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UNSUPERVISED CHANGE DETECTION OF MULTISPECTRAL IMAGERY USING MULTI LEVEL FUZZY BASED DEEP REPRESENTATION

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ABSTRACT

Change detection in remote sensing images provides useful information for various applications. This paper proposes a robust methodology for the analysis of multispectral imagery using Deep belief network (DBN) and Fuzzy interference system (FIS). Initially Euclidean distance and cosine angle distance features are extracted from the image. Deep learning is a robust machine learning method in which the extracted features are processed through set linear mapping and the changes are detected. However, the coarse spatial resolution indicating the intensity of modifications in class proportion instead of accounting for the change using discrete land covers classes is used in fuzzy image classification. Hence, the FIS is combined with DBN which allows defining our own rules to detect the changes accurately. It uses triangular membership function to plot the changes. The experimental results show that the proposed method enhanced the change detection by improving the performance parameters.

1. INTRODUCTION

Change detection is used for detecting the changes from the remote sensing images which were taken over same geographic regions but at two different times [1]. Disaster management, urban studies, geology, mineral exploration, geo botany, planetary mapping, etc., are some of the applications of change detections [2].Change detection significantly reduces the ideal overlap present in previous reviews giving a compact nomenclature with which to understand and apply change detection work flows. The main idea of this paper is to highlight the changes where the features within have been replaced and arrest the insignificant changes caused by the environments such as illumination, calibration, parallax, registration, diurnal, and seasonal variations [3].

Many methods have been proposed to identify the changes between bi-temporal images: Change vector analysis is a process of detecting change based on its magnitude and direction [4]. It is described based on the feature vector of each data set and their interconnecting vectors [5]. The main drawback of CVA technique is manual selection of threshold value to discriminate 'change' and 'no-change' pixels. The spectral channels are easily affected by noise interference, and there is redundancy in data.

PCA is a widely used image transform algorithm and it is a statistical procedure that uses an orthogonal conversion to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables [6]. To enhance the change information from stacked multi sensor data PCA was used. It greatly depends on the statistical property of considering images but its easily affected by unbalanced data and fails to reproduce the original behavior of image time varying can be confused with the incorrect value of constant one when the decreasing (or increasing) ratio is small but not negligible.

Sparse hierarchical clustering method is used to cluster the change features such as center symmetric local binary pattern and to learn the tree structured dictionary from all the change features to represent the multimodal distribution [2]. It is used to overcome the limitations that are imposed on traditional clustering methods for unsupervised change detection of high resolution images due to multimodal distribution of change features. Sparse reconstruction error is the key to measure the sample to class distance. The disadvantage of this method is that time complexity is high in dimension and sensitive to direction of data record.

IR-MAD method is where series of iterations in order of increasing mainly focus on the difficult observations applies over a different time that shows little change [7]. IR-MAD based on the canonical analysis for the multivariate data of two point in time of same geographical area. The calculated canonical variants of two data input are subtracted from each other. The drawback of IR-MAD is some form of regularization may be needed and it ignores the significant inner relationship between bi-temporal bands.

C^2VA is often applied to the available spectral channels of multispectral images acquired at different times [8]. Here, the spectral channels denote the calibrated radiance data. But the spectral channels are easily affected by the noise and there is redundancy in data. Therefore, we use deep belief network to transform the available spectral channels into an abstract feature space due to their limited representation power and noise resistance ability.

This paper is organized into six sections. The section II briefly describes about the Deep Belief Network. Section III describes about the Fuzzy Inference System. Section IV explains about the proposed methodology. Section V discusses the experimental part. Finally, Section IV concludes the work.

2. DEEP BELIEF NETWOK

Recently, the Deep learning has become popular which is used for processing features of the image [9]. Deep learning is a branch of machine learning which depends on a set of algorithms that aims for high level intellections in data. Deep learning has many layers that include invisible layers and sets of complicated propositional method. Each layer consists of many nonlinear processing units for extracting the feature. The output from one layer is used by the successive layer as input. They are structured in the form of deep generative models known as deep belief network.

