ADAPTIVE FEATURE-SPECIFIC SPECTRAL IMAGING CLASSIFIER (AFSSI-C)

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ABSTRACT

The AFSSI-C is a spectral imager that generates spectral classification directly, in fewer measurements than are required by traditional systems that measure the spectral datacube (which is later interpreted to make material classification). By utilizing adaptive features to constantly update conditional probabilities for the different hypotheses, the AFSSI-C avoids the overhead of directly measuring every element in the spectral datacube. The system architecture, feature design methodology, simulation results, and preliminary experimental results are given.

Keywords: Compressive Sensing, hyperspectral imaging, spectral imager

1. INTRODUCTION

Spectral imaging is a technique used for *in-situ* material classification for a variety of applications [1-3]. Traditional hyperspectral analysis requires recording a vast amount of data, acquired over the course of many measurements, generated by scanning through one or two dimensions of the spectral datacube—the optical data consisting of two spatial dimensions and one spectral dimension. Scanning is one solution to the challenge of reading 3-dimensional data with a 2-dimensional detector. In the traditional approach, once the datacube has been acquired, classification is performed by comparing the measured spectra to a library of known spectra [4].

We have introduced a system architecture called the adaptive feature-specific spectral imaging classifier (AFSSI-C) for the purpose of direct classification. In contrast to traditional approaches, the AFSSI-C makes feature-based measurements to arrive at a classification without sampling the entire spectrum [5]. Previous work with our feature-based spectrometer (as opposed to *spectral imager*), the Adaptive Feature-Specific Spectrometer (AFSS), demonstrated reductions in time-to-classification of up to 150X compared to traditional approaches [6]. The AFSS utilized a programmable micromirror array to measure projections of the input spectrum onto an arbitrary set of spectral filters. Bayesian updates to likelihood ratios then tracked the probability of a match with each individual library spectra. The AFSSI-C extends this approach to spectral imaging by performing spectral classification across multiple spatial locations in parallel. Simulation of the AFSSI-C predicts a reduction in classification error by three to four orders of magnitude, compared to traditional architectures (e.g. pushbroom, whiskbroom, tunable filter) over the same number of measurements. This paper will describe system architecture, prototype design, and initial results, along with proposed improvements and design goals.

2. SYSTEM DESIGN

The foundation of the AFSSI-C is the creation of an adaptive spectral filter at every spatial location. The architecture is a modification of the 'dual disperser' configuration described in [7] and can be thought of as two back-to-back 4*f* spectrographs linked by a Texas Instruments digital micromirror device (DMD) that implements the filter features. A schematic of the optical layout is shown in Fig. 1.

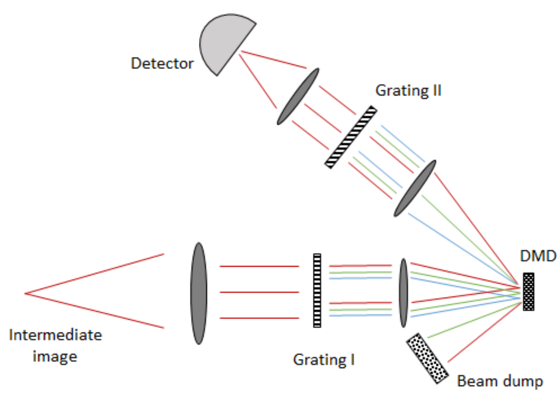

Figure 1: Schematic of the optical design for the AFSSI-C. Light from the scene enters the first arm of the system from the lower left, is dispersed and imaged onto the DMD, and then enters the second arm (where the dispersion is reversed) before detection.

Light from the object enters the system at the bottom left of Fig. 1. The first lens of the system collimates the incident light before it is incident on the first grating (grating 1 in Fig. 1). The dispersed light from the grating is then re-imaged at the DMD, where the individually-actuated mirrors direct the light to either the beam dump or the second arm of the system, depending on the desired filters. The encoded signal is collimated before the second grating, which removes the dispersion imparted by the first grating. The final lens in the system creates an image at the detector, spatially congruent with the object scene. As a result of this process, the spectral information at each spatial location encounters a structured spectral filter, the nature of which is determined by the specific pattern of mirrors on the DMD.

