CHANGE DETECTION USING ITERATIVELY REWEIGHTED REGRESSION WITH NEURAL NETWORKS

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1. INTRODUCTION

Non-linear regression is a common application of neural networks [1]. In the words of Bishop [1], " [… feed forward] networks can approximate arbitrarily well any functional continuous mapping from one finite dimensional space to another, provided the number of hidden units is sufficiently large." There have been earlier studies to utilize this application of neural networks for detecting changes in multi-temporal remote sensing datasets [2]. In this article, we propose a new method for change detection in multi-temporal datasets by means of regression using feed forward neural networks. The regression is performed several times by reweighting the pixels based on the output of the previous regression. In this way, the influence of the changed pixels on regression is reduced and hence a better result is ensured. Currently, we are investigating to find a way to select appropriate parameters for the neural network and to identify the suitable number of iterations. The concept of reweighting is similar to the iteratively reweighted multivariate alteration detection (IRMAD) method [3]. We outline ways to utilize the weights of the pixels after every regression to train the neural networks.

2. METHODOLOGY

Consider two images *U, V* representing a bi-temporal dataset at a given location. If there are no temporal changes between the acquisition times and the differences in the pixel values between the two images are only due to the geometry, atmospheric effects and electronics, then, without loss of generality, we can write,

$$V = f(U)\,, \tag{1}$$

implying that the two images are functional mappings of each other. The function, f can also be called as the calibration function to normalize the radiometric values temporally. Theoretically, it is possible to approximate the function, f by means of regression using a suitable model when a sufficiently large number of samples are available. Neural network is one of the several available tools for regression.

The changes occurred in between the acquisitions of the two images can be seen as the outliers in the functional mapping between the images. In general, when the number of *no-change* pixels is sufficiently large compared to the *change* pixels, due to the generalization capability of the regression methodology, the function, f can still be approximated with a reasonable accuracy. Under these conditions, the change pixels can in turn be identified by simply subtracting the real and expected values of the pixels using the approximation of f (say $\tilde{f}$) i.e., the image, $D = V - \tilde{f}(U)$ can be used to identify the change pixels.

In the multivariate case, i.e., when the images *U, V* contain more than one band, the difference image, *D* also consists of multiple image layers. Since the values in *D* represent the differences, it is convenient to assume that the values of the pixels in each of the image layers of the difference image will have approximately a Gaussian distribution. Also, when we assume that the bands of the original images are independent, it follows that the sum of the squares of the values of *D* at every pixel normalized to unit variance will have approximately a Chi-squared distribution with the degrees of freedom equal to the number of bands in *V*.

For j^{th} pixel, the value c_j is a sample drawn from a chi-square distribution and is calculated as

$$c_j = \sum_{i=1}^{n} \left(\frac{D_{ij}}{\sigma_{D_i}} \right)^2 , \tag{2}$$

where n is the number of bands in image V and σ_{D_i} is the standard deviation of the difference image D_i.

Based on this, Nielsen [3], suggested that we can represent the probability of no-change as

