LEVEE ANOMALY DETECTION USING POLARIMETRIC SYNTHETIC APERTURE RADAR DATA

Lalitha Dabbiru[1], James V. Aanstoos[1], Majid Mahrooghy[1], Wei Li[2], Arjun Shanker[3], Nicolas H. Younan[2]

[1]Geosystems Research Institute, Mississippi State University, MS 39762, USA
[2]Department of Electrical and Computer Engineering, Mississippi State University, MS 39762, USA
[3]Department of Aerospace Engineering, Mississippi State University, MS 39762, USA
email: lalitha@gri.msstate.edu

ABSTRACT

This research presents results of applying the NASA JPL's Uninhabited Aerial Vehicle Synthetic Aperture Radar (UAVSAR) quad-polarized L-band data to detect anomalies on earthen levees. Two types of problems / anomalies that occur along these levees which can be precursors to complete failure during a high water event are slough slides and sand boils. The study area encompasses a portion of levees of the lower Mississippi river in the United States. Supervised and unsupervised classification techniques have been employed to detect slough slides along the levee. RX detector, a training–free classification scheme is introduced to detect anomalies on the levee and the results are compared with the k-means clustering algorithm. Using the available ground truth data, a supervised kernel based classification technique using a Support Vector Machine (SVM) is applied for binary classification of slides on the levee versus the healthy levee and the performance is compared with a neural network classifier.

Index Terms— Synthetic Aperture Radar (SAR), image classification, anomaly detection, RX detector, support vector machine, neural network classifier

1. INTRODUCTION

Monitoring the physical condition of levees is vital in order to protect them from flooding. Synthetic Aperture Radar (SAR) technology, due to its high spatial resolution and potential soil penetration capability, is a good choice to identify such problem areas so that they can be treated to avoid possible catastrophic failure.

In this paper, we are focused on analyzing different algorithms to study the performance of the anomaly detection using multi-polarized SAR images. The polarimetric SAR data with HH, HV (H denotes transmitted signal is horizontal polarized and V denotes return is vertical polarized) and VV polarizations is very effective for classification because it contains different scattering characteristics of each target and hence contributes changes in the backscatter signal. Several supervised and unsupervised classification algorithms have been applied to SAR data for efficient land cover classification [1] [2]. Polarimetric decomposition parameters entropy (H), anisotropy (A), and alpha (α) derived from the coherency matrix calculated using the SAR data have been used to detect anomalies such as slough slides along the levee [3]. Melamed *et al*. [4] applied SRC algorithm and a classification algorithm by Cloud and Pottier [5] to polarimetric SAR data for anomaly detection.

For this research we used NASA JPL's UAVSAR polarimetric L-band (λ = 23.98 cm) data with a range bandwidth of 80 MHz (resulting in better than 2 m range resolution). The multi-polarized radar image acquired in June 2009 has been analyzed in detail for detecting the anomalies. In addition to the radar data, we relied on ground truth data collected by US Army Corp. of Engineers (USACE) and our team in field collection trips. This data documented the exact location and timing of slough slide appearance and repair. There were 17 active slide events identified as of that image date. The levee is segmented into a 40 meter buffer from the levee centerline and the algorithms were applied to that area. The ground truth was also compared to the optical NAIP (National Agriculture Imagery Program) data to visually confirm the slide events and training masks were created based on those results. Training samples of slides and healthy levee areas were obtained from the UAVSAR data using the training masks for feature extraction analysis.

2. METHODOLOGY

The study area is a stretch of 230 km of levees along the lower Mississippi River. Quick and early detection of anomalies can assist levee managers in prioritizing their inspection and repair efforts. Several supervised and unsupervised techniques have been developed to classify ground terrain types from the polarimetric SAR images. Supervised techniques yield higher accuracy than unsupervised techniques, but suffer from the human interaction to obtain the ground truth data. Therefore two approaches of unsupervised techniques, the RX detector and the *k*-means clustering have been employed to detect the problem areas along the levee. In addition to these training-free methodologies, multiple supervised learning techniques have also been investigated to study the levee problems and the results are compared to unsupervised methods.

