for discriminating between changed and unchanged pixels in the difference image. Such discrimination is usually performed by using empirical strategies or manual trial-and-error procedures, which affect both the accuracy and the reliability of the change-detection process. To overcome such drawbacks, in this paper, we propose an automatic technique for the analysis of the difference image. Such technique allows the automatic selection of the decision threshold. Due to the variability on background, different change types, and different light conditions and noise in images, the difference image, segmentation based on a single threshold usually performs poorly. To improve the segmentation we used a variable threshold. The threshold was adapted for each pixel of the difference image, through a self-adaptive network based on an unsupervised artificial neural network classifier. The adaptive system approach is attractive for classifications tasks due to its self-organizing, generalizable, and fault-tolerant characteristics. In contrast to the supervised neural network, the adaptive system does not rely on user-defined training data. The desired response is guided by an internal mechanism designed to solve the specific classification problem. The adaptive systems can be classified in terms of open-loop or closed-loop adaptation. The closed-loop systems has proven to be more powerful, especially for nonlinear process. We used closed-loop adaptation, based on both input and feedback from the output. The self-adaptive classifier employs a variable threshold in conjunction with an adaptation algorithm to segment a difference image. The classification is achieved through an iterative process in which the expected input is estimated from the system output and compared to the actual input. The comparison produces an error signal that controls the thresholding parameter. Experimental results confirm the effectiveness of proposed technique.

*Key-Words:* - Self-adaptive classifiers, unsupervised change-detection, neural networks, image processing, multitemporal images, remote sensing.

## 1 Introduction

There has been a growing interest in the development of automatic change-detection techniques for the analysis of multitemporal remote sensing images. This interest comes from the wide range of applications in which change detection methods con be used, like environmental monitoring, agricultural surveys, urban studies, etc. Change detection involves the analysis of two registered multispectral remote sensing images acquired in the same geographical area at two different times. Such analysis identifies land cover changes that have occurred in the study area between the two times considered. In the remote sensing literature, two main approaches to the change-detection problem have been proposed: the supervised and the unsupervised. The former is based on supervised classification methods, which require the availability of a multitemporal ground truth in order to derive a suitable training set for the learning process of the classifiers. Although this approach exhibits some advantages over the unsupervised one, the generation of an appropriate multitemporal ground truth is usually a difficult and expensive task. Consequently, the use of effective unsupervised change-detection methods is fundamental in many applications in which a ground truth is not available. In this paper, we work on one of the unsupervised change-detection techniques so-called “difference image”. These techniques process the two multispectral images acquired at two different dates in order to generate a further image - the difference image. The values of the pixels associated with land cover changes present values significantly different from those of the pixels associated with unchanged areas. Changes are then identified by analyzing the difference image. In the widely used change vector analysis (CVA) technique [2], [4], [5], several spectral channels are used and, for each pair of corresponding pixels "spectral change vector" is computed as the difference between the feature vectors at the two times. Then, the pixel values in the difference image are associated with the modules of the spectral change vectors. So, the unchanged pixels present small gray-level values, whereas changed pixels present rather large values. In spite of their simplicity and widespread use, the described above change-detection methods exhibit a major drawback: a lack of automatic and nonheuristic techniques for the analysis of the difference image.

An intuitive approach is to apply a grayscale threshold on the difference image – assume that the pixel values of the changed pixels are generally higher than the values of the unchanged pixels. If the histogram of the difference image is bimodal showing a peak for unchanged pixels and a peak for changed pixels, the appropriate value for the threshold can be either manually selected or statistically determined. However, due to the large variability on the change types and noise on the images, segmentation based on a single threshold usually performs poorly. To improve the segmentation a variable threshold can be used. The threshold is adapted for each pixel based on the neighborhood of the pixel. We use the formulation of a self-adaptive network for the image segmentation, which use an unsupervised artificial neural network classifier. A similar approach was used for medical imaging [3]. The adaptive system approach is attractive for classifications tasks due to its self-organizing, generalizable, and fault-tolerant characteristics. The adaptive systems can be classified in terms of open-loop or closed-loop adaptation. We used a closed-loop adaptation, based on both input and feedback from the output. The closed-loop system has proven to be more powerful, especially for nonlinear process. In contrast to the supervised neural network, the adaptive system does not rely on user-defined training data. The desired response is guided by an internal mechanism designed to solve the specific classification problem.

