Change Detection from Satellite Images Using PNN

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Abstract. This paper presents a supervised change detection technique for satellite images using a probabilistic neural network (PNN). The proposed method works in two phases. In the first phase a difference image is computed. The most commonly used techniques for computing the difference image such as ratio images or log ratio images degrade the performance of the algorithm in the presence of speckle noise. To overcome the above mentioned limitations the difference image in this work is computed using normalized neighborhood ratio based method. In the next phase the PNN is used to detect efficiently any change between the two images. An estimator is used by the PNN to estimate the probability density function. The ratio of two conditional probability density functions, called the likelihood ratio is computed. Finally, the log likelihood ratio test is used to classify the pixels of the difference image into changed and unchanged classes to create a change map. The change map highlights the changes that have occurred between the two input images. The proposed method was compared quantatively as well as qualitatively with other existing state of the art methods. The results showed that the proposed method outperforms the other methods.

Keywords: Change detection, Probability density function, Probabilistic neural network (PNN).

1 Introduction

Satellite images are widely used for monitoring urban expansion and land use/cover changes at a medium or large scale, to help better observe and understand the evolution of urbanization and advance the sustainable development process. In all these application change detection methods are widely used. Change detection aims at identifying the changes in spatial representation of any point by observing it at different times [1]. The change detection methods can be broadly classified into the following groups based on the technology they use: algebra, transformation, classification and other approaches. The simplest types of methods are based on algebra like image rationing, differencing, background subtraction, change vector analysis and vegetation index differencing. The drawback with these methods is that they do not provide complete change information. Classification based methods identify the features occurring in an image in terms of the object or type of land cover these features actually represent on the ground and assigns them a unique gray level (or color).Normally, multispectral data are used to perform the classification and,

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indeed, the spectral pattern present within the data for each pixel is used as the numerical basis for categorization [2].The change detection methods based on unsupervised classification perform multi date image classification and then the classified images comparison is done to discover changes that occur between the two images. A framework for the detection of multiple changes in bi-temporal and multispectral remote sensing images is proposed in [3]. They used all available spectral changes to build up a feature space and developed a compressed 2-D representation of change information which could be easily understood and visualized in polar coordinate system. To identify actual changes an automatic two step method was proposed. To separate changed and unchanged pixel the EM algorithm was used. In [4] a binary semisupervised support vector machine (S^3VM) classifier is proposed. The classifier takes as input multitemporal images. It uses CVA technique and Bayesian thresholding for deriving an initial set of seed pixels having a high probability to be correctly assigned to the classes of changed and unchanged pixels. Using these training sets the classifier develops an unsupervised map which is used to obtain the final change detection map using similarity measures.[5] presents a method based on Gaussian mixture model (GMM) of the difference image and Bayes theory to perform change detection. The difference image is first modeled using GMM .The components of the GMM are then classified into changed and unchanged pixels using Bayes theory. Another method is given in [6] the neighborhood data around each pixel form a sample and are modified by the so-called local gradual descent matrix (LGDM), values of which are descending from center toward outside. Expectation maximization (EM)-based approach [7] analyses the difference image and through automatic selection of the decision threshold it minimizes the overall change detection error. Another technique based on Markov-random-field (MRF), uses the spatial contextual information included in the neighborhood of each pixel to analyze the difference image [7].The PNN has proved to be quite efficient as it has a fast training process, an inherent parallel structure, and guaranteed optimal classification performance [8].

This paper presents a change detection method for identifying change between bi-temporal satellite images based on the Probabilistic neural network (PNN).A difference image is obtained by using neighborhood ratio based method. This difference image is used by the PNN to create a change map showing changes between the two images. The network architecture is made up of four types of units: input units, pattern units, summation units and output unit. The network has an estimator for probability density function (pdf). The pdfs are used to compute likelihood ratio. Finally, log likelihood ratio test is done to assign the pixels of the difference image into changed and unchanged classes to create a change map.

2 Network Architecture

The architecture of the network is shown in fig.1.The architecture is made up of four types of units.

1. Input units: The input units are the pattern vectors $\boldsymbol{x}_1, \boldsymbol{x}_2 \ldots \boldsymbol{x}_n$ where $\boldsymbol{x}_k$ is the pattern vector of the k_{th} pixel in the image.

