SAR IMAGE CLASSIFICATION USING BACK PROPAGATION NEURAL NETWORK

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ABSTRACT*:* Image change detection is a process that analyzes images of the same scene taken at different times in order to identify changes that may have occurred between the considered acquisition dates. In the last decades, it has attracted widespread interest due to a large number of applications in diverse disciplines such as remote sensing, medical diagnosis and video surveillance. With the development of remote sensing technology, change detection in remote sensing images becomes more and more important. Among them, change detection in synthetic aperture radar (SAR) images exhibits some more difficulties than optical ones due to the fact that SAR images suffer from the presence of the speckle noise. However, SAR sensors are independent of atmospheric and sunlight conditions, which make the change detection in SAR images still attractive. Neural network, which is the supervised method proposed for analyzing the difference image. Neural network-based change detection system is implemented using back propagation-training algorithm. This trained network is designed to be able to detect efficiently any variation between two images and provide adequate information about the type of changes.

Keywords: *Back-propagation, Change detection, difference images, Feature, Neural network, Remote Sensing.*

1 INTRODUCTION

Neural Networks (NNs) is a machine learning technique which is inspired by the function of a human brain. The human brain consists of billions of neurons, which isconnected with synapses in a very complex network. NNs is very well suited for approximation of unknown complex functions (and their derivatives), and pattern recognition. The problem is to find a learning algorithm that in a fast and reliable way trains the network to function in a desirable way. Training in this context is to update the weights and tries to find values that give good results. There are different ways to train a network depending on situation and application. Unsupervised learning is used to have a good way to know if a certain input should map to some distinct output. In supervised learning, have a set of training data, the set consists of some input examples connected with the correct output, and the output value is often referred to as the target value . It focuses on main techniques to train artificial neural networks in a supervised way is the classic back propagation. Back propagation is a method where with help of derivates and the mean square error of the output makes a gradient search to find new values to the weights. This algorithm is one of the oldest and most used. In Genetic algorithms are another approach when training artificial neural networks. In this the 'survival of the fittest' is applied together with some random mutations and, as in nature, the strongest and best solution is found after some generations. In [6] the hypothesis of Gaussian distribution for changed and unchanged classes, the estimation of the parameters of the Gaussian model is carried out using the expectation– maximization (EM) algorithm.

The whole performance of SAR-image change detection is mainly relied on the quality of the difference image and the accuracy of the classification method. The "multitemporal" SAR images are three dimensional (3-D) datasets with two axes corresponding to the conventional spatial domain and the third axis to the temporal direction. Most of the sought-after information is located in transition areas where the contrast or the texture differences in the radiometry reveal temporal changes and spatial features. Temporal changescorrespond to physical changes that may occur on the ground surface and can be observed in the variations of the SAR backscattering coefficient. Spatial featurescorrespond to point targets such as buildings, linear features such as roads or thin rivers, and borders of surface features such as lakes, large rivers, etc. For the remote sensing images, differencing (subtraction operator) and rationing (ratio operator) are well-known techniques for producing a difference image. In differencing, changes are measured by subtracting the intensity values pixel by pixel between the considered couple of temporal image. In rationing, changes are obtained by applying a pixel-by-pixel ratio operator to the considered couple of temporal images. However, in the case of SAR images, the ratio operator is typically used instead of the subtraction operator since the image differencing technique is not adapted to the statistics of SAR images and non-robust to calibration errors. The back propagation algorithm is applied for classification of image, for each input in both local and global classifications. In local classification, the neural network is trained using a particular image and that the same image is given as input. In global classification, a new input is given for the network rather than the images with which it has been trained. Accuracy is calculated for both local and global classification.

This paper is organized as follows: section II gives the detailed specifications of image and its reference data, the different features extracted, and classification techniques. Section III shows the experimental results and section IV concludes the paper.

II SYSTEM MODEL

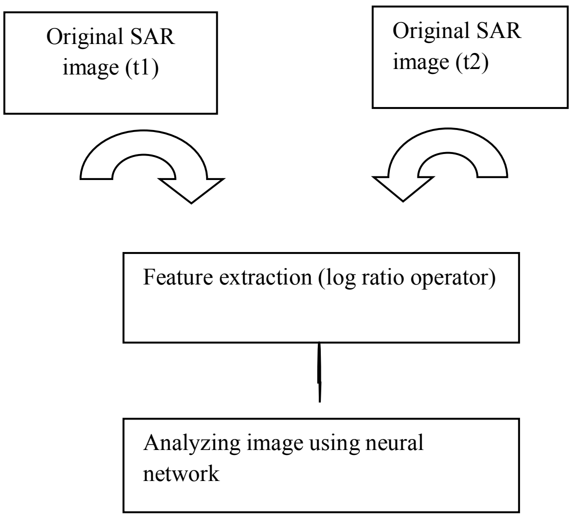

Figure 1:System modelof the change detection approach

Consider the two coregistered intensity SAR images X1={X1(i,j),1 <i< H,1 < j < W} and X2={X2(i,j),1 <i< H,1 < j < W} of size HXW , i.e., acquired and , respectively. Objective is aiming at producing a difference image that represents the change information between the two times; then, a binary classification is applied to produce a binary image corresponding to the two classes: change and unchanged. As shown in Fig. 1, the proposed supervised distribution- free change detection approach is made up of two main phases: 1) Generate the difference image using the log-ratio image; and 2) Automatic analysis of the difference image by using an improved back propagation algorithm.