3. CODE DESIGN AND CLASSIFICATION

The filtered spectra at each spatial location are spectrally integrated by the detector and are then compared to the elements in the spectral library as projected onto the same spectral filter. A weight is assigned to each element of the library, based on the conditional probability of the hypothesis given the measurement. Using Bayes' theorem, the probability of hypothesis (library element) H_i given a sequence of k feature-based measurements $\{m\}_k$ is

$$\Pr(H_i|\{m\}_k) = \frac{\Pr(\{m\}_k|H_i)\ \Pr(H_i)}{\Pr(\{m\}_k)} \tag{1}$$

By working with likelihood ratios, we can eliminate the need for knowing the probabilities of a specific measurement history $\Pr(\{m\}_k)$, and by taking the prior $\Pr(H_i)$ as the conditional probability after the *(k-1)*-th measurement, $\Pr(H_i|\{m\}_{k-1})$, we derive a simple update procedure. The weighted library is then used to determine the feature, implemented in the following measurement, which will discriminate between the elements in the library with the highest probability values. To this end, probabilistically-weighted principal component analysis is used (pPCA). The first principal component is the largest eigenvalue of a probabilistically-weighted covariance matrix Q_k of the m individual spectra s_i in the spectral library:

$$Q_k = \sum_{i=1}^{m} \Pr(H_i|\{m\}_k)(s_i - \bar{s}_i)(s_i - \bar{s}_i)^T, \tag{2}$$

with the mean spectrum $\bar{s}$ being the probabilistically-weighted mean given by

$$\bar{s} = \frac{1}{m}\sum_{i=1}^{m} \Pr(H_i|\{m\}_k)s_i. \tag{3}$$

Within this Bayesian approach, after each measurement we provisionally classify each spatial location as the spectra having the highest probability at that time. In simulation and experiment, system performance is assessed in terms of the fraction of spatial locations that are correctly classified after each measurement step.

The signal at the DMD is spatially and spectrally multiplexed, and the design of the code necessarily accommodates this multiplexing. Spectral filters for each spatial location along a row—the direction of dispersion—cannot be independent because the dispersed light from one spatial location is incident on the same DMD mirrors as dispersed light from adjacent spatial locations in that row. While design of adaptive features in the AFSS could use pPCA [6] of just a single probabilistically-weighted library, the AFSSI-C must take into account the weighted libraries of each spatial location along a row. To do this, the weighted library from each spatial location in a row is put on the diagonal of a larger matrix. The first principal component—a vector in the direction of greatest variance—of this larger matrix is found and translated into the feature for the following measurement. This design framework is referred to as joint-pPCA, and is described further in [5].

4. SIMULATION RESULTS

Simulations of the AFSSI-C with joint-pPCA design show improvement over traditional approaches to spectral imaging. The simulations also compare AFSSI-C behavior using randomly generated spectral features and static joint-pPCA (the design is not updated during the measurement sequence).

Comparisons are made to different levels of task-SNR (tSNR), a metric developed for the AFSS to describe the difficulty of a classification task [6]. Defining the minimum pairwise Euclidean distance:

$$d_{lib}=\min(\sqrt{s_i^T s_j}) \tag{3}$$

where s_i and s_j represent two spectra in the library, the definition of tSNR is then:

$$tSNR = 10\log_{10}\frac{d_{lib}}{\sigma_n}, \tag{4}$$

with σ_n being the standard deviation of the AWGN.

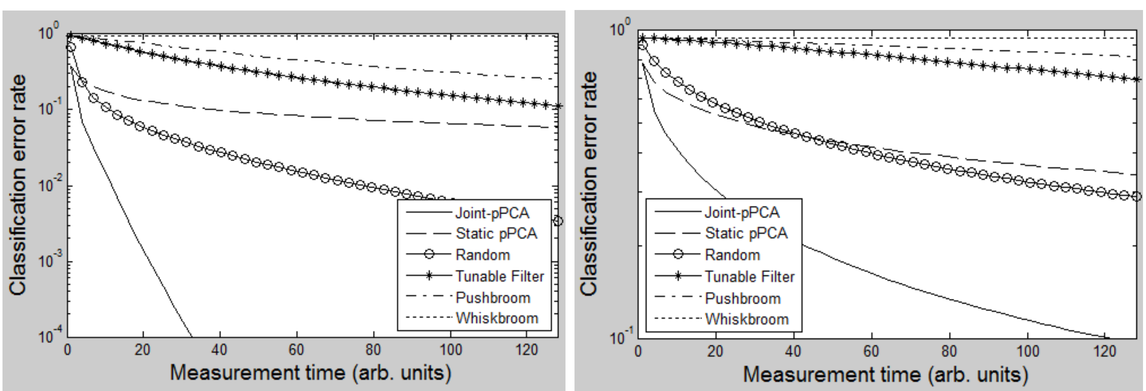

Figure 2: (Left): Simulation results comparing traditional spectral imagers to the AFSSI-C using different spectral feature design strategies at 0dB tSNR; (Right): Simulation results at -10dB tSNR.