## 2 The Self-Adaptive Classifier

Let us consider two multispectral images, $X_1$ e $X_2$ acquired in the same geographical area at two different times, $t_1$ e $t_2$. Let us assume that such images have been coregistered. Let X represents the values of the pixels in the difference image obtained by applying the CVA technique to $X_1$ and $X_2$. For the sake of simplicity, the proposed technique will be presented in the context of the CVA method. However, a generalization to other methods based on the difference image is straightforward. The self-adaptive classifier employs a variable threshold in conjunction with an adaptation algorithm to segment a difference image. The classification is achieved through an iterative process in which the expected input is estimated from the system output and compared to the actual input. The comparison produces an error signal that controls the thresholding parameter. The variable threshold for each pixel (i,j) is $T_{ij}$ is determined according to

$$T_{ij} = F\left(W_{ij}\right) \tag{1}$$

where *F(.)* is a function that guarantees that $T_{ij}$ will be between 0 and 1, and $W_{ij}$ is the weight that controls the threshold for pixel (i,j). Once the local thresholds are computed, the entire image is transformed to a binary image:

$$y_{ij} = \begin{cases} 0, \text{ if } \mathrm{x}_{ij} \le T_{ij} \text{ is a unchanged pixel} \\ 1, \text{ if } \mathrm{x}_{ij} > T_{ij} \text{ is a changed pixel} \end{cases} \tag{2}$$

In most adaptive systems the error signal is the difference between the desired output and the actual output. In our case, however, we do not have the desired output because the information about the changed pixel location is not available *a priori* in the unsupervised situation. Thus, instead of comparing the outputs, we compare the inputs. The adaptive system presented here obtains its error signal from the distance between the actual input $\mathrm{x}_{ij}$ and the estimated input $\hat{\mathrm{x}}_{ij}$ computed in a neighborhood w of $\mathrm{x}_{ij}$. The equation (3) describe the error signal at the kth iteration within an *wxw* window:

$$e^k = \sum_w \left(\mathrm{x}_{ij} - \hat{\mathrm{x}}_{ij}\right)^2, \tag{3}$$

The estimate of input signal is based on the mean value of each class (changed pixels or not changed pixels) in the moving window. At each iteration, the estimated input for a changed (unchanged) pixel is set to the mean value of all detected changed (not changed) pixels within the *wxw* window. If the system output is a binary image consisting of ones and zeros, the input estimate is given by:

$$\hat{x}_{ij} = m_c^k y_{ij}^k + m_{nc}^k \left(1 - y_{ij}^k\right), \tag{4}$$

where $m_c^k$ and $m_{nc}^k$ are the means for the changed class and the unchanged class respectively. That is,

$$\hat{x}_{ij} = \begin{cases} m_c^k, \text{ if } y_{ij}^k = 1, \\ m_{nc}^k, \text{ if } y_{ij}^k = 0. \end{cases} \tag{5}$$

The mean of each class can be estimated by

$$m_c^k = \frac{\sum_w x_{mn}^k y_{mn}^k}{\sum_w y_{mn}^k}, \qquad m_{nc}^k = \frac{\sum_w x_{mn}^k \left(1 - y_{mn}^k\right)}{\sum_w \left(1 - y_{mn}^k\right)}. \tag{6}$$

Our adaptation algorithm requires differentiability along the signal path. The adaptation process would be blocked by the hard-limiter because its derivative does not exist. Substituting the hard-limiter by a soft-limiter for the above input estimator will introduce some error. This error, however, should be negligibly small, especially of a soft-limiter that has an abrupt transition between 0 and 1. The error diminishes as the output pixel values converge to either 0 or 1. When the soft-limiter is used, the system output comes from the sigmoid function. The sigmoid function is continuous and varies monotonically form 0 to 1. The output is not exactly binary, it can be considered as the probability that pixel (i,j) belongs to the change class. The derivative of the sigmoid exists allowing us to carry the adaptation process through the nonlinearity.

The adaptation developed is analogous to the steepest descent method in the sense that the operating point descends on the performance surface toward the minimum. The weights (thresholds) are initialized to random values. At kth iteration the weights are adjusted in the direction oppose to the gradient of the error signal *e*:

$$W_{ij}^{k+1} = W_{ij}^k - b \left.\frac{\partial e^k}{\partial W_{ij}}\right|_{W_{ij}^k} \tag{7}$$

where *b* is the adaptation coefficient or learning rate that regulates the speed and stability of the system. The partial derivative $\partial e_{ij}^k / \partial W_{ij}$ can be evaluated using the chain-rule.

