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Semi-supervised change detection using modified self-organizing feature map neural network

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ABSTRACT

In the present article, semi-supervised learning is integrated with an unsupervised context-sensitive change detection technique based on modified self-organizing feature map (MSOFM) network. In the proposed methodology, training of the MSOFM network is initially performed using only a few labeled patterns. Thereafter, the membership values, in both the classes, for each unlabeled pattern are determined using the concept of fuzzy set theory. The soft class label for each of the unlabeled patterns is then estimated using the membership values of its K nearest neighbors. Here, training of the network using the unlabeled patterns along with a few labeled patterns is carried out iteratively. A heuristic method has been suggested to select some patterns from the unlabeled ones for training. To check the effectiveness of the proposed methodology, experiments are conducted on three multi-temporal and multi-spectral data sets. Performance of the proposed work is compared with that of two unsupervised techniques, a supervised technique and two semi-supervised techniques. Results are also statistically validated using paired t-test. The proposed method produced promising results.

1. Introduction

Change detection is a process of detecting temporal effects of multi-temporal images [1–3]. This process is used for finding out changes in a land cover over time by analyzing remotely sensed images of a geographical area captured at different time instants. The changes can occur due to natural hazards (e.g., disaster, earthquake), urban growth, deforestation. Change detection is one of the most challenging tasks in the field of pattern recognition and machine learning [4]. There are various applications of change detection like land use change analysis [5,6], monitoring urban growth [7,8], burned area identification [9], etc.

Change detection can be viewed as an image segmentation problem, where two groups of pixels are to be formed, one for the changed class and the other for the unchanged one. Process of change detection can be broadly classified into two categories: supervised [10–12] and unsupervised [13–21]. Supervised techniques have certain advantages like they can explicitly recognize the kinds of changes occurred and are robust to different atmospheric and light conditions of acquisition dates. Various methodologies exist in literature to carry out supervised change detection e.g., post classification method [1,11,22], direct multi-date classification method [1], kernel based method [12]. Besides several advantages, applicability of supervised methods in change detection is poor due to mandatory requirement of sufficient amount of ground truth information which is expensive, hard and monotonous. On the contrary, in unsupervised approach [13–20], there is no need of additional information like ground truth. Due to depletion of labeled patterns, unsupervised techniques seem to be compulsory for change detection. Generally, three consecutive steps are followed for unsupervised change detection. These are image preprocessing, image comparison and image analysis [1]. Images of the same geographical area captured at different time instants constitute the input of the change detection process. In the preprocessing step, these images are made compatible by operations like radiometric and geometric corrections, co-registration and noise reduction [1]. After preprocessing, image comparison is carried out, pixel by pixel, to generate a difference image (DI) which is used for change detection. There are various methods for generating DI like univariate image differencing, change vector analysis (CVA), image ratioing [1]. In the present work, CVA technique [1] is used for creation of DI. Unsupervised change detection process can be of two types: context insensitive [1,15] and context sensitive [13,14,16–19]. Histogram thresholding [1,15] is the simplest unsupervised context insensitive change detection method which has the main disadvantage of not considering spatial correlation between neighborhood pixels in the decision process. To overcome this difficulty, context sensitive methods using Markov random field (MRF) [16,17] are developed. These techniques also suffer from

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certain difficulties like requirement of the selection of proper model for statistical distribution of changed and unchanged class pixels. On the contrary, change detection methodologies based on neural networks are free from such limitations. Work along this direction is already being carried out employing neural networks for change detection, both using supervised and unsupervised learning [13,14,18,20].

In change detection, a situation may occur where the categorical information of a few labeled patterns can be collected easily by the experts. If the number of these labeled patterns is less, then this information may not be sufficient for developing supervised methods. In such a scenario, knowledge of labeled patterns, though not much, may be completely unutilized if unsupervised approach is considered. Under this circumstance, semi-supervised approach [23–25] can be opted instead of unsupervised or supervised ones. Semi-supervision uses a small amount of labeled patterns with abundant unlabeled ones for learning, and integrates the merits of both supervised and unsupervised strategies to make full utilization of collected patterns [23,24]. Semi-supervision has been used successfully for improving the performance of clustering and classification [26–34] when insufficient amount of labeled data are present. Semi-supervised learning using neural networks is explored in various domains [35–38]. Though research is carried out using multilayer perceptron (MLP) for change detection [39] in semi-supervised classification framework, there is no such application of neural network using semi-supervised clustering approach for change detection problem. This motivated us to pursue the present study using neural networks to improve the performance of change detection process.

