ON LAND SLIDE DETECTION USING TERRASAR-X OVER EARTHEN LEVEES

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ABSTRACT:

Earthen levees have an important role to protect large areas of inhabited and cultivated land in the US from flooding. Failure of the levees can threaten the loss of life and property. One of the problems which can lead to a complete failure during a high water event is a slough slide. In this research, we are trying to detect such slides using X-band SAR data. Our methodology consists of the following four steps: 1) segmentation of the levee area from background; 2) extracting features including backscatter features and texture features; 3) training a back propagation neural network classifier using ground-truth data; and 4) testing the area of interest and validation of the results using ground truth data. A dual-polarimetric X-band image is acquired from the German TerraSAR-X satellite. Ground-truth data include the slides and healthy area. The study area is an approximately 1 km stretch of levee along the lower Mississippi River in the United States. The output classification shows the two classes of healthy and slide areas. The results show classification accuracies of approximately 67% for detecting the slide pixels.

1. INTRODUCTION

Earthen levees have an important role to protect large areas of inhabited and cultivated land in the US from flooding. A failure of the levees can threaten the loss of life and property. There are more than 150,000 kilometres of levee structure with different designs and conditions over the entire US. Therefore, monitoring the levee system in order to detect and classify the levee vulnerabilities can help levee boards and federal agencies to repair them rapidly with lower costs than traditional methods which can cost many millions of dollars (Aanstoos, 2010). One of the problems which can lead to a complete failure during a high water event is a slough slide. Slough slides are slope failures along a levee. A slough slide leaves areas of the levee vulnerable to seepage and failure during high water events. The roughness and corresponding textural characteristics of the soil in a slide can change the amount and pattern of radar backscatter (Aanstoos, 2011). The reasons that a slide occurs are studied in Hossain et al. (2006).

Early detection of slide events can assist levee boards in beginning their efforts to fix and repair the problems and prevent more costly damage. One efficient and cost effective way to detect these vulnerabilities is to use remote sensing, which is more effective than frequent site visits.

In addition, the type of vegetation that grows in a slide area differs from the surrounding levee vegetation, which can also be utilized in detecting slides (Hossain, 2006). Also, since there is a relationship between the SAR backscatter and soil moisture (Oh, 2004), SAR images can be used to monitor the soil moisture for detecting the slides around levees (Mahrooghy, 2011).

Other remote sensing based methods of detecting landslides have utilized digital elevation models (Tsutsui et. al. 2007 and McKean et. al,, 2004) and two-pass differential interferometry based on SAR images from RADARSAT-1 (Bulmer et. al., 2006).

In this paper, an algorithm based on a neural network is developed to detect landslides on levees from single-pass polarimetric SAR. The paper is organized as follows: the data used in this study is explained in section 2. In section 3, the methodology and block diagram of the algorithm is described. The result of applying the algorithm in the area of study is discussed in the results and validation section, and finally, a conclusion and summary of this study is provided in section 5.

2. DATA

Our area of study is part of the levee system along the lower Mississippi River and the western boundary of the state of Mississippi. Two parts of the study area (about a 1 Km stretch of levees) in this region are studied for algorithm training and testing. Radar imagery from the German TerraSAR-X satellite was acquired over the study area. TerraSAR-X is a SAR sensor imaging at 9.65 GHz with variable incidence angle and ground resolution. It acquires quad polarized images in experimental mode and single and dual polarized HH/VV in other situations. The TerraSAR-X data used for this study was acquired on September 04, 2010 with 1.5 m ground resolution. The image is

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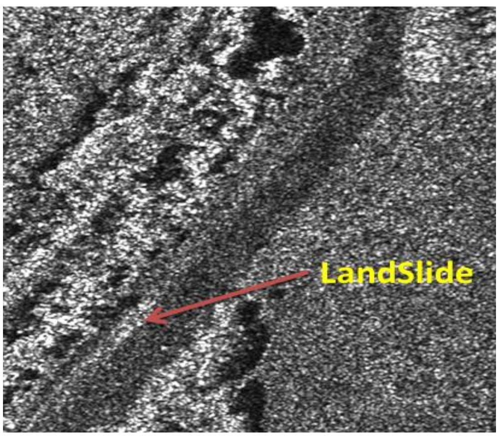
obtained in spotlight mode with Enhanced Ellipsoid Corrected (EEC).

A satellite such as TerraSAR-X has an advantage for monitoring the levee system to detect slides versus an airborne platform since it has better temporal resolution, lower cost of data acquisitions, and high spatial resolution in general. However, the relatively short X-band wavelength does not penetrate vegetation well. This reduces the amount of information about the soil present in the backscatter.

Figure 1 shows the part of the area of study used for training. Figure 1(a) depicts the optical image of the area of study and along with a slide occurring in this area. The corresponding TerraSar-X data (HH polarization) is depicted in Figure 1(b). As can be seen, the area of the slide is brighter than the surrounding area. Note that the optical and radar image were not taken at exactly the same time.