Some background variations can be incorrectly classified as changed pixels and result in speckled artifacts scattered over the background area in the resulting image. These speckled artifacts that appear as isolated small clusters can be removed by one of the various filtering techniques based on mathematical morphology. In this paper, after assigning all output pixels that have not reached change class to the no change class, we used a majority filter to remove the speckled artifacts (a particular case of a median filter if the image is a binary image).

## 3 Experimental Results

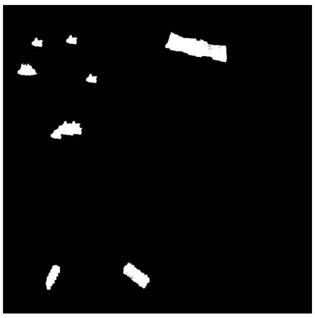
In order to evaluate the robustness of the proposed technique for the analysis of the difference image, we considered a synthetic data set artificially generated. An image acquired by the Landsat-7 Thematic Mapper (TM) sensor, composed of bands 3, 4 and 5, in the middle west of Brazil was used as the reference image. In particular a section (700x700 pixels) of a scene acquired was selected. This image was assumed to be $X_1$ image of the data set. The $X_2$ image was artificially generated from the reference one. A first version of the $X_2$ image was obtained by inserting some changes in the $X_1$ image in order to simulate land cover variations. Then the histogram of the resulting image was slightly shifted to simulate different light conditions in the two images. Finally, three versions of the $X_2$ image were generated by adding different realizations of zero-mean Gaussian noise to the $X_2$ image (Signal-to-Noise-Ratio (SNR)=10, 5, and 0 dB). For simplicity, we assumed the spatial independence of the noise components in the images. As an example, Fig. 1(a) and 1(b) shown the band 4 of $X_1$ image and the $X_2$ image for an SNR=0 dB, respectively. The map of the areas with simulated changes is presented in Fig. 1(c). For the three pairs of synthetic images considered, the corresponding difference images were obtained by applying the CVA technique. The initialization weights were generated randomly.

Table 1 shows the results obtained for the three SNR values selected. In all cases, the estimates provided by the proposed technique accurately approximate the true values of the changed and unchanged pixels. In particular, even the case characterized by high level of noise (i.e., SNR = 0 dB) the obtained map of changes turned out to be very close to the corresponding true map of changes. The results obtained point out the validity of the presented technique. The largest error concern to the estimate of the changed pixels for SNR=0 dB, the overall error made was equal to 1916 pixels (0.4 % of total area). The number of false detection, in worst case, SNR=0 dB, was only 0.17% of entire image. Figure 2 shows the change-detection map resulting form the application of the proposed technique in the case of SNR=0 dB.

## 4 Conclusion

In this paper, a technique for the analysis of the difference image in unsupervised change-detection problems have been proposed. Such technique performs an automatic analysis of the difference image by exploiting unsupervised neural network classifier. The technique allows the automatic selection of a locally determined decision threshold. Further research should be conducted to test the potential improvements associated with such approach. Another selection of the initialization weights (thresholds) of self-adapter could be used, others adaptation algorithms and input estimates could be experimented. In spite of the simplicity adopted, even the case characterized by high level of noise, the experimental results confirm the effectiveness of the presented technique.


(a) (b)



(c)

Fig. 1. Synthetic data set utilized in the experiments. (a) $X_1$ image, (b) $X_2$ image (for SNR = 0 dB), (c) map of the areas with simulated changes used as the reference map in the experiments.

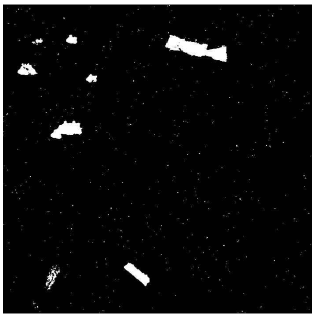


Fig. 2. Change-detection map obtained for the synthetic data set (SNR = 0 dB) by using the proposed technique.

| SNR (dB) | False Detection | Missed Detection |
|---|---|---|
| 0 dB | 849 pixels | 1067 pixels |
| 5 dB | 206 pixels | 393 pixels |
| 10 dB | 0 | 27 pixels |

Table 1. False detections and missed detections resulting from the proposed technique for different values of SNR.

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