Preparation for HyspIRI spaceborne imaging spectrometer observations for precision vegetation mapping

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Hyperspectral sensors, or imaging spectrometers, can be used to provide a dense recording of reflectance values over a wide region of the electromagnetic spectrum. Availability of this rich spectral information makes it possible to design classification systems that can perform very precise ground cover classification and target recognition [1], [2], [3]. HyspIRI – an NRC decadal survey mission is much anticipated by researchers to aid in answering a wide variety of global ecological and anthropological questions. For example,

- What are the composition, function, and health of terrestrial and aquatic ecosystems?
- How are these ecosystems being altered by human activities and natural causes?
- How do these changes affect fundamental ecosystem processes upon which life on Earth depends? [4], [5]

In order to tackle these research topics and effectively exploit the seasonal global imaging spectroscopy provided by HyspIRI, there will be a great need for reliable hyperspectral-based products for use by domain experts. Arguably, easily accessible data products have been the key to the success of engaging domain experts and end-users in cases such as Landsat and MODIS. In those cases, simple multispectral products, such as NDVI, are well understood by both the mission teams and end-user communities. However, even though a great deal of research is conducted in hyperspectral image analysis, standard hyperspectral-based products do not currently exist, particularly products that have minimized sensitivity to image non-uniformities to which space-based spectrometers are susceptible, such as cross-track non-uniformity.

In this work, the authors are creating simulated (proxy) HyspIRI data from a vegetation species hyperspectral database and are studying the performance of current state-of-the-art classification paradigms for classifying this proxy data. In this database, spectral data was originally collected using handheld Analytical Spectral Devices (ASD) spectroradiometers and SpecTIR airborne hyperspectral sensors [6, 7]. The spectral resolution of this dataset makes it ideal for synthesizing HyspIRI proxy data. When the spectral sampling of the proxy hyperspectral sensor is denser than that of the HyspIRI sensor, HyspIRI data can be “simulated”, or “synthesized” by combining (by using a weighted average) adjacent bands of the original data into a single “HyspIRI band”. In the absence of the actual HyspIRI modulation transfer function, weights for such an averaging procedure can be assumed to follow a Gaussian shape, where the width of the Gaussian shape is governed by the full-width-half-maximum bandwidth of the sensor. Figure 1 illustrates sample proxy HyspIRI signatures generated by the above-mentioned technique.

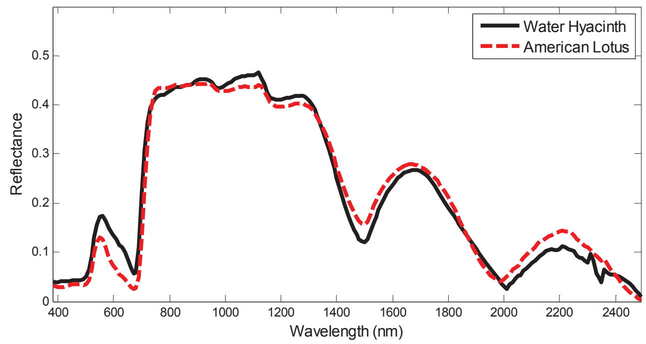

Figure 1: HyspIRI proxy data generated from handheld ASD data

The efficacy of current state-of-the-art classification systems are studied on this proxy HyspIRI data. In particular, the authors compare classification performance of (i) Single maximum-likelihood classification systems, using conventional dimensionality reduction techniques, such as Principal Components Analysis (PCA), Fisher's Linear Discriminant Analysis (LDA), Stepwise-LDA [8], and, (ii) cutting edge techniques, such as the Multi-Classifier and Decision Fusion (MCDF) framework [9] for classification under small training sample size conditions. This study provides valuable insight into the efficicacy of HyspIRI observations for robust land-cover classification tasks, such as mapping of vegetation species. The authors also investigate the sensitivity of these classification techniques under different sensor fidelity and uniformity conditions, such as additive noise and cross-track non-uniformity [4], [5].

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