Potassium-Phosphorus-Nitrate Detection and Spectral Segmentation Using Polarized Hyperspectral Imagery in High Reflective Glare Environments

Nicholas V. Scott, Riverside Research, Open Innovation Center, Beavercreek, OH 45431

Jack McCarthy, University of Dayton, Dept. of Computer Science, Dayton, OH 45469

1. Introduction/Motivation

- Military and law enforcement organizations are often tasked with target detection and scene characterization in various types of environments where light scattering intensity is high representing a significant source of optical noise.
- Mitigation of this noise using classical digital filters can be difficult due to heterogenous environments which have complex light scattering processes. The lack of clear and tractable post-image processing methods for taking out this photonic noise in turn inhibits high resolution target detection and machine learning-based pattern recognition which facilitate the delivery of reliable intelligence.
- Polarized filters are a possible method for ambient glare reduction by allowing only certain modes of the electromagnetic field to be imaged providing greater scene contrast.
- An experiment was carried out utilizing a polarized lens attached to a Resonon, Inc. hyperspectral imagery (HSI) camera for the purpose of exploring the degree to which polarized HSI scenes allow for improved (or degraded) target detection, image segmentation, and feature extraction.
- The results of this work have great implications for understanding not only desert areas, where reflective glare is a potent issue potentially inhibiting defensive forces from engaging in optimal performance, but marine environments where surface riverine sediment-water response is strongly tied to polarization.

2. Data Acquisition and Hyperspectral Imagery Data Structure

- An 8 ft. square tarp with a sand and cow manure target was laid down on a grass lawn. The sand/manure target was 22 ft. from the camera head which was 5 ft. above the ground. This produced a 13-degree angle of descent with the horizontal.
- Ambient lighting conditions were characterized by sunny skies. The average air temperature was approximately 93° F during the experiment.

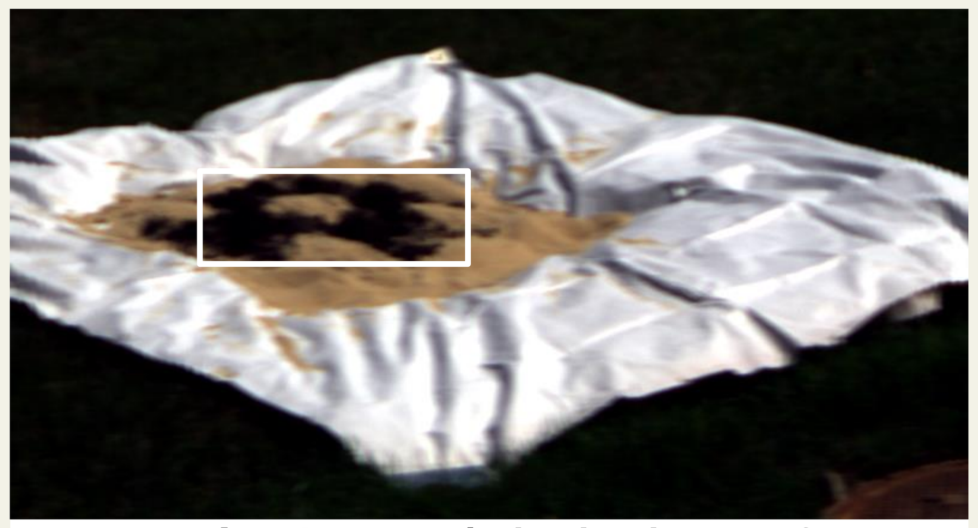


Figure 1: RGB no polarization image of tarp, sand, and cow manure. Experiment took place on July 18, 2019 at approximately 10 am.

