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Discriminating Tailing Piles using VNIR Imagery and SVMs

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Discriminating Tailing Piles in VNIR Satellite Imagery using a Support Vector Machine

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Introduction

This report describes a brief investigation into the use of multispectral satellite imagery and a machine learning technique to discriminate between the soils in two tailing piles in the U1a Complex at the Nevada National Security Site. The south pile dates from the late 1960s and the north pile dates from the early 2000s and is where recent tailings have been dumped. Our approach is to use commercially available satellite imagery of the U1a tailing piles and a Support Vector Machine (SVM) to discriminate between the soils in these piles. Experiments were performed using multispectral pixels selected from around the U1a Complex to train the support vector machine. Pixels in the scene were then classified by the SVM. Classification performance was assessed qualitatively through study of the classification imagery output by the SVM. These qualitative assessments provide the conclusions drawn by the investigation:

- A SVM can be used to discriminate between different types of materials in satellite imagery.
- The VNIR imagery used in this investigation does not provide the features needed by the SVM to discriminate between the two tailing piles at the U1a Complex—the soils look too similar in these spectral bands to discriminate.

The remainder of the report details the experiments performed to reach these conclusions and the limitations and caveats associated with the conclusions.

Imagery from the DigitalGlobe Global Enhanced GEOINT Delivery (G-EGD) was used in this investigation. The G-EGD catalog lists five Visible Near Infrared (VNIR) multispectral collections imaged by the WorldView-3 satellite over the U1a Complex dating from 16 March 2016 to 24 May 2018. No collections were identified that contained Short Wave Infrared (SWIR) imagery of the U1a Complex in the G-EDG archive. The most recent collection, dated 24 May 2018, was selected for the experiments. Imagery used in the experiments was radiometrically and sensor corrected, but not orthorectified. The ground sampling distance for this multispectral imagery ranged from approximately 1.3 to 1.4 meters and the band names and wavelength spans of the VNIR imagery are listed in the table below.

Band	**wavelengths**	**Band**	**wavelengths**
Coastal	400–450 nm	Red	630–690 nm
Blue	450–510 nm	Red Edge	705–745 nm
Green	510–580 nm	Near IR1	770–895 nm
Yellow	585–625 nm	Near IR2	860–1040 nm

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A Support Vector Machine (SVM) is a supervised machine learning technique that is used to classify data. Training data is used to construct a hyperplane (called a support vector) that maximizes the distance between the classes of the training data and the hyperplane [Jakkula06]. SVMs have been used to great effect in classifying surface materials in satellite imagery [Johnson 17]. The ENVI image analysis software (v4.1.6) was used to display the imagery and perform the classifications. Regions of Interest (ROIs) around the U1a Complex were used to select training data (i.e., ensembles of multispectral pixels) and the SVM was trained using default parameters.

Experiments

Three classification experiments were performed on the selected image using four regions of interest (see Figure 1). The image on the left of Figure 1 is a GoogleEarth image of the U1a Complex collected on 15 March 2016 and the image on the right is from the G-EGD archive collected on 24 May 2018. The scene contains a number of regions including desert landscape, soils, buildings, vehicles and roads. The four ROIs shown in the right image are rectangularly shaped and each contain approximately 200 multispectral pixels. The yellow ROI contains pixels of desert landscape consisting of desert soil and scrub brush; the magenta ROI contains pixels of soil from the north tailing pile; the green ROI contains pixels of soil from the south tailing pile; and the red ROI contains pixels from a rooftop. For reference, the north tailing pile was created more recently (c. 2000) than the south tailing pile (c. 1968).

After the SVM was trained with pixels from the ROIs, the SVM was run and classification imagery produced. The imagery color codes each pixel in the image into one of two colors (for binary experiments) or three colors (for experiments with three classes). The classification imagery was visually inspected and compared to context imagery (Figure 1 without the ROIs) for an indication of how the classifier performed.