2. Pattern units: The pattern units are mean values m_1, m_2 and covariance matrices C_1, C_2 of class ω_c and ω_{uc} respectively. The mean value and covariance matrix of each class are computed using training vectors.
3. Summation Units: The summation units are the estimator function of both the classes. The estimator function estimates the probability density function.
4. Output Unit: The output unit is the final change map (CM).

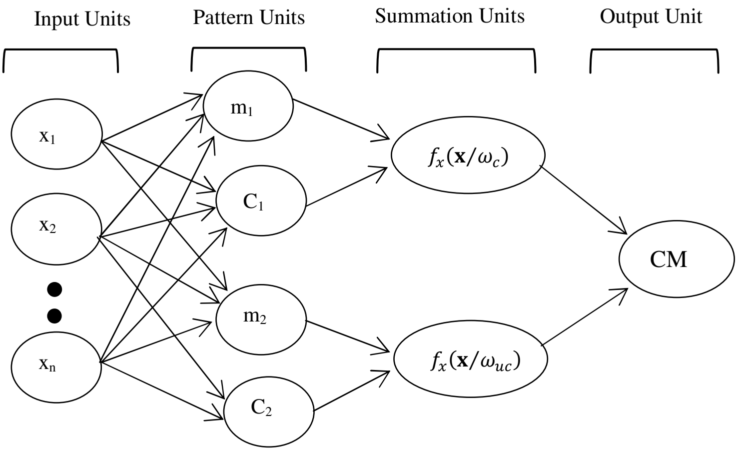

Fig. 1. Architecture of probabilistic neural network for change detection

3 Proposed Method

The change detection method proposed here takes as input two images taken at two different times over the same geographical area. The proposed method works in two phases in the first phase difference image is created and in the next phase the difference image is fed as input to the PNN to obtain change detection map. The overview of the proposed method is shown in fig.2.Input pattern vectors are created for each pixel location from the difference image I_d. The weight vectors w_c and w_{uc} are obtained from the training patterns of both the classes.

Phase I: Creation of Difference Image

Let us consider two satellite images I_1 and I_2 of size $M \times N$ taken at time t_1 and t_2 which are co-registered with respect to each other. In general, the change detection algorithms work on the difference image computed from the abovementioned satellite images. The most commonly used techniques for computing the difference image are ratio method [9] and the Log ratio method [10], but these method suffer from a serious limitation. These methods are sensitive to the presence of speckle noise and thus reduce the performance of the algorithm to a great extent. Thus, in this paper a

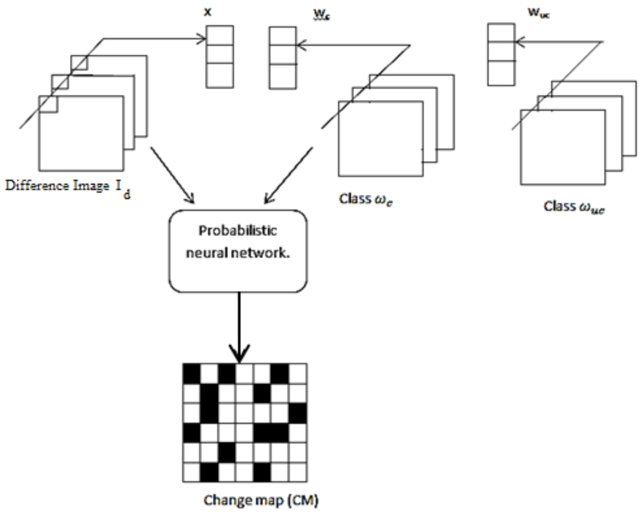

Fig. 2. Pictorial representation of the proposed method

normalized neighborhood ratio approach is used to generate the difference image which is an improved form of neighborhood ratio approach[11]. The proposed method of finding the difference image overcomes the effect of speckle noise. The difference image can be computed using equation 1,

$$I_d(x) = \delta \frac{\max\{I_1(x),I_2(x)\}-\min\{I_1(x),I_2(x)\}}{\max\{I_1(x),I_2(x)\}+\min\{I_1(x),I_2(x)\}} + (1-\delta)\frac{\sum_{i \in N}\max\{I_1(i),I_2(i)\}-\min\{I_1(i),I_2(i)\}}{\sum_{i \in N}\max\{I_1(i),I_2(i)\}+\min\{I_1(i),I_2(i)\}} \quad (1)$$

where $\delta = \frac{\sigma_N}{\mu_N}$.

