COMPARISON OF L-BAND AND X-BAND POLARIMETRIC SAR DATA CLASSIFICATION FOR SCREENING EARTHEN LEVEES

Lalitha Dabbiru[1], James V. Aanstoos[1], and 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

ABSTRACT

The main focus of this research is to detect vulnerabilities on the Mississippi river levees using remotely sensed Synthetic Aperture Radar (SAR) imagery. Unstable slope conditions can lead to small landslides which weaken the levees and increase the likelihood of failure during floods. This paper analyzes the ability of detecting the landslides on the levee with different frequency bands of synthetic aperture radar data using supervised machine learning algorithms. The two SAR datasets used in this study are: (1) the X-band satellite-based radar data from DLR's TerraSAR-X (TSX), and (2) the L-band airborne radar data from NASA JPL's Uninhabited Aerial Vehicle Synthetic Aperture Radar (UAVSAR). The Support Vector Machine (SVM) classification algorithm was implemented to detect the landslides on the levee. The results showed that higher accuracies have been attained using L-band radar data compared to the X-band data, likely due to the longer wavelength and deeper penetration capability of L-band data.

Index Terms— Levee classification, remote sensing, synthetic aperture radar, support vector machine

1. INTRODUCTION

Slough (or slump) slides are small landslides due to slope failures along a levee, which leave areas of the levee vulnerable to seepage and failure during high water events [1]. The levee managers are responsible for the rehabilitation, evaluation, maintenance, and repair of the levees in a timely way to mitigate risk of catastrophic failures.

On-site inspection of levees is expensive and time-consuming, so there is a need to develop efficient techniques based on remote sensing technologies to identify levees that are more vulnerable to failure under flood loading. Synthetic Aperture Radar (SAR) technology, due to its high spatial resolution and potential soil penetration capability, is a good choice to identify problem areas along the levee so that they can be treated to avoid possible catastrophic failure. Improved knowledge of the status of these levees would significantly improve the allocation of precious resources to inspect, test, and repair the ones in most need. This research and development effort is leading to new methods to detect the problem areas along the levee such as slough slides and give levee managers new tools to prioritize their tasks.

Synthetic aperture radar data has been widely used in disaster management. Radar polarization and incidence angle are important factors that effect the radar backscatter [2]. The satellite radar data acquired from TerraSAR-X has an incidence angle of 33°and the L-band UAVSAR data has multiple incidence angles vary from approximately 20° to 55° nadir. The radar backscatter is strong for lower incidence angles and decreases with increasing incidence angles. However, in case of rough surfaces (the landslides in this case), the backscatter is almost independent of the incidence angle.

The other important factors influenced by the radar frequency bands are described below.

1.1. Radar Penetration for different radar frequency bands

The radar wavelength influences the penetration below the ground surface and the depth of penetration increases with the wavelength λ. Therefore, the L-band radar penetrates deeper than the X-band sensor. Because of the capability of deeper penetration, the L-band UAVSAR can penetrate through the vegetation on the levee to better detect the landslides. The vegetation on the levee contains different types of grass with a height varying from few centimeters to approximately one meter, depending on the season.

1.2. Surface Roughness estimation with different radar frequency bands

Roughness on the levee refers to multiple irregularities that relate either to textures of the surface or the objects on them such as vegetation. The height of an irregularity, together with wavelength of the radar determines the behavior of a surface as smooth or rough. For example, to quantify the effect of different radar bands, a surface with small irregularity height (in cm) will reflect Ka-band (λ = 0.85 cm), X-band (λ = 3 cm), and L-band (λ = 24 cm) radar waves as if it were a rough, intermediate, and smooth

surface, respectively. Greater height variations compared with the wavelength will appear rough even to the L-band. Therefore, the landslides which are rough in texture on larger scales will be discriminated by L-band more prominently than the X-band. However, the advantage of acquiring X-band data is of its high spatial resolution and 11-day revisit cycle which help in detecting the temporal changes on the levee.