The first experiment assessed the performance of the SVM on two very different materials, namely soil from the south tailing pile and a rooftop. The context and classification imagery for the first experiment is shown in Figure 2 on the left and right respectively. The context image shows the locations of the ROIs used for training the SVM and a box is drawn around the south tailing pile ROI as a guide to its location in the classification image. In the classification red pixels have been classified as materials similar to the rooftop and the green pixels have been classified as materials similar to soil in the south tailing pile. Comparison of the red regions in the classification image with corresponding locations in the context image show a close correspondence between the red pixels and buildings and the green pixels with non-manmade materials. With this image and training set, the SVM appears to be able to discriminate between soil and rooftop-like materials.

The second experiment classified pixels in the scene using training data from the north and south tailing piles (magenta and green ROIs respectively). The context image showing the ROIs for this experiment and the classification image are shown in Figure 3. Examination of the classification image reveals that there is no clear distinction between soils in the north and south tailing piles. Figure 4 illustrates a zoom image of the classification image with the left image showing the north pile and the right image the south pile. The extent of the zoom imagery is depicted by the boxes in the context and classification imagery in Figure 3. Considerable pixel misclassification is evident in these images.

A third experiment was performed with three classes: soils from the north and south tailing piles and soil from the desert landscape around the U1a Complex (yellow ROI). This experiment was performed to get a sense for the classifier's performance on the north and south tailing piles if given an alternate class. The results of this experiment are illustrated by the context and classification imagery in Figure 5. Casual examination of the classification image indicates that desert scrub brush regions in the image were appropriately classified as desert landscape and the soil regions were either classified as north or south tailing soils with little discrimination between these two classes.

Figure 1: The image of the left is a color image of the U1a Complex. The image on the right depicts the locations of the Regions of Interest (ROIs) that were used to train the support vector machine. The yellow ROI in the upper left portion of the right image is desert landscape, the magenta ROI in the upper center of the image is soil from the north tailing pile, the green ROI below the center and to the left is soil from the south tailing pile and the red ROI is a rooftop. These images provide context for the classification imagery that follows.

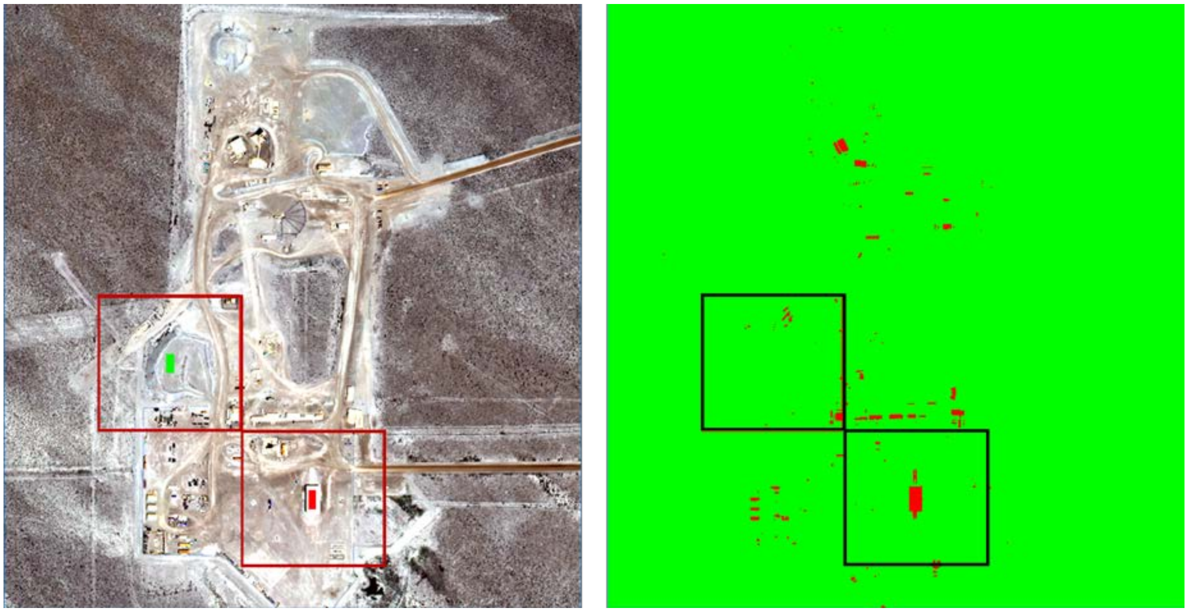

Figure 2: Context and classification image (left and right respectively) with soil from the south tailing pile (green) and a rooftop (red). The SVM performs adequate discrimination between these two classes.