2.1 Unsupervised Techniques

2.1.1 Anomaly detection – RX detector

Reed and Yu developed a method referred to as the RX detector which has shown success in anomaly detection of multispectral and hyperspectral data [6]. The RX detector is often presented as a benchmark for anomaly detection. This anomaly detector typically detects the signatures that are distinct from the surroundings with no prior knowledge. Essentially, the algorithm uses the covariance matrix which calculates the Mahalanobis distance from the test pixels to the mean of the background pixels. We considered the global sample mean of the image subset. Superior classification performance for the SAR data has been demonstrated using texture features in the wavelet domain with a window size of 4. The features applied to the RX detector are the magnitudes of the HH and VV polarimetric backscattering coefficients and the wavelet features computed from them.

2.1.2 k-means clustering

k-means is one of the simplest unsupervised learning algorithms to solve clustering problems. The algorithm classifies a given data set with a certain number of pre-defined clusters (*k*). This is achieved by assigning each pixel of the image to one of the clusters according to the minimum Euclidean distance between the pixel's feature vector and the mean feature vector of the clusters. The features applied to this algorithm are the magnitudes of the HH and VV polarimetric backscattering coefficients and the wavelet features computed from them.

2.2 Supervised Techniques

2.2.1 Support Vector Machine (SVM) classifier

SVM, a nonparametric classification method, has been used successfully in remote sensing studies [7]. SVMs discriminate two classes by fitting an optimal separating hyperplane to the training data within a multidimensional feature space. The advantage of SVM is that it works well with small training datasets. In this paper, the concept of SVM is applied to the polarimetric SAR data. The SAR backscattering coefficients HH, HV and VV and wavelet features computed from them are used as features to the classifier. A Gaussian radial basis kernel was used and the training process involves the estimation of the kernel parameter γ and the regularization parameter C. To simplify the parameter selection, the datasets were normalized before the classifier training and optimal parameters for γ and C were defined.

2.2.2 Neural network classifier

In this work, we apply and evaluate the Back Propagation (BP) neural network classifier, which is a multilayer feed-forward network that contains one input layer, one or more hidden layers and an output layer [8]. The SAR backscattering coefficients HH, HV and VV and wavelet features computed from them are used as features to the classifier. The neural network designed has two hidden layers with three neurons in the first hidden layer, and eight in the second layer. The training data was given to the input layer and propagated through the hidden layer to the output layer. The number of iterations was set to 500. The differences between the computed and desired outputs were computed and fed backwards to adjust the network. The algorithm adjusts the weights of each connection in order to reduce the value of the error function.

3. EXPERIMENTAL RESULTS

In this section, the results of both supervised and unsupervised classification of SAR imagery are presented. Since detection of anomalies (slough slides in this case) is of prime importance, we report the performance of supervised classification systems as measured by the individual class accuracies such as the slide class and the healthy class. The UAVSAR image data subset for part of the study area shown in Figure 1 (a) is used for the analysis. The red polygons within the figure illustrate the training areas for the slide and healthy classes. Figure 1(b) displays the optical data for the study area subset.

The classification map obtained from the RX Detector (RXD) unsupervised classifier is displayed in Figure 1(c). The output produced by the RXD is a grayscale image, so the anomaly detection will be done by the visual interpretation. To avoid human errors, a threshold can be used to distinguish the targets from the background. Anomalies are detected as the pixels with a large spectral distance to the background spectral signatures and thus the landslides were shown as anomalies on the levee. This result is compared with the *k*-means algorithm (k = 4) and the result is shown in Figure 1 (d). The four clusters identified are the slide, healthy levee, road, and the areas with higher roughness. The slide and healthy classes were clearly distinguished from the other clusters. These unsupervised techniques are very fast and do not depend on ground truth information, so these results guide levee managers to investigate the areas shown as anomalies in the classification map.