The first term computes the normalized ratio of the pixel under consideration and the second term computes the sum of the normalized ratio of the pixels in the $w \times w$ neighborhood N of the pixel under consideration.σ_N and μ_N are the variance and mean of the gray level in the neighborhood respectively.

Phase II: Creation of Change Map Using PNN

A probabilistic neural network for change detection is presented here to classify the difference image (I_d) into two classes changed (ω_c) and unchanged (ω_{uc}). The PNN shown in fig.1 is used. pattern vector $\boldsymbol{x}$ is a three dimensional vector where each component represents the grey level value of a pixel of the difference image (I_d) in the three bands (RGB).Thus, $\boldsymbol{x}$ can be defined as

$$\boldsymbol{x} = [I_{dR} \quad I_{dG} \quad I_{dB}]^T \quad (2)$$

where I_{dR} ,I_{dG} *and* I_{dB} represent the red , green and blue band of the difference image (I_d). Thus, for the difference image with n (where n = M×N) pixels there will be $x_1, x_2, \ldots\ldots x_n$ input pattern vectors one for each pixel location. For change detection problem the number of classes is two. Each class has a mean value $m_k$and covariance matrix C_k that depends on whether it belongs to class ω_c or class ω_{uc}.The following estimator is used by the probabilistic neural net to estimate the probability density function.

$$f_x(\boldsymbol{x}/\omega_k) = \frac{1}{(2\pi)^{n/2}\,|C_k|^{1/2}}\; e^{-\frac{1}{2}[(x-m_k)^T C_k^{-1}(x-m_k)]} \tag{3}$$

Where $f_x(\boldsymbol{x}/\omega_k)$ is the probability density function of the pattern vectors $\boldsymbol{x}$ of class ω_k , n is the dimensionality of the pattern vector $\boldsymbol{x}$. C_k *and* m_k are the covariance matrix and mean vector of the pattern population of class ω_k and $|C_k|$ is the determinant of C_k.The PNN creates a change map by applying the following rule,

If the condition

$$P_c f_x(\boldsymbol{x}/\omega_c) > P_{uc} f_x(\boldsymbol{x}/\omega_{uc}) \tag{4}$$

holds, assign the input vector to class ω_c.*Otherwise assign x to* ω_{uc}.

P_c and P_{uc} are the probabilities of occurence of patterns in classes ω_c and ω_{uc} respectively. To further simplify matters, the ratio of two conditional probabilities called the likelihood ratio is used. The likelihood ratio $(\Lambda(x))$ is defined as,

$$\Lambda(x) = \frac{f_x(\boldsymbol{x}/\omega_c)}{f_x(\boldsymbol{x}/\omega_{uc})} \tag{5}$$

From computational point of view , it is more convinient to work with the log of the likelihood ratio.Therefore in equivalent form eq.(5) , reduces to a linear classifier , as described by the relation

$$y = w^T\boldsymbol{x} + b \tag{6}$$

where

$$y = \log\Lambda(x) \tag{7}$$

$$w = C_1^{-1}m_1 - C_2^{-1}m_2 \tag{8}$$

$$b = \frac{1}{2}(m_2^T C_2^{-1} m_2 - m_1^T C_1^{-1} m_1) \tag{9}$$

On the basis of equation (6), the log likelihood-ratio test for the change detection problem as follows,

If the output y of the linear combiner (including the bias b) is positive, assign the input vector $\boldsymbol{x}$ *to class* ω_c.*Otherwise assign it to class* ω_{uc}.

Thus,

$$CM(k) = \begin{cases} \omega_c & if\ y_k > 0 \\ \omega_{uc} & otherwise \end{cases} \tag{10}$$

where y_k is the output for input pattern vector x_k.