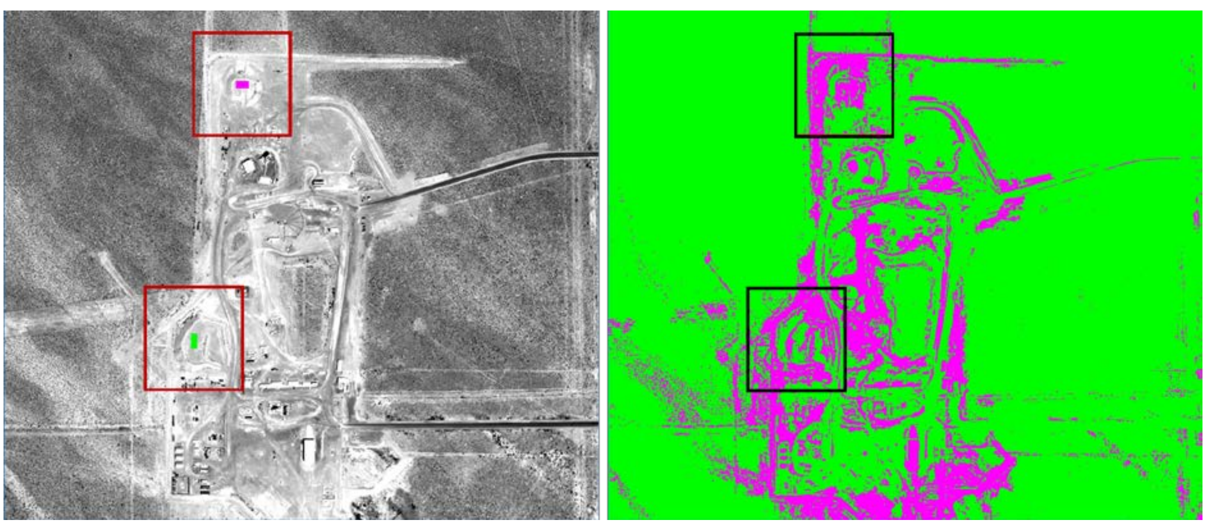

Figure 3: Context and classification imagery for soil in the north tailing pile (magenta) and south tailing pile (green). Discrimination between soils in the north and south piles is not evident in the classification image.

Figure 4: Zoom images centered at the south pile (left) and north pile (right). The zoom area in these images is depicted by the boxes in Figure 3. Considerable misclassification of pixels in the tailing piles is evident.