The results in Fig. 2 (left) show that in simulation the AFSSI-C with adaptive, designed joint-pPCA features shows roughly 3 orders of magnitude lower classification error in the 0 dB tSNR case ($\sigma_n = \sigma_{lib}$ in eq. (2)) at approximately measurement 20. The simulations also demonstrate adaptive, joint-pPCA designed codes are superior to either random or static joint-pPCA features.

5. PROTOTYPE

The optical design was optimized using ZEMAX optical modeling software, and the layout of the lens configuration was reproduced in SolidWorks. Fig. 3 (left) is a rendering from SolidWorks; the components of this model were then fabricated on a rapid prototype 3D printer. Figure 3 (right) is an image of the prototype (light baffles are removed to reveal the components).

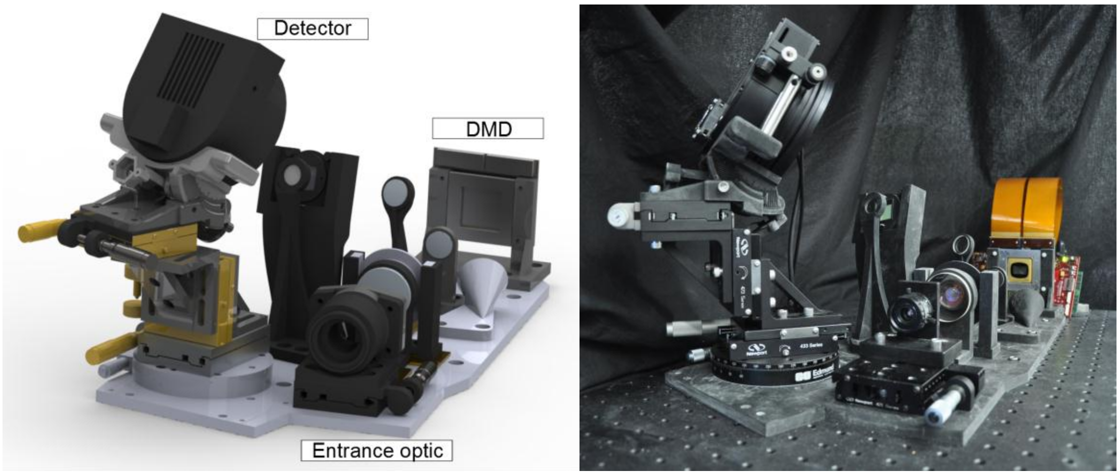

Figure 3: (Left): A rendering of the prototype design for the AFSSI-C; (Right): Prototype AFSSI-C with light restricting baffling removed.

The spectral datacube used for testing the prototype system is generated with an LED monitor. The source spectra are created by adjusting the intensity of the colors available from the monitor. Initial testing has relied on a four spectra library, shown in Fig. 4.

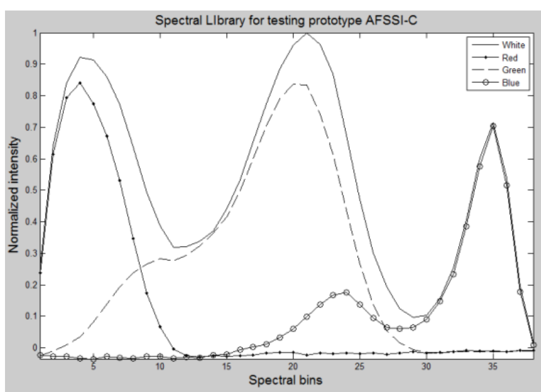

Figure 4: Four-class spectral library using the individual colors available from the monitor.

The spectra shown in Fig. 4 are measured with the AFSSI-C for spectral library calibration. Similar to the operation of a tunable-filter spectrometer, a given spectrum is presented to the system while the code on the DMD is adjusted to measure a single spectral channel. The code is then swept across the DMD to build the full spectrum. This process is repeated for every library member.

To create the source spectral datacube, an image is downsampled to the desired spatial resolution, and posterized to the number of spectra in the library being used for the experiment. Each level of posterization is assigned a member of the spectra, and the result is displayed on the monitor. Initial experiments used 64x64 spatial locations with 38 spectral channels; more recent experiments involve 128x128 spatial locations and 76 spectral channels. Figure 5 shows experimental results; the left-most column is the source image, where the grayscale colors represent different members of the spectral library. The remaining columns show the scene as classified by the system in the first three measurements.