The SVM technique with Gaussian kernel and log C = 4 was used to classify the data. Since the accuracy of the classification varies with the γ parameter, the relationship between accuracy and γ, sampled over the range 0.03 – 0.1 was defined for the analysis and plotted as shown in Figure 2. The results show that SVM performed very well with a highest accuracy of 100% for the slide detection and 92.66% for the healthy levee. The classification map is shown in Figure 3.

The result of back propagation (BP) neural network classifier as shown in Figure 4 indicate that the BP neural network generated promising results for the SAR image data. The overall accuracy achieved with this classifier is 94%. Table 1 depicts the confusion matrix of the classification.

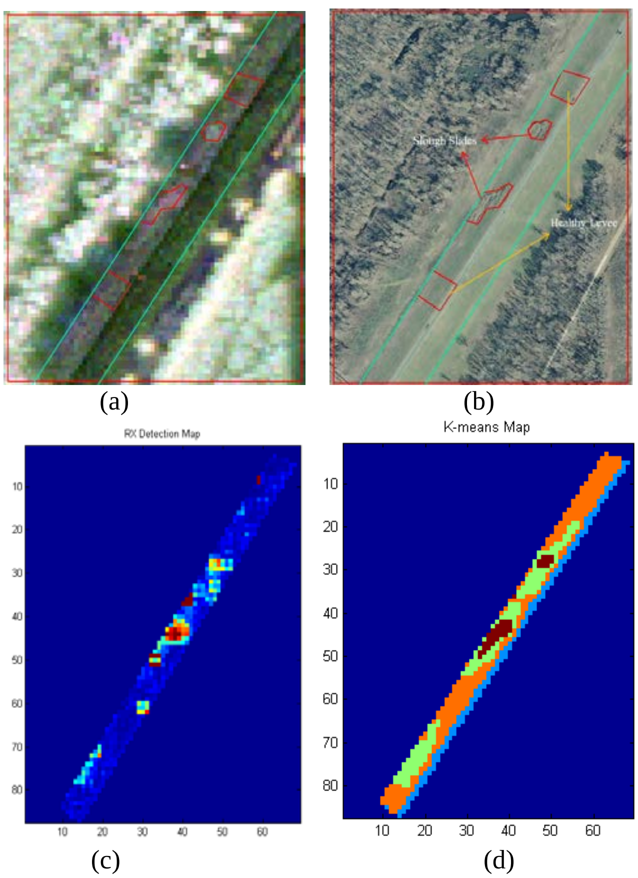

Figure 1. (a) UAVSAR image of 16 June 2009 with in the study area subset which also shows the training areas for slide and healthy pixels (b) Optical data of the study area (c) RX anomaly detector classification result (d) *k*-means clustering

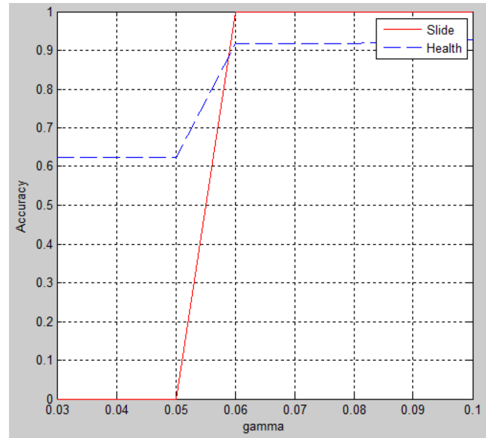

Figure 2. SVM tuning: relationship between classification accuracy and γ with a constant regularization parameter log C = 4

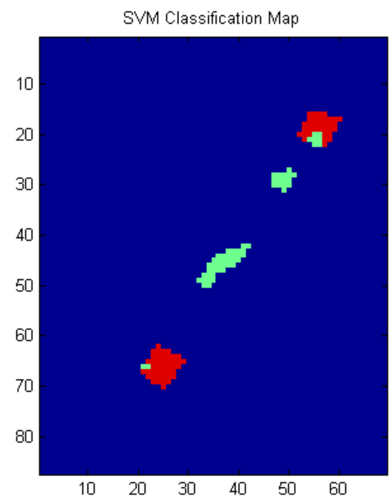

Figure 3. SVM classification map (blue = background, green = slide, red = healthy levee)