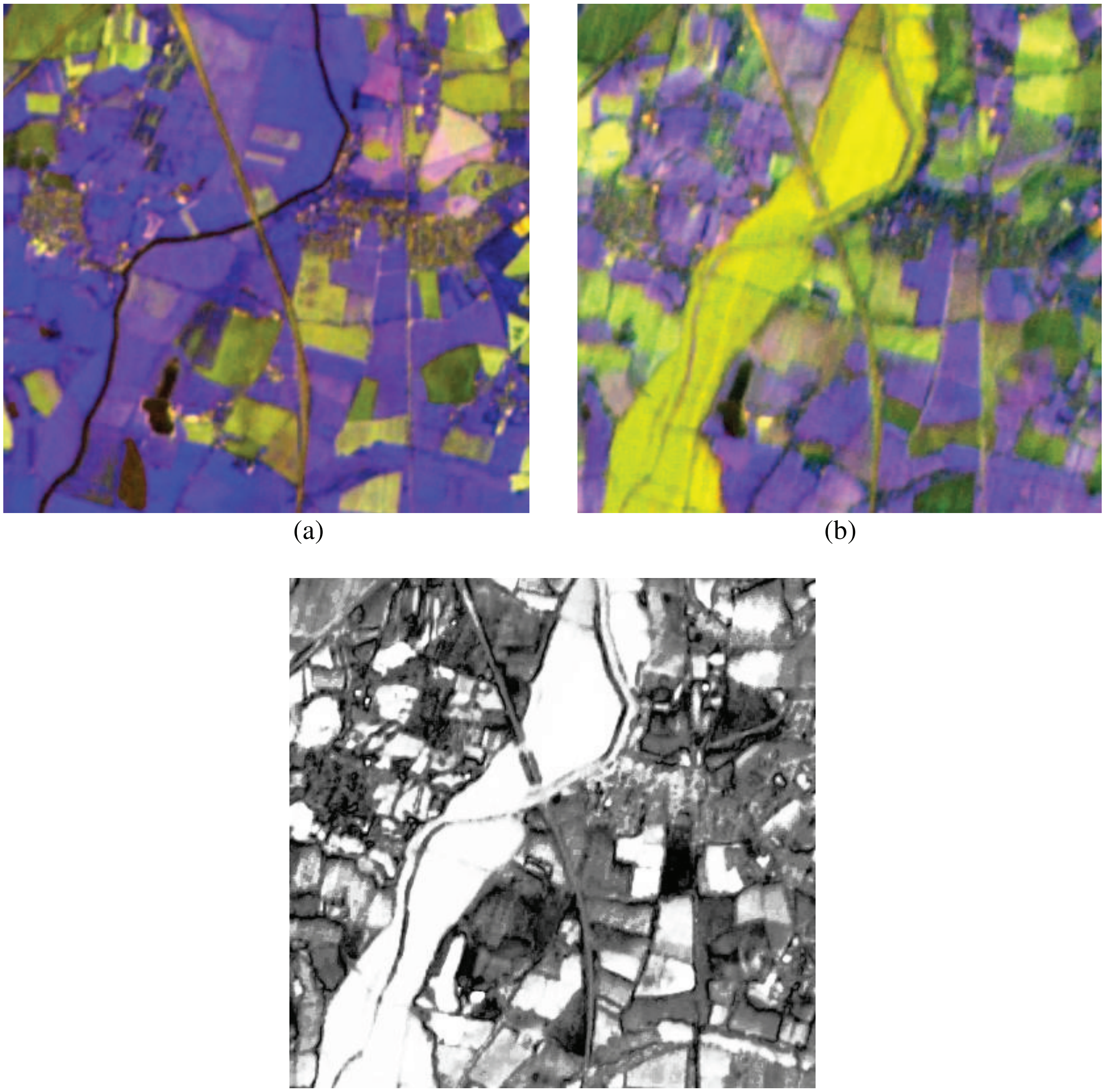
$$\Pr(\text{no-change}) = 1 - P_{\chi^2;n}(c) , \tag{3}$$

where, χ^2 represents chi-square distribution with n degrees of freedom. Pr (no-change) is the probability that a sample c drawn from a chi-square distribution could be that large or larger. The smaller the value of c, the higher is the probability of no-change. These probabilities of change can be used as the weights of the observations and the entire process can be repeated till we achieve a proper mapping.

There are two ways in which the weights can be utilized while training the neural network in the next iteration.
i) In the beginning if we assume that the training samples are drawn from a uniform distribution, then the new weights can be used to modify the distribution and the training samples for the next iteration are drawn from the modified distribution.
ii) The weights can be used as multipliers to the value of the cost function while training. In this way, we can assure that the samples having higher probability of change contribute less to the total error.

3. PRELIMINARY RESULTS

The method is applied to a small subset of bi-temporal images consisting of 3 bands acquired using the SPOT satellite. The images represent a flooding event as shown in Fig. 1. Only 5000 samples are randomly selected uniformly over the image and used for training the neural network. Kalman filter training is used to train the neural network as it converges to the global minimum of the cost function very fast unlike the traditionally used backpropogation algorithm which is very slow and has the problem of converging at the local minima of the cost function [4]. The weights as described in Sec. 2 are used to modify the distribution to select the samples from the available 5000 samples for training. Fig. 1 shows the pre-event (a) and post-event (b) images and the corresponding image representing the chi-square value after 2 iterations (c). It can be observed that the pixels representing the flooding event show high chi-square values implying change. A change map can be generated either by thresholding the image consisting of the chi-square values or by thresholding the image representing the probability of change/ no-change.



(a) (b)

(c)

Fig. 1: A false color composite representation of pre-event (a) and post-event (b) image of a flooding event and the image showing the chi-square values after 2 iterations (c).

4. CONCLUSION

A new method for change detection using neural network regression is proposed. The regression is repeatedly performed by modifying the weights of the samples, hence reducing the effect of the outliers. The improved results of this method and comparison with other classical change detection methods will be presented.

5. REFERENCES

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