The high resolution, low-noise UAVSAR L-band data was used in the detection, migration, and impact of oil from the Deepwater Horizon oil spill [3]. Zhang *et al.* [4] implemented the SVM algorithm for the classification of polarimetric SAR images using scattering and textural features. Cui *et al.* [5] have implemented a multi-classifier decision fusion framework for levee health monitoring using texture features derived from the grey level co-occurrence matrix.

In this paper, we propose a classification method which utilizes the polarimetric and texture features of the X- and L-band SAR data for efficient classification and detection of slough slides.

2. STUDY AREA AND DATA SETS

2.1. Study Area

The study area is a stretch of 230 km of levee along the lower Mississippi river along the western boundary of the state of Mississippi in USA. At the time of image acquisition there was one active landslide located at (32.5685, -91.0393) north of Vicksburg, Mississippi. A subset of the study area which has this active landslide was chosen as the area of analysis. Based on the ground truth data collected by US Army Corp. of Engineers (USACE), the training masks were created and utilized in the classification tasks.

2.2. Data Sets

2.2.1. UAVSAR data
This study uses the data from NASA Jet Propulsion Laboratory's UAVSAR instrument, a polarimetric L-band (1.25 GHz / 24 cm wavelength) synthetic aperture radar [6]. The multi-look HH, HV, and VV polarization data with a spatial resolution of 5.5 m is used in the analysis. UAVSAR is capable of penetrating dry soil to a few centimeters depth, and identifying vertical displacements on the order of a few millimeters. Thus it is valuable in detecting changes in levees that are key inputs to the classification system.

2.2.2. TerraSAR-X data
TerraSAR-X is a German radar satellite which carries a high frequency X-band (9.6 GHz / 3 cm wavelength) synthetic aperture radar and can be operated in different modes and polarizations [7]. The Spotlight, Stripmap, and ScanSAR modes provide high resolution data with single, dual, and quad-polarizations.

3. METHODS

The process used is shown in the block diagram of Figure 1. The UAVSAR multi-polarized (HH, HV and VV), multi-look radar image acquired on 25th January 2010 and the TerraSAR-X dual polarization data (HH and VV) acquired on 15th September 2010 were used in the analysis (unfortunately, closer acquisition dates were not available). The spatial resolutions for UAVSAR and TerraSAR-X imagery are 5.5 m and 1 m respectively.
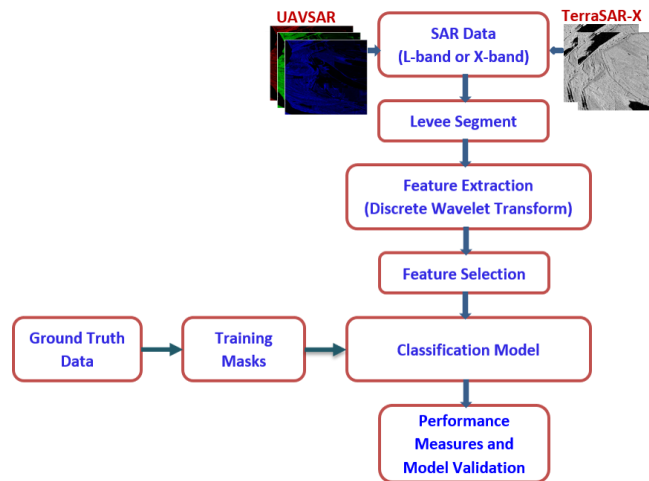

Figure 1. Block diagram of the supervised classification approach

3.1. Texture Features

Texture and intensity are two important parameters for levee classification for detecting the landslides. The proposed method first calculates the Discrete Wavelet Transform (DWT) of every pixel vector of L-band and X-band SAR imagery. The ability of wavelet analysis to decompose the image into different frequency sub-bands makes it suitable for image classification [8]. In some applications, the energy of each sub-band is used as a texture feature. In our application, we have selected the approximation coefficients as these provide the coarse textural information from the image. Other parameters to be considered include the choice of mother wavelet function, and the neighborhood window size. For our application, we used wavelet features with one decomposition level from each of the radar polarization channels. We have tested with different window sizes and mother wavelets. The Daubechies mother wavelet with a window size of 4 gave better performance.