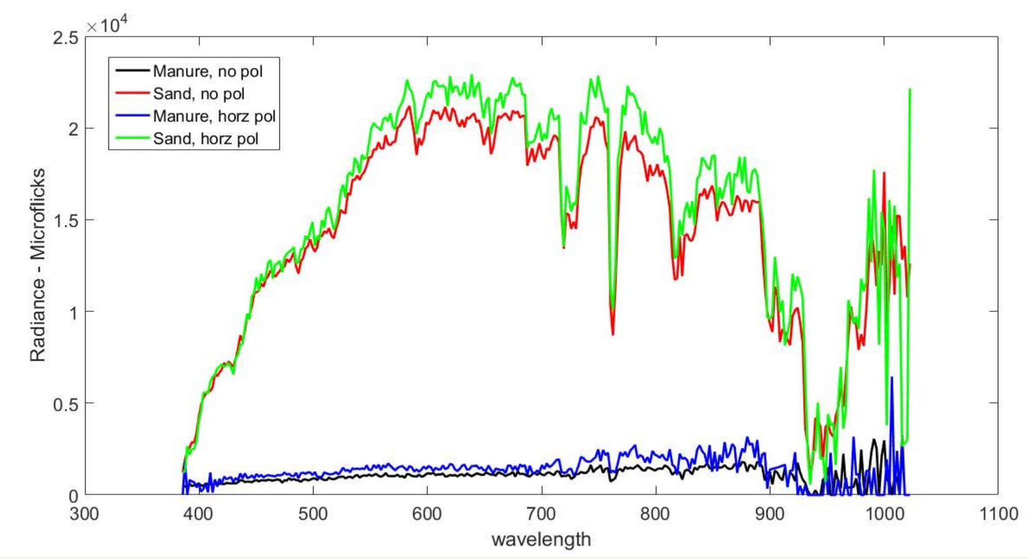


Figure 2: HSI 300 band sample spectra of manure and sand. Legend delineates different spectral curves for sand and manure.

2. Hyperspectral Imagery Data Structure (cont.)

- Three HSI cubes were taken of the target using the HSI camera with no polarization filter and with the polarization filter on aligned with the camera's vertical and horizontal center line. These configurations allowed horizontally and vertically polarized light into the camera respectively. An RGB image of the target is shown in Figure 1.
- Each HSI cube possessed 800 scan lines where a single line had 900 pixels. The frame rate was set to 59 Hz and the integration time to 0.18 seconds. The gain was set to 1 and the hardware spectral binning was set for averaging over 2 spectral bins. The scanning rotation speed was 1.0 degrees/sec.
- Sample HSI spectra for sand and manure from the no polarization and horizontal polarization data sets are shown in Figure 2. Spectral amplitudes for the horizontally polarized data are slightly greater. Spectral signatures for manure and sand are clearly different with sand exhibiting a higher spectral amplitude due to its higher reflectivity.

3. Data Analysis and Results

a) Principal Component Analysis (PCA) for Non-polarized, and Polarized HSI

- Principal components (PCs) for 100 X 100 pixel non-polarized and polarized imagery chips are shown in Figure 3. The first PC image exhibits significant contrast in all 3 data sets at comparable spectral levels. The polarized imagery suffers noise degradation sooner than the non polarized imagery with significant noise being visible in the 3rd PC image.
- The dark blue area in the first PC image is manure whereas the aqua/green area is sand. The red area is part of the white tarp.