A DBN is a neural network with deep architecture. It has many hidden layers. DBN has been successfully applied to dimensionality reduction (image compression), digit recognition, acoustic representation and it is still developing in many fields. DBN is made up of stacks of Restricted Boltzmann Machine (RBM) [10]. These are energy based models that define probability distribution through an energy function. A Boltzmann machine is a network that consists of visible layer of neurons and hidden layer of neurons. The probability of a neuron depends on the connections of the neurons with all other neurons in the network. To reduce the training time complexity, DBNs use the Restricted Boltzmann Machine. It only allows connections between a hidden neuron and a visible neuron, and it doesn't allow connections between two visible neurons or between two hidden neurons.

The algorithm of DBN is as follows:

1. The first layer is the visible layer and the second layer is the hidden layer.
2. Each nodes in the visible layer receives a pixel value x.
3. At node 1 of the hidden layer, x is multiplied by a weight w and a bias b. This process is called as activation function and it gives the output a as shown in Fig. 1.

Activation f((weight w * input x) + bias b) = output a

4. Each node having the pixel value x in the visible layer is multiplied with separate weights summed and the result is added with the bias of the node 1 in the hidden layer to give the output.

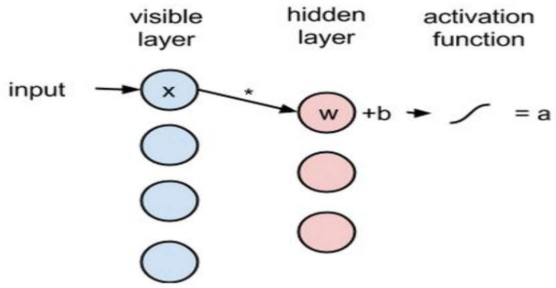

Figure-1. One input path

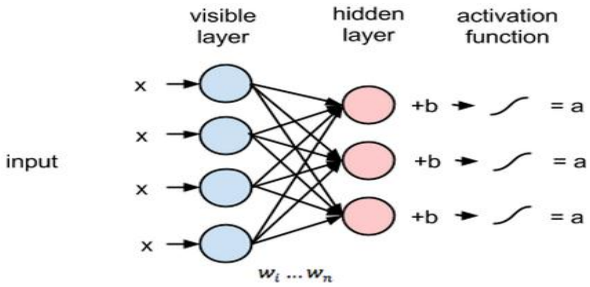

Figure-2. Multiple weighted inputs combined at hidden node

5. This calculation is repeated for all the nodes in the visible layer as shown in Fig. 2. A matrix is formed by the weights of the two layers, where the rows are equal to the input nodes and the column s are equal to the output nodes.
6. Each hidden node receives four inputs multiplied with their respective nodes (forming 12 inputs altogether)

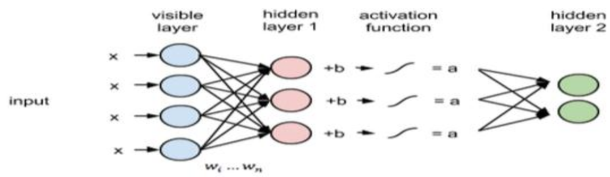

Figure-3. Multiple hidden layers

7. The outputs of the hidden layer 1 is passed as inputs to the hidden layer 2 and the process is repeated until it reaches the final layer. The final output is obtained from the final layer as shown in Fig. 3.

This algorithm can be used for change detection but one main problem of DBN is that retraining the data is complicated.

3. FUZZY INFERENCE SYSTEM

Fuzzy logic is a very popular and a robust method. The method uses fuzzy sets and fuzzy logic to detect changes especially from the remotely sensed data [11]. The changes detected can be fed into the decision support system for the accurate results. The membership function is used to find the probability of the change undergone.