2.1Generation of difference image using log-ratio operator

The ratio difference image is usually expressed in a logarithmic or a mean scale because of the presence of speckle noise. In the past dozen years, there was a widespread concern over the logarithm of the ratio image since the log-normal model was considered as a heuristic parametric probability distribution function for SAR intensity and amplitude distributions. With the log-ratio operator, the multiplicative speckle noise can be transformed in an additive noise component. Furthermore, the range of variation of the ratio image will be compressed and thereby enhances the low-intensity pixels.

2.2 Analyzing difference image using back propagation algorithm

In this paper back propagation neural network has been used for classifying satellite images and accuracy is calculated for each output. The result shows that the accuracy of the classified images increased as the training data increased. The back propagation algorithm is a generalization of the least mean square algorithm that modifies network weights to minimize the mean squared error between the desired and actual outputs of the network.

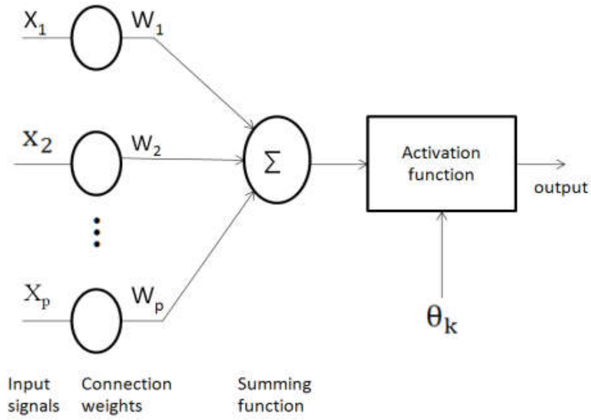

Figure.2. Artificial neuron model

Back propagation uses supervised learning in which the network is trained using data for which inputs as well as desired outputs are known. Once trained, the network weights are frozen and can be used to compute output values for new input samples.The basis for this weight update algorithm is simply the gradient – descent method as used for simple perceptrons with differentiable units.

The error back – propagation algorithm can be outlined as

Step 1: Initialize all weights to small random values.

Step 2: Choose an input-output training pair.

Step 3: Calculate the actual output from each neuron in a layer by propagating the signal forward through the network layer by layer (forward propagation).

Step 4: Compute the error value and error signals for output layer.

Step 5: Propagate the errors back ward to update the weights and compute the error signals for the preceding layers.

Step 6: Check whether the whole set of training data has been cycled once, yes – go to step 7; otherwise go to step 2.

Step 7: Check whether the current total error is acceptable; yes- terminate the training process and output the field weights, otherwise initiate a new training epoch by going to step 2.

III EXPERIMENTS RESULTS

In this section, in order to validate the effectiveness of the proposed SAR-image change detection method, we will show the performance of the proposed methods by presenting numerical results on three data sets. The first data set represents a section (301x301 pixels) of two SAR images acquired by the European Remote Sensing 2 satellite SAR sensor over an area near the city of Bern, Switzerland, in April and May 1999, respectively. Between the two dates, the River Aare flooded entirely parts of the cities of Thun and Bern and the airport of Bern. Therefore, the Aare Valley between Bern and Thun was selected as a test site for detecting flooded areas. The available ground truth (reference image), which waswas created by integrating prior information with photo interpretation based on the input images

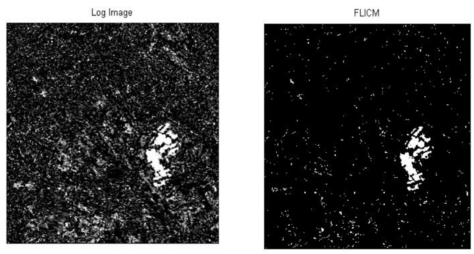

Fig.3. Change detection results of the Bern data set achieved by (a) log ratio operator, (b) FLICM

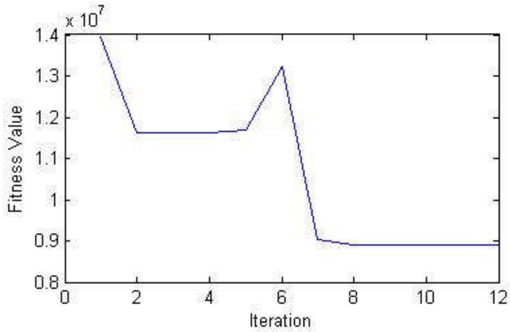

Figure 4. graph representation of bern data set

To verify the suitability of the proposed approach for the difference image, we presented comparative analysis of the performances of our proposed algorithm with that of the traditional FCM algorithm. From the above iteration count value it is clear that, classification is done for less iteration count that is 10 to 11. Accuracy obtained is 98%.

4 Conclusion

Unsupervised distribution-free change detection approach for synthetic aperture radar (SAR) images based on an fuzzy C-means clustering algorithm is the existing method for classifying changed and unchanged regions in the difference image. The accuracy of this method depends on the accuracy of the classification results. FCM algorithm is very sensitive to noise and it is useful for single database at a time. Whereas neural network is useful for multiple databases, once it is trained for it. Neural network retains more information from synthetic aperture radar image than unsupervised method, and gain better accuracy.

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