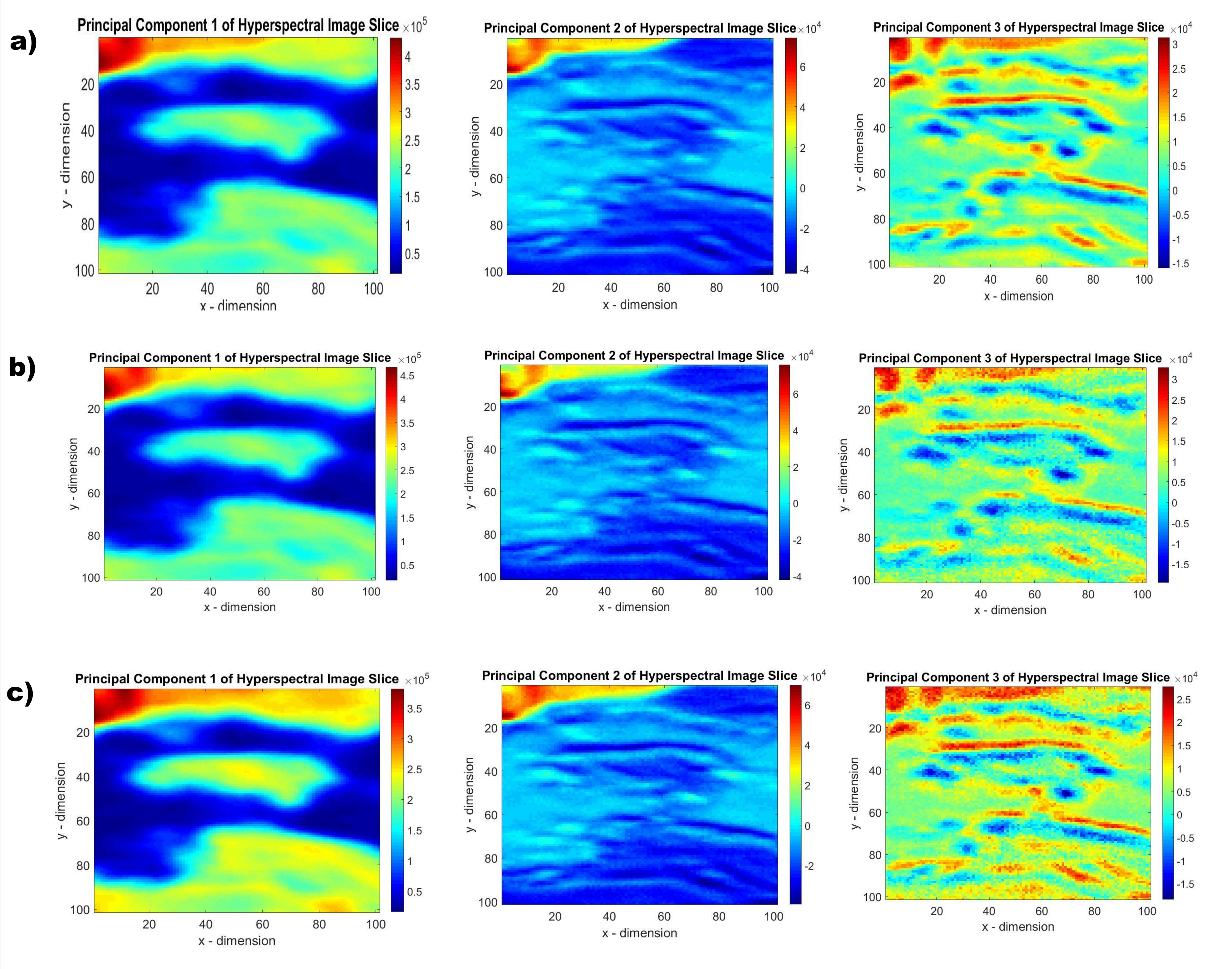


Figure 3: First, second, and third PC images for **a)** non polarized HSI, **b)** horizontally polarized HSI, **c)** and vertically polarized HSI. Physical dimensional scale is approximately 1 square foot.

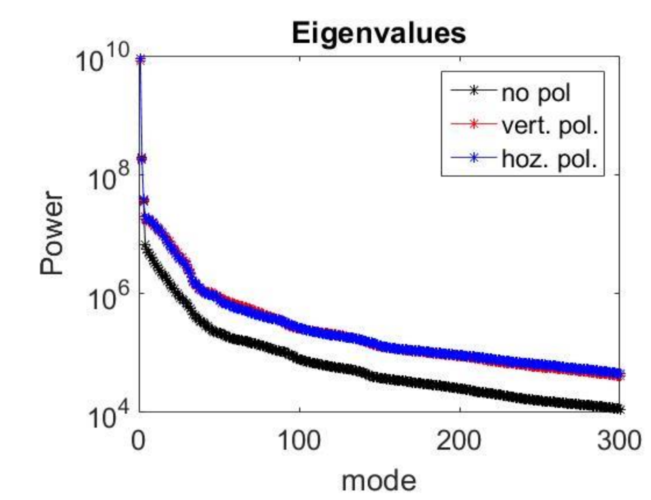
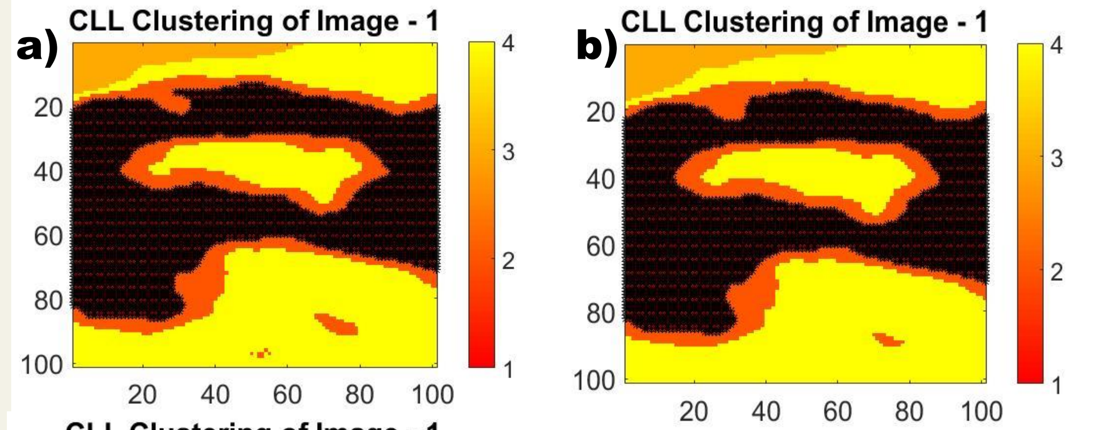


Figure 4: Eigenvalues for non-polarized, horizontally polarized, and vertically polarized imagery. Legend designates specific HSI data set.