Figure 2 shows a photograph of a typical slough slide in this area which appeared recently in spring 2011 from flooding of the Mississippi River (Aanstoos, 2011).

(a)



(b)

Figure 1. (a) a part of the study area; (b) the corresponding TerraSAR-X data for Sept 04, 2010.

Figure 2. A typical levee slide. This one appeared in the spring of 2011

3. METHODOLOGY

A block diagram of the slide/no-slide classification using a back propagation neural network (BNN) is depicted in Figure 3. First the TerraSAR-X images are used as input data. The levee area and the area of study are segmented from the images. In the next section, the features are extracted from the segmented area. The features used include the magnitudes of the polarimetric backscattering coefficients HH and VV as well as their ratios HH/VV along with texture features such as window statistics (mean and variance), GLCM (Grey-Level Co-occurrence Matrix), and wavelet features. The wavelet features used are the mean and standard deviation of the energy of approximation and the vertical, horizontal, and diagonal detail coefficients of a two-level decomposition of each pixel and its neighbours (sliding window size 7). In total 36 features have been used for the classification. The BNN weights and other parameters are trained based on the ground-truth data. In testing mode, the features at each pixel in the study area are computed and input into the BNN using the weights derived in training mode. The output then gives the slide/no slide classes at each pixel location. In order to verify the algorithm, the results are validated to the ground truth data and the accuracy of the classification is obtained.

The back propagation neural network is a multilayer, feed-forward network trained by the back propagation method (Fausett, 1993). It is structured by the input, output, and hidden layers; the weight parameters; and the specified transfer function. The first layer has weights (W) which are applied to the input feature values. The number of hidden layers is dependent on the application. The weights of each hidden layer are applied to the outputs of the previous layer. All layers have biases, and the last layer is the network output. The BNN used in this work includes one hidden layer and one output neuron. Figure 4 shows a graph of the BNN used in this work.

The input features (x_i) are put into the input layer. The weights in the hidden layer (W) and output layer (V) are initialized and trained using a portion of the ground-truth measurements allocated to training.

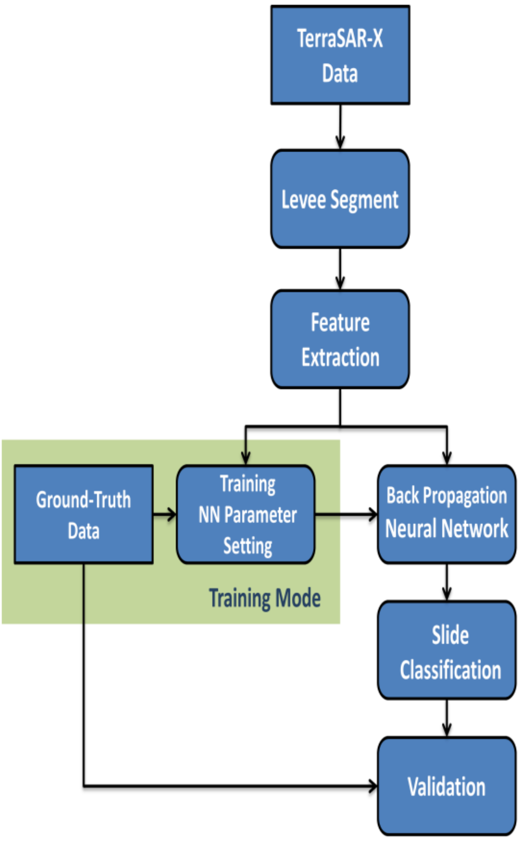


Figure 3. Block diagram of the slide detection algorithm

Throughout the training phase, the errors are propagated from the output layer back to hidden layer using the delta rule such that the total squared error of output is minimized.