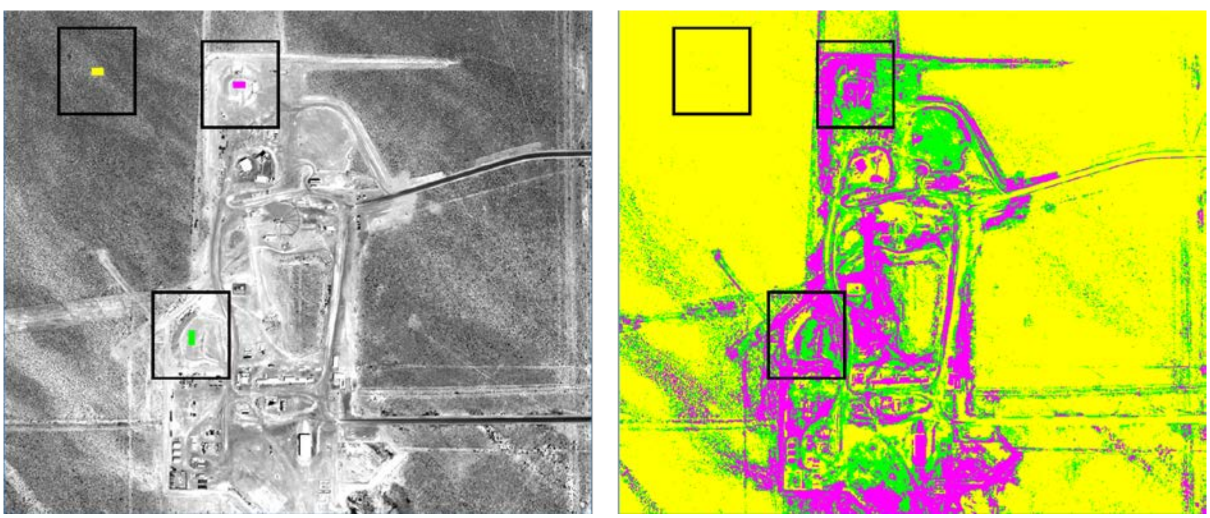

Figure 5: Context and classification imagery of three classes: desert landscape (yellow), and soils from the north and south tailing piles (magenta and green respectively). The desert landscape appears to be appropriately classified. In contrast, bare soil at the site is classified as a mix of soils from the north and south tailings. That is, the soils from the north and south tailing piles look the same in these spectral bands.

Discussion

Figure 6 depicts exemplar spectra from each ROI. The spectra look very similar aside from an offset between the rooftop and desert spectra and the north and south tailing pile soils. The north and south soil spectra track each other very closely. There are slight distinctions between these spectra as illustrated in Figure 6, the most notable being the slight offset of the north pile soil from the south pile soil. The manifestation of this offset in imagery is that the soil in the north pile ROI appears slightly brighter than the soil in the south pile ROI in gray scale imagery (see Figure 1). The other minor variations between the two spectra could be attributed to a number of factors including natural variations and the fact that spectra from only one pixel in each ROI is displayed in Figure 6 rather than an average of spectra.

In contrast, the spectra of the desert landscape and rooftop appear to track one another but have different slopes between some bands. These apparently minor variations are adequate for the SVM to classify the scene into desert landscape and rooftop as seen in Figure 7. Although a quantitative evaluation of the classification was not performed, the SVM appears able to distinguish between these two classes.