The fuzzy inference system has 3 main components namely, Fuzzifier, Rule Selector and the Defuzzifier. The fuzzy inference system first gets the input variables. The fuzzifier converts the input variables into feature values. Now the membership functions are created for the feature values. Then the rules are framed for the feature values based on the importance of the sentences. If the feature value is very low, then it is considered of least importance. If the feature has a low value, it is considered of low importance. If the feature has a medium value, it is considered of medium importance. If the feature has a high value, it is considered of high importance. If the feature has a very high value, it is considered of very high importance. Likewise the rules can be framed according to the requirement of the process by the fuzzifier. The rule selector selects the important set of rules for the output. The defuzzifier selects the needed rules and assigns the fuzzy score for every sentence to form a new feature matrix. This is given as the input to the deep learning algorithm.

4. PROPOSED WORK

The block diagram of the proposed work is shown in Fig.4. Data 1 from Landsat 7 satellite images of Hanoi, Vietnam on august 1995 and 2nd dataset of same image was taken on august 2000.

4.1. Preprocessing

Preprocessing is the process that suppresses unwanted distortions and enhances the features of the image which is used for further processing. We have chosen Euclidean distance as a key factor [12]. It is used to measure the magnitude of the available spectral channels and enhances image features in image data for further processing. The Euclidean distance of the two datasets are measured using

$$d_e(\mathbf{d}_i, \mathbf{d}_j) = \sqrt{(\mathbf{d}_i - \mathbf{d}_j)'(\mathbf{d}_i - \mathbf{d}_j)}$$

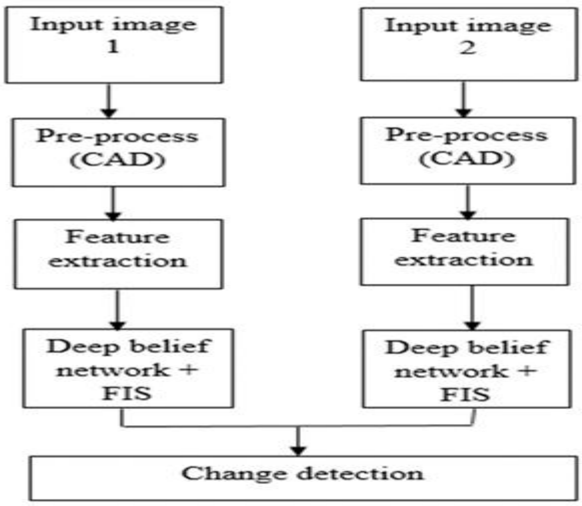

Figure-4. Proposed Block Diagram

4.2. Feature Extraction

The next stage is feature change analysis in which we obtain the differences between two images and to highlight the changes. Here we have taken the cosine angle distance as the parameter for feature change analysis. Euclidean distance alone may not be effective because it ignores several vector components that are equal or close to zero and it does not differentiate changed and unchanged pixels. So it is combined with cosine angle distance so that it is more effective. It is defined as the measure that calculates the cosine of the angle between the two vectors.

$$\vec{a} \cdot \vec{b} = ||\vec{a}|| \cdot ||\vec{b}|| \cos \Theta$$

4.3. Combination of DBN and FIS

The next stage of the process is to carry out the set linear mapping by deep belief network. The input datasets are separated into tested set of nodes and trained set of nodes. These set of nodes are compared with each other using linear mapping to get the single set of nodes. These nodes are then combined to get the final image that highlights the changes. The Euclidean distance from the two datasets are combined and fed into deep belief network. It performs set linear mapping and the image is obtained which highlights the changes. But the accuracy is not enough for the change detection from deep belief network.

When fuzzy inference system is combined with the deep belief network the accuracy and the kappa co efficient is improved.Kappa coefficient is a metric that gives the difference between actual agreement and the agreement expected by chance. The kappa co-efficient is obtained by

$$\hat{K} = \frac{\text{observed accuracy - chance agreement}}{\text{1 - chance agreement}}$$

The change detector fuzzy inference system is initialized. The image gradients (rows and columns) are specified as the input for change detection. The Gaussian membership function is used for each input. The triangular membership function is used for the output. The triplets specify the start, peak, and end of the triangles of the membership functions. These parameters influence the intensity of the detected changes. The membership functions of the inputs and outputs are plotted. Then the fuzzy inference system rules are framed. Evaluate the output of the Change detector for each row of pixels in the image. Finally, the fuzzy evaluated image is compared with the original image and then change detected is displayed in the output image.