- The **virtual dimension** estimate using the covariance matrix for all data sets was about 15 suggesting that the noise floor for all 3 data sets will occur around the same characteristic spectral wavelength.
- Eigenvalue spectra for all 3 data sets are shown in Figure 4. All 3 data sets demonstrate that over 80% of the variance is captured in the first PC. The vertical and horizontally polarized spectra have a higher spectral amplitude and seemingly attain a 'spectral elbow' slightly earlier than the non polarized spectrum. This suggests that the polarized imagery is efficiently pushing more energy into fewer spectral bands.

b) Competitive Leaky Learning (CLL) Clustering and Class Separation Quantification

- CLL clustering has a neural network structure with a competitive hidden layer. A competitive neuron consists of a vector of weights where the CLL calculates the similarity between the input spectral data vector and the weight vector. For every input spectral vector, the competitive neurons "compete" with each other to see which one is the most similar to the input vector. With each iteration, spectral data vectors become more affiliated with certain weight vectors allowing for clustering of spectral signatures.
- A four-cluster heat map is shown in Figure 5a-c for non polarized and polarized HSI. The figures demonstrate clear distinction between grass, sand, manure, and tarp.



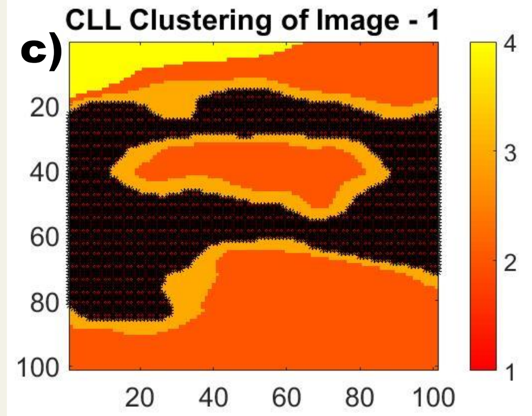


Figure 5: Four cluster CLL image segmentation for a) non polarized HSI, b) horizontally polarized HSI, and c) vertically polarized HSI. Manure segmented into 2 groups with perimeter reflecting sand mixing. a-b) Pure manure appears black and manure-sand mixture dark orange. Sand appears yellow. Tarp is light orange. c) Pure manure appears black and manure-sand mixture light orange. Sand appears dark orange. Tarp is yellow.

- Using the manure and sand clustering groups, mean values and covariances were calculated using 100 spectral signatures from each group. The PCA bands up to the virtual dimension number were used in the calculation of the means and covariances.
- The Kullback-Leibler divergence (KLD), and the Bhattacharyya distance (BD), distance metrics sensitive to covariance, were calculated as a measure of the distance between sand and manure classes. **Large values for these quantities indicate strong separation of the manure and sand.**

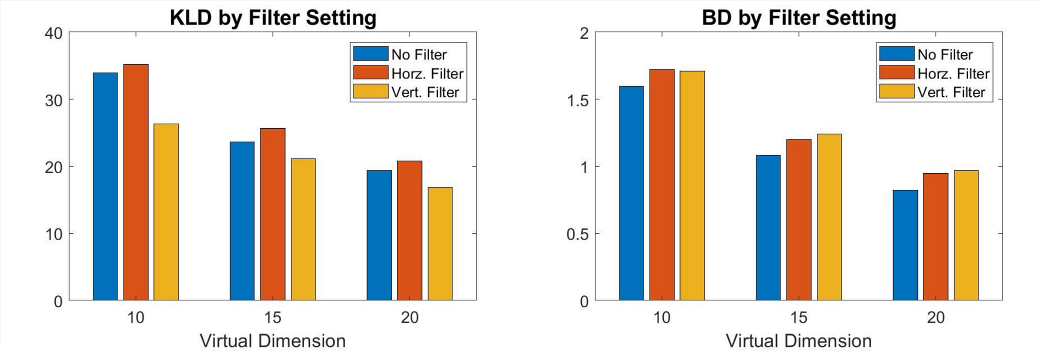


Figure 6: a) KLD and **b)** BD of PCA image data for 10, 15, and 20 PCA spectral wavelengths for the 3 HSI data sets.

- BD and KLD for sand and manure classes for the horizontally polarized HSI are **slightly higher** than for the non polarized HSI indicating **polarized imagery class separation power that is on par with non-polarized imagery**. The BD suffered negative infinities around PCA spectral wavelength cut off of 22 suggesting a class spanning space less than 22.
- **Results suggest that HSI target detection power is possibly <u>slightly</u> augmented via the use of a horizontal polarization filter.**