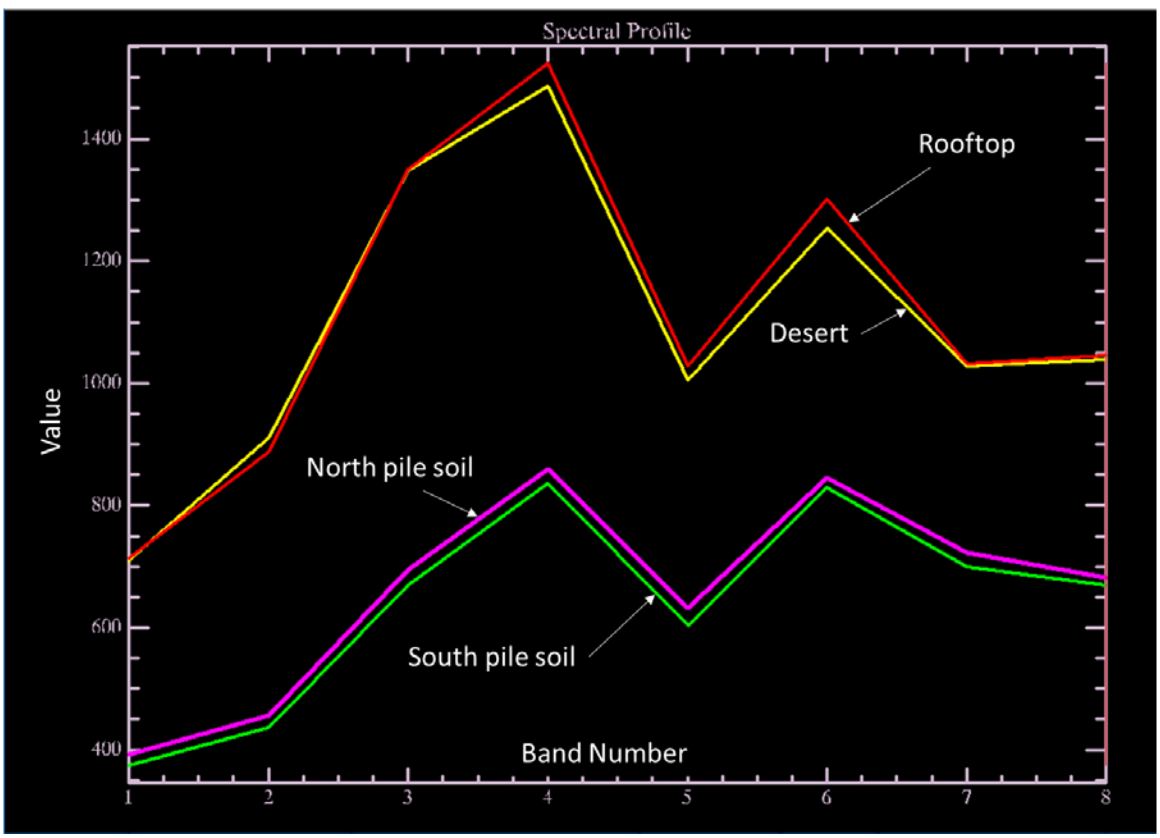

Figure 6: Exemplar spectral from the four ROIs. Each plot represents one pixel from each ROI.

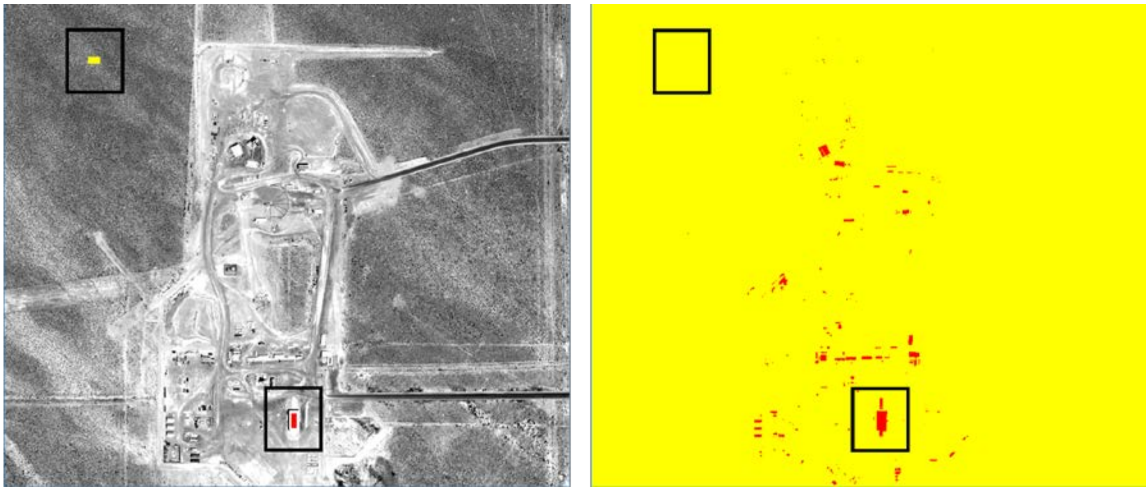

Figure 7: Context and classification imagery for the desert landscape and rooftop ROIs. The SVM appears to be able to adequately discriminate between these two classes.

Summary

The results from this brief investigation have several caveats. First, VNIR imagery was used as opposed to VNIR+SWIR. It has been demonstrated that SWIR imagery is effective at discriminating different kinds of soil [Johnson17]. But, due to the unavailability of SWIR imagery, the investigation was performed using available VNIR imagery. Second, a very small amount of imagery was used to train the SVM. Typically, an ensemble of imagery is used to determine the discrimination ability of a machine learning technology which in turn indicates whether different types of materials can be discriminated. Finally, the parameters of the support vector machine used in this investigation were not tuned, and it might be possible to enhance the performance of the SVM through tuning.

Given the caveats noted above, two qualitative conclusions can be drawn from this investigation. First, support vector machines have the potential to effectively discriminate between different types of materials in satellite imagery. In this case the materials were desert landscape, soil from a tailing pile, and a rooftop. Secondly, this investigation does not support the use of SVMs to discriminate between soils in tailing piles in the VNIR spectral bands. The spectra between soils in the two tailing piles are too similar for the SVM to discrimination.

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