3.2. Classification Method

The support vector machine (SVM) is a state-of-the-art classification method introduced by Vapnik [9]. It is a powerful supervised learning method for analyzing and recognizing patterns. 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 and while training an SVM we need to consider number of factors like: a) how to preprocess the data b) what kernel to use and finally, c) setting the parameters of the SVM and the kernel. The kernel function plays a critical role in SVM training and classification. The SVM has another set of parameters called hyper parameters and these are soft margin constant 'C' and the width of the Gaussian kernel γ $(1/2\sigma^2)$.

4. RESULTS

The goal of this research is to detect landslides on the levee, so the subset with an active landslide was chosen as the area of analysis. The training mask for the classification analysis is shown in Figure 2, which has two ground truth classes; a) landslide, and b) healthy levee. The support vector machine supervised learning algorithm has been implemented on the SAR datasets with Gaussian radial basis function (RBF) kernel and the performance of the classification was tested with different values of kernel parameter γ.

Figure 2: Training mask for UAVSAR subset with two ground truth classes: 1. Landslide and 2. Healthy Levee

4.1. UAVSAR Classification Results

Each pixel of multi-look, multi-polarized UAVSAR imagery is 5.5m X 5.5m and the size of the subset is 98 X 94 pixels, out of which 58 are landslide pixels and 121 are healthy levee pixels. For this subset 30% of the labeled samples are randomly selected as training, and the rest as testing. The

SVM classification algorithm was implemented on the extracted texture features of the subset. The results show that the SVM classifier performed very well with a highest accuracy of 88% for landslide detection and 86% for healthy levee at γ = 0.22. The classification map for the UAVSAR subset is shown in Figure 3.
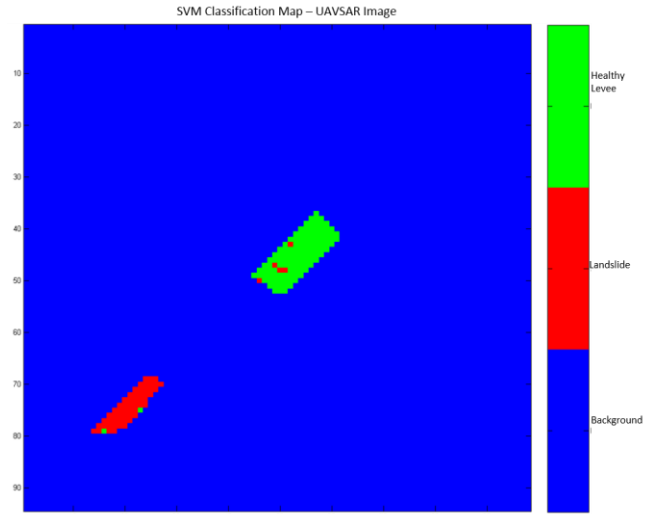

Figure 3: Classification map of SVM classifier for UAVSAR imagery

4.2. TerraSAR-X Classification Results

Each pixel of dual-polarized TerraSAR-X imagery is 1m X 1m and the size of the subset is 500 X 562 pixels, out of which, 1984 are landslide pixels and 3630 are healthy levee pixels. For this subset 30% of the labeled samples were randomly selected as training, and the rest as testing. The SVM classification algorithm was implemented and the results show highest accuracies of 74.77% for landslide and 73.88% for healthy levee detection at γ = 1.5. The classification output map for TerraSAR-X image is shown in Figure 4.
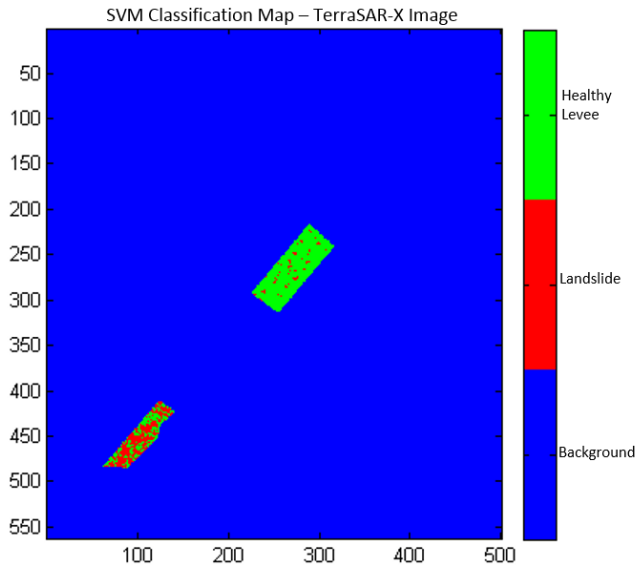
Figure 4: Classification map of SVM classifier for TerraSAR-X imagery