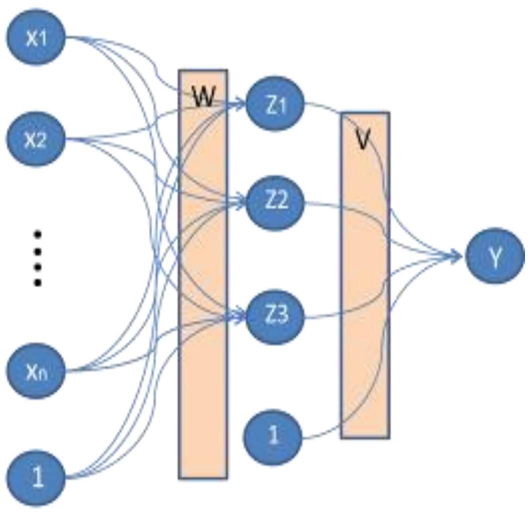
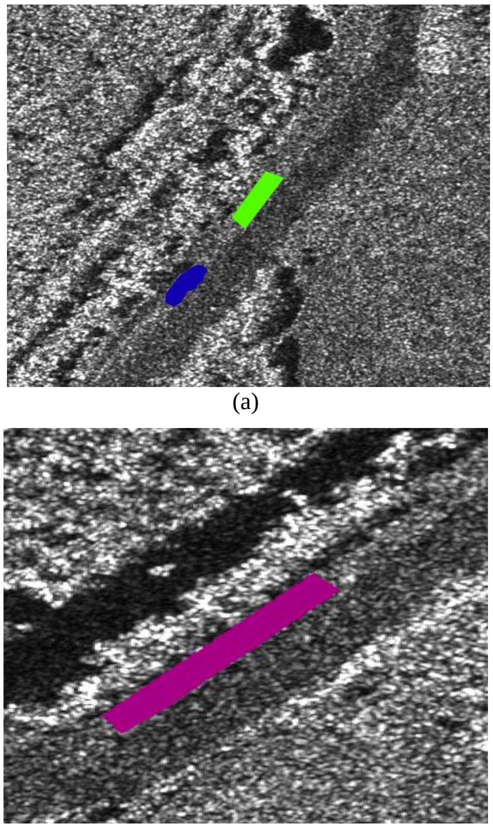


Figure 4. Back propagation neural network with one hidden layer



(a)

(b)

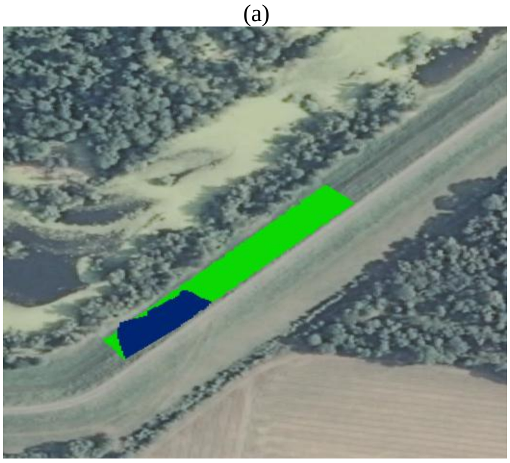
Figure 5. TerraSAR-X radar data (HH polarization) overlaid with masks for training (a) and testing (b)

4. RESULTS AND VALIDATION

Figure 5 shows the training and testing area. In (a) the training area which includes slide (blue) and healthy (green) pixels are shown. Figure 5 (b) depicts the testing area, from a nearby but different section of the levee system. Based on the algorithm explained in section 3, first the training area is used to train the BNN parameters. Around 300 pixels from each class (slide and non-slide) are used for training the BNN. The BNN has 36 input neurons, one hidden layer with three neurons, and one output neuron. The transformation function is a hyperbolic tangent sigmoid, and the training function is Levenberg-Marquardt back propagation. The maximum number of epochs for training is set to 100. For each pixel of testing area, the features are extracted and the BNN decides whether that that pixel is a slide or healthy pixel. The result of applying the algorithm to the testing area is depicted in Figure 6(a) showing the detected healthy (non-slide) and slide pixels. The healthy pixels are green and the slides are blue. Figure 6 (b) shows the ground truth and target data. In this figure, blue shows the slide and the green pixels are the healthy area. As we compare the two images we see that most of the slide area is correctly detected. However, a portion of the healthy area is classified as slide. Table 1 shows the class confusion matrix for the classification. As can be seen, slide pixels are classified with 50% accuracy. The overall accuracy is 67% for this testing area.

It appears that the area which was classified as slides has a high surface roughness, which is detected as slide pixels. Also, since the TerraSAR-X is sensitive to vegetation, any changes in the vegetation can contribute to miscalculation of roughness and detection as slides.

(a)



(b)

Figure 6. (a) Slide classification using the algorithm and TerraSarX data; (b) The ground truth data for testing area

Table 1. Confusion matrix

Classification/ Target	**Slide**	**Healthy Area**	**Accuracy**
Slide	**486**	**463**	**0.5**
Healthy Area	**563**	**1616**	**0.7**
Accuracy	**0.5**	**0.8**	**0.67**

5. CONCLUSIONS

Slough slides are slope failures along a levee. The roughness and corresponding textural characteristics of the soil in a slide can change the amount and pattern of radar backscatter. Exploiting these changes in texture and backscatter pattern, an algorithm based on a neural network and TerraSAR-X data is developed to detect a landslide on the levee system. The methodology includes: 1) segmentation of the levee area from background and; 2) extracting features 3) training a back propagation neural network classifier; and 4) testing and validation of the results using ground truth data. A dual polarimetric X-band image is acquired from the German TerraSAR-X satellite on Sep 04, 2011. Ground-truth data include the slides and healthy area. The results show that the algorithm is able to detect the slide area with around 67% accuracy. Since the TerraSAR-X is sensitive to changes in texture and roughness and also vegetation, some pixels which are not reported as slide zones are incorrectly classified as slide pixels.

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