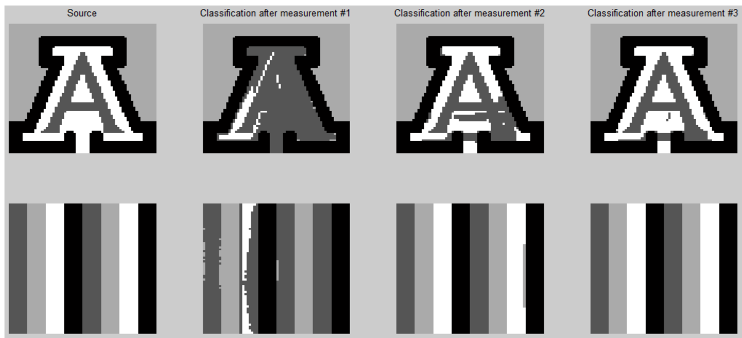

Figure 5: Experimental results (64x64 with 38 spectral channels). Both sources are made up of the four colors in the spectral library (see Fig. 4).

The experimental results in Fig. 5 show system performance varies with the complexity of the input image. The vertical bars of color in the bottom row are correctly classified by the third measurement, while there are still classification errors in the third measurement when the source is the University of Arizona logo. In these experiments, the source was comprised of 64x64 spatial locations and a 4-member spectral library (with 38 spectral channels each). Direct measurement of the 1.5×10^5 elements in the source spectral datacube would require at least 4000 measurements with a whiskbroom spectral imager; a pushbroom style spectral imager would require 64 measurements. The output of either of these traditional systems would still need interpretation to make spectral classification.

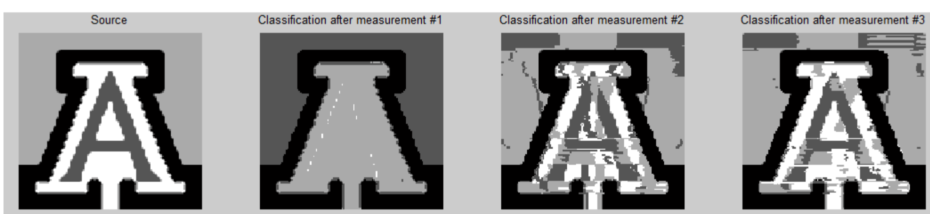

Figure 6: Experimental results (128x128 with 76 spectral channels). Here, the same four colors are used, but each is made up of 76 spectral channels.

The experimental results in Fig. 6 are for the same reference image as in Fig. 5 (top), but with 128x128 spatial locations and a 4 element, 76 spectral channel library. Error in spectral classification is greater for the higher resolution experiments.

6. FUTURE WORK

Initial experimental results with the AFSSI-C prototype are promising, but there are a number of elements to address. The original design resolution was 256x256 with 128 spectral channels, with large spectral libraries (much more than the four classes). Though early results at 128x128 spatial locations with 76 spectral channels are encouraging, another doubling of the spectral and spatial resolution is not yet within reach. As the optics continue to improve, advanced techniques for accurately mapping the code to the DMD are needed, and work continues to improve focus at intermediate planes where focus is difficult to measure (i.e. at the DMD).

Further work is required to quantify the inherent noise in the system. Simulations of the system inject noise and measure the classification error per measurement for various noise levels. Without a firm understanding of the noise in the system prior to the introduction of additive Gaussian noise, it is difficult to make direct comparisons between simulated and experimental results.

7. SUMMARY

The AFSSI-C is a spectral imager that directly determines spectral classification by leveraging a library of potential spectra and utilizing Bayesian probability to compare spectrally encoded signals from the input scene. The system utilizes a DMD as an adaptive spectral filter, applying features at each measurement event determined from the results of previous measurements. Multiplexing at the DMD requires joint-pPCA to determine spectral features that take into account the weighted spectral libraries along an entire row.

Simulations of the system show reduced time to classification over traditional methods. Adaptive, designed codes are found to be the best method for feature design, based on classification rate.

The prototype results show great promise, demonstrating accurate classification of a low resolution spatial scene in a few measurements. Experimental classification of higher spatial and spectral resolutions is our immediate goal, with clear understanding of system noise so that comparison to simulation results can be made.

8. REFERENCES

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