In one of the earlier works, the self-organizing feature map (SOFM) network [40,41] was modified (named as, modified self-organizing feature map (MSOFM) [42]) and was used for unsupervised context sensitive change detection [14]. In the proposed methodology semi-supervised learning is incorporated within the said MSOFM framework [14]. The network architecture considered is similar to the one used in [14]. The network consists of two layers: input and output. For each feature of the input pattern, there is a neuron in the input layer. The output layer is two dimensional and each (i, j)th neuron in the output layer represents the (i, j)th pixel position in the difference image (DI). Here, we have a few labeled patterns. So, some neurons in the output layer correspond to these labeled patterns (labeled neuron); others corresponds to unlabeled patterns (unlabeled neurons). There is a weighted connection between each neuron in the output layer and all the neurons in the input layer. In the present work, connection weights are initialized differently for labeled and unlabeled neurons. The weight vectors for unlabeled neurons are initialized randomly in [0, 1]. The weight vectors for labeled neurons are initialized by the normalized feature values of the corresponding labeled patterns (to introduce the effect of supervision). To normalize the feature values of the input patterns between [0, 1], a mapping function (Eq. (2)) is used.

At the onset, the network is learned by the labeled patterns only. Then, the unlabeled patterns are passed through the network and the membership values of the unlabeled patterns for the changed and the unchanged classes are calculated (from the trained network) depending on some pre-fixed threshold value. If the similarity measure between an unlabeled pattern and the weight vector of the corresponding neuron in the output layer is greater than the said threshold, then the membership value of that unlabeled pattern in the changed class will be more than that of the unchanged class; and vice versa. A method is also suggested for computing the membership values of unlabeled patterns for both the classes. In [14] a correlation based and an energy based techniques were used for selecting suitable thresholds. In the proposed methodology, the threshold selection process is the same as it was used in [14]. Thereafter, soft class label (or, target value) of each of the unlabeled patterns is updated using the membership values of K nearest neighbors [39] of the corresponding pattern. After each training step, the unlabeled patterns, which are more likely to belong to the changed class, are selected and the MSOFM network is re-iterated by considering the labeled patterns along with these selected unlabeled patterns. Thus, learning of the MSOFM network and modification of soft class labels for the unlabeled patterns are continued iteratively until a given convergence criterion is satisfied or the number of training steps exceeds a certain value.

To assess the effectiveness of the proposed method, experiments are carried out on three multi-temporal and multi-spectral data sets of Mexico area, Island of Sardinia and the southern part of the Peloponnesian Peninsula, Greece and the results are compared with those of the existing unsupervised method based on MSOFM [14], a robust fuzzy clustering technique [43], a supervised method based on MLP [41], a semi-supervised technique based on MLP [39] and constrained k-means algorithm [44] (a semi-supervised clustering algorithm).

The rest of the article is organized into five sections. Section 2 describes the methodology of the proposed semi-supervised change detection technique. Description of the data sets used to carry out the investigation is provided in Section 3. In Section 4, implementation details and experimental results are discussed. Conclusion is drawn in Section 5. The performance measures used for investigation are concisely explained in Appendix A.

2. Proposed methodology for semi-supervised change detection

In some of our earlier works, we have developed different change detection techniques [13,14,19,43] in unsupervised framework. In [13,14], context-sensitive change detection techniques were proposed using unsupervised learning based neural networks i.e. Hopfield-type neural network and modified self-organizing map neural network. Various fuzzy clustering techniques (i.e. fuzzy c-means and Gustafson–Kessel clustering) are used for unsupervised change detection in [19]. These fuzzy clustering based change detection techniques are further improved by incorporating local information in [43]. We have also developed a semi-supervised change detection technique in [39] by modifying the learning of supervised neural network (i.e., multilayer perceptron) in such a way that it can utilize the abundant unlabeled patterns along with a few labeled patterns during learning. As already mentioned, no research work is carried out in this direction using unsupervised neural network when a few labeled patterns are available. In the present work, modified self-organizing map neural network is integrated with the concept of semi-supervised learning for better change detection. Detailed description of the proposed change detection technique is presented in the subsequent sections.

2.1. Generation of input pattern

The difference image $D = \{l_{mn}, 1 \le m \le p, 1 \le n \le q\}$ is produced by the CVA technique [1] from two co-registered and radiometrically corrected γ-spectral band images Y_1 and Y_2, each of size $p \times q$, of the same geographical area captured at different times T_1 and T_2. Here, gray value of the difference image D at spatial position (m, n), denoted as l_{mn}, is calculated as,

$$l_{mn} = (int)\sqrt{\sum_{\alpha=1}^{\gamma}(l_{mn}^{\alpha}(Y_1) - l_{mn}^{\alpha}(Y_2))^2}, \tag{1}$$

where $l_{mn}^{\alpha}(Y_1)$ and $l_{mn}^{\alpha}(Y_2)$ are the gray values of the pixels at the spatial position (m, n) in the αth band of the images Y_1 and Y_2, respectively.