5. RESULTS AND DISCUSSION

The proposed methodology is performed on data 1 from Landsat 7 satellite images of Hanoi, Vietnam on august 1995 and 2nd dataset of same image was taken on august 2000 as shown in Fig. 5 and Fig. 6. The image selected for the experiment is 425*352 pixels.

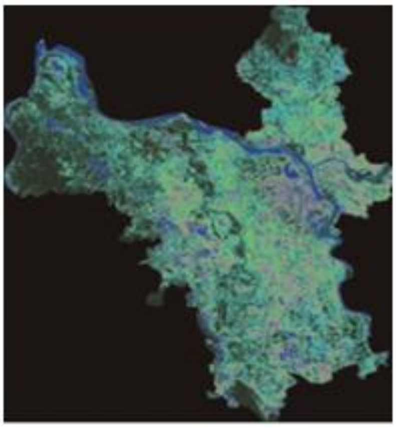

Figure-5. Input image1

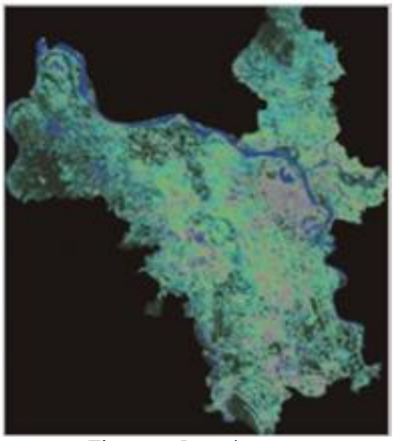

Figure-6. Input image 2

Then the input images are converted into black and white images. The Euclidean distance of these black and white images are computed and plotted as shown in Fig. 7 and Fig. 8. The cosine similarity is found between the two images. The Euclidean distance of the two black and white images are obtained. Next the Euclidean distance of the two images are fed into the deep belief network. Here, the Euclidean distance extracted from the two images are processed through set linear mapping in deep belief network and the change detected image from DBN is obtained. The change detected image from the DBN is shown in Fig. 9.The accuracy and the kappa co-efficient are calculated.

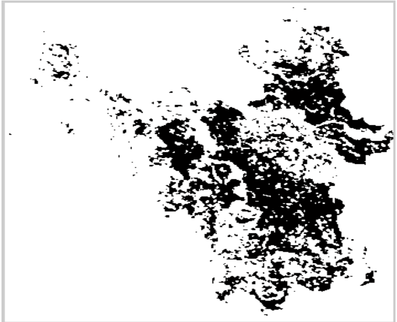

Figure-7. Euclidean distance of image 1

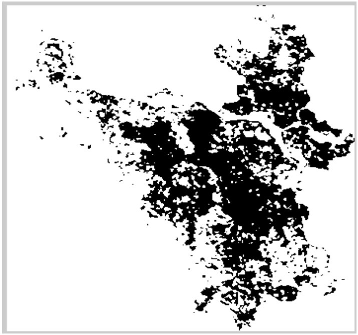

Figure-8. Euclidean distance of image 2

Figure-9. Change detection using DBN

The disadvantage of DBN is that it is difficult to retrain the data. It is likely that the computing is quite not feasible.

But the accuracy can be enhanced when the fuzzy inference system is combined with DBN. The variables are rows and columns of the image. The range of the input rows and input columns are taken as Kuremoto, et al. [10]. The zero Gaussian membership function is used for each input so that if there is a change in a pixel it indicates zero. The membership functions for inputs are plotted as shown in Fig. 10. The triangular membership function is used for the output. The range of the output image is taken as Hui, et al. [1]. The pixel is made white if it belongs to uniform region. Otherwise, it is made black.

The rules that are framed for change detection are:

1. If the input row and column variables are zero then the output variable is white.
2. If the input and the output variables are not zero then the output variable is black.