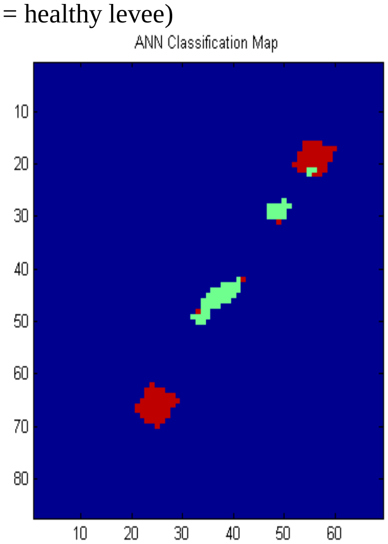

Figure 4. Back Propagation Neural Network classification result (blue = background, green = slide, red = healthy levee)

Table 1. Classification matrix for the study area subset using back propagation neural network

	Slide	Healthy	Accuracy
Slide	38	3	0.9268
Healthy	3	65	0.9559
Accuracy	0.9268	0.9559	0.9450

4. SUMMARY AND CONCLUSION

In this study, we utilized a NASA UAVSAR image to detect anomalies on a levee. We have used supervised and unsupervised classification algorithms to analyze the polarimetric SAR image. The RX anomaly detector detected the targets but cannot discriminate them from one another. A threshold can be used to segment the targets from the background. The clusters detected by the *k*-means algorithm differentiated the slide and healthy classes from the other clusters. The results of supervised learning have shown that the SVM classifier outperformed the neural network classifier in detecting the slough slides.

5. ACKNOWLEDGMENT

This work was funded by the Department of Homeland Security Southeast Region Research Initiative (SERRI) at the Department of Energy's Oak Ridge National Laboratory, as well as the NASA Applied Sciences Division. The authors would like to thank the US Army Corps of Engineers, Engineer Research and Development Center and Vicksburg Levee District for providing ground truth data and expertise.

6. REFERENCES

[1] Eric Rignot, Rama Chellappa, and Pascale Dubois, "Unsupervised segmentation of polarimetric SAR data using the covariance matrix", *IEEE Transactions on Geoscience and Remote Sensing,* Vol. 30, No. 4, July 1992.

[2] S. Fukuda, and H.Hirosawa, "Support vector machine classification of land cover: Application to polarimetric SAR data", *IEEE,* 0-7803-7031-7/01, 2001.

[3] Lalitha Dabbiru, James V. Aanstoos, and Nicolas H. Younan, "Classification of levees using polarimetric synthetic aperture radar imagery", *39th IEEE Applied Imagery Pattern Recognition Workshop,* Proc. 2010.

[4] Georgy Melamed, Stanley R. Rotman, Dan G. Blumberg, and Anthony J. Weiss, "Anomaly detection in multi-polarimetric radar images", *IEEE,* 1-4244-2482-5/08, 2008.

[5] E. Pottier, J. S. Lee, and L. Ferro-Famil, "Advanced concepts in polarimetric SAR image analysis – A Tutorial Review" *EUSAR 2004,* Neu-Ulm, Germany, May 2004.

[6] Chein-I Chang, and Shao-Shan Chiang, "Anomaly detection and classification for hyperspectral imagery", *IEEE Transactions on Geoscience and Remote Sensing,* Vol. 40, No. 6, June 2002.

[7] Bjorn Waske, and Jon Atli Benediktsson, "Fusion of support vector machined for classification of multisensor data", *IEEE Transactions on Geoscience and Remote Sensing,* Vol. 45, No. 12, December 2007.

[8] Philip D. Heermann , and Nahid Khazenie, "Classification of multispectral remote sensing data using a back-propagation neural network", *IEEE Transactions on Geoscience and Remote Sensing,* Vol. 30, No.1, January, 1992.