5. CONCLUSION

In this research, we analyzed the ability to detect landslides using different frequency bands of synthetic aperture radar data and the Support Vector Machine (SVM) supervised classification algorithm. SAR data from UAVSAR L-band and TerraSAR-X X-band sensors are used in this study. Experimental results showed that higher accuracies were attained using L-band radar data compared to the X-band data. The landslides are rough in texture at scales more compatible with the longer L-band wavelength. This factor, and also the greater penetration through vegetation and soil, likely explain the better performance. The performance of the X-band classifier was however still good enough that it should be considered for this application when a suitable L-band sensor is not available or practical.

More testing of this method is needed, and the authors are continuing the research as more slough slide examples become available.

6. ACKNOWLEDGEMENT

7. REFERENCES

[1] Aanstoos, J.V., Dabbiru, L., Gokaraju, B., Hasan, K., Lee, M. A., Mahrooghy, M., Nobrega, R.A.A., O'Hara, C. G., Prasad, S., Shanker, A., 2012. Levee assessment via remote sensing SERRI Projects, SEERI Report 80023-02.

[2] Yousif A. Hussin, "Effect of polarization and incidence angle on radar return from urban features using L-band aircraft radar data," *IEEE*, 1995.

[3] Cathleen E. Jones, Brent Minchew, Benjamin Holt, and Scott Hensley, "Studies of the deepwater horizon oil spill with the UAVSAR radar," *Monitoring and Modeling the Deepwater Horizon Oil Spill: A Record-Breaking Enterprise, American Geophysical Union,* 2011.

[4] Lamei Zhang, Bin Zou, Junping Zhang, and Ye Zhang, "Classification of polarimetric SAR image based on support vector machine using multiple-component scattering model and texture features," *EURASIP Journal on Advances in Signal Processing*, vol. 2010, doi:10.1155/2010/960831.

[5] Minshan Cui, Saurabh Prasad, Majid Mahrooghy, James V. Aanstoos, Matthew A. Lee , and Lori M. Bruce, "Decision fusion of textural features derived from polarimetric data for levee assessment", *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing,* vol. *5*, no. *3*, June 2012.

[6] Rosen P.A., S. Hensley, K. Wheeler, G. Sadowy, T. Miller, S. Shaffer, R. Muellerschoen, C. Jones, H. Zebker, and S. Madsen, "UAVSAR: A new NASA airborne SAR system for science and technology research," *IEEE Radar Conference*, Verona, NY, April 24–27, 2006.

[7] Roth A., J. Hoffmann, and T. Esch, "TerraSAR-X: How can high resolution SAR data support the observation of urban areas?", In: Proceedings of the ISPRS WG VII/1 "Human Settlements and Impact Analysis" 3rd International Symposium Remote Sensing and Data Fusion Over Urban Areas (URBAN 2005) and 5th International Symposium Remote Sensing of Urban Areas (URS 2005), Tempe, AZ, USA, March 14–16, 2005.

[8] Huang, K., Aviyente, S., "Wavelet Feature Selection for Image Classification," *IEEE Transactions on Image Processing*, vol.17, no.9, pp. 1709-1720, Sept. 2008.

[9] V. Vapnik. *Statistical Learning Theory*. John Wiley and Sons, Inc., New York, 1998.