Likewise the if-then rules are framed based on our requirements. The graph for the output membership function is shown in Fig. 10. Finally the evaluated image is compared with the original image and the final image is displayed. It highlights the changes as shown in Fig. 11. The image displayed uses jet map. It is a color map which is used by contour, surf and p-color. It helps to differentiate the regions of the image such as water, land, forest, etc.

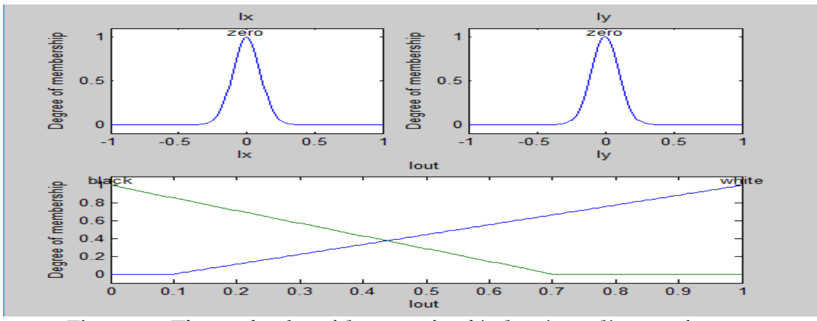

Figure-10. The graphs plotted from membership functions of input and output

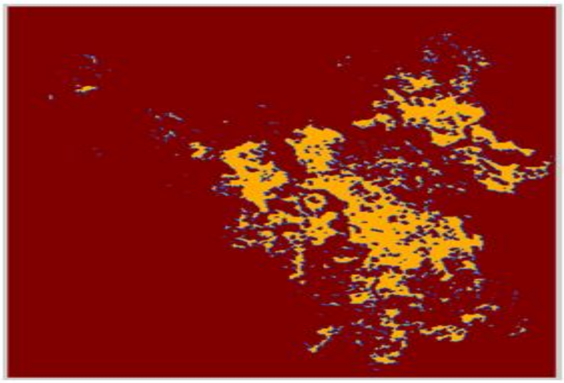

Figure-11. Change detection using fuzzy and DBN

Here the parameters used to differentiate the DBN and the fuzzy based DBN is accuracy and kappa co-efficient.. The classification accuracy of the existing and the proposed method is shown in Fig. 12.

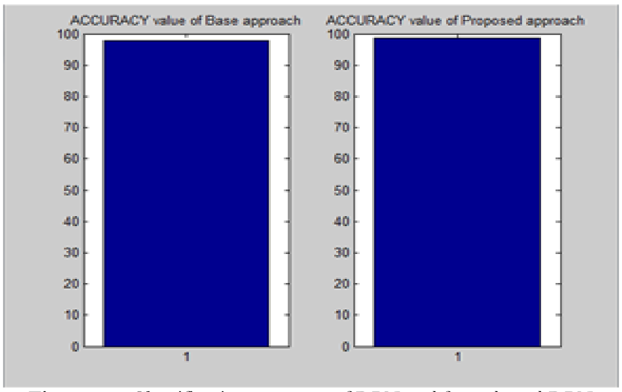

Figure-12. Classification accuracy of DBN and fuzzy based DBN

The accuracy and the kappa co-efficient are compared and displayed in table 1.

Table-1. Performance Evaluation

Methodology	Kappa co-efficient	Accuracy
DBN method	0.7447	97.7872
Fuzzy based DBN method	0.7719	98.5586

Thus when the DBN is combined with fuzzy inference system the kappa co-efficient and the accuracy is increased.

6. CONCLUSION

In this paper a robust method has been proposed for change detection by combining the deep belief network and fuzzy inference system. The proposed method successfully detected the changes by extracting Euclidean

Distance and Cosine Angle Distance from the image and processed through set linear mapping in DBN. Then the fuzzy inference system is combined with DBN which framed rules for change detection. The experimental results shows that the deep belief network when combined with fuzzy inference system have improved the classification accuracy, Kappa coefficient and enhanced the change detection in multispectral satellite imagery.

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