4 Experimental Results

In order to study the performance of the proposed method, the data set used is taken from [12], which contains a large set of ASAR images. Two images one acquired on 26 July 2007 and another on 12 April 2007 that highlights the flooding in Bangladesh and parts of India brought on by two weeks of persistent rain were selected. A small area with 131×133 pixels as shown in fig.3(a) and (b) is used for simulation in this paper. The ground truth of the change detection mask shown in fig.3(c) is created by manual analysis. The proposed method was implemented in Matlab7. The qualitative as well as quantitative comparison of the proposed method was done with EM based approach [7], MRF based method [7] and LGDM based method [6].The qualitative results are shown in fig.3 For quantitative comparison the change detection mask obtained from each method and the ground truth image is used. The following parameters are used:

TP (True Positive), the number of changed pixels correctly identified.
TN (True Negative), the number of pixels correctly identified as unchanged.
FN (False Negative), the number of changed pixels wrongly identified as unchanged pixels;
FP (False Positive), the number of unchanged pixels identified as changed pixels;

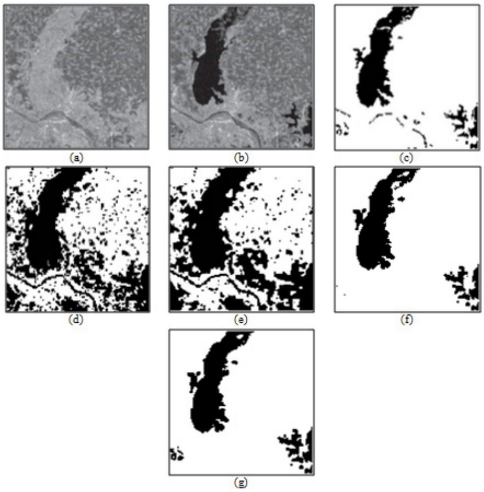

Fig. 3. (a) Small region of ESA/Envisat ASAR image acquired on April 12, 2007. (b) Small region of ESA/Envisat ASAR image acquired on July 26, 2007. (c) Ground truth of the change detection mask (d) EM-based approach (e) MRF-based approach (f) LGDM method with h = 4, $\psi = 3.5$ (g)Proposed Method(PM).

Several metrics can be derived from the above quantities to assess the performance of an method [13]. In this paper, the following metrics are adopted:

1) Omission error (OE), indicates the probability that a changed pixel is wrongly identified as unchanged pixels; OE = FN/(FN + TP)
2) Commission error (CE), indicates the probability that a unchanged pixel is wrongly identified as a unchanged pixel; CE = FP/(TN + FP)
3) Overall Accuracy (OA) is an indication of the overall accuracy of the method in identifying changed pixels as changed and unchanged pixels as unchanged; OA = (TP+TN)/(TP+TN+ FP+FN)

The proposed method achieves 0.14% omission error ensuring that the misclassification are low in the proposed method as compared to the other methods[6,7].The overall accuracy of the proposed method is 98.07 which is quite satisfactory. The other methods show high degradation in performance as compared to the proposed method. It is observed from fig.3(d) and (e) that the results obtained from EM and MRF based approaches are quite noisy. The reason for this is that the difference image is modeled incorrectly.

Table 1. Result of various Parameters used for quantitative comparison

Method	TP	TN	FP	FN	OE(%)	CE(%)	OA(%)
EM	8304	3159	63	5897	41.52	1.95	65.79
MRF	9069	3174	48	5132	36.14	1.49	70.27
LGDM	14165	2760	462	36	0.25	14.33	97.14
PM	14180	2908	314	21	0.14	9.74	98.07

5 Conclusion

In this paper a change detection method based on PNN is presented. The PNN based method has a fast training process and guaranteed optimal classification performance.

The proposed method first produces a difference image by finding the normalized ratio of the gray level information of neighborhood pixels and thus, reduces the negative effect of speckle noise. This difference image is then fed as input to the PNN. The estimator function of the PNN finds the Probability density functions. The pdfs are then used to compute likelihood ratio. The pixels of the difference image are then assigned to change and unchanged classes based on the log likelihood ratio test.

The change map shows the changes between the two images taken as input. The method was compared with some of the existing methods and the results show that the proposed method yields satisfactory results with high overall accuracy. Thus, the proposed method can be used to effectively detect changes in satellite images.

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