I. INTRODUCTION

Traditional spectral imaging sensors entail the acquisition of high-dimensional data that is used for the discrimination of objects and features in a scene. Recently, a novel architecture known as coded aperture snapshot spectral imaging (CASSI) system has been proposed for the acquisition of compressive spectral image data of a scene with just a few coded focal plane array (FPA) measurements [1]. In this work, a supervised classification approach of hyperspectral images directly from a small set of optimal CASSI compressive measurements, without first reconstructing the full datacube, is proposed. The classification method is based on finding a sparse representation of each observation pixel in an overcomplete dictionary learned directly from the training samples. It provides a more discriminative sparse representation of the datacube, and therefore a better classification accuracy can be obtained [2]. An estimated sparse vector is obtained from the optimal CASSI measurements by solving a sparsity-constrained optimization problem, and is then used to directly determine the class of the unknown pixel. Optimal CASSI compressive measurements are obtained when optimal coded apertures in the optical system are used [3]. The set of optimal coded apertures are designed such that the CASSI sensing matrix satisfies a Restricted Isometry Property (RIP) with high probability [4]. Simulations results illustrate the performance of the proposed coded apertures in the optical system are used [3]. The set of optimal coded apertures are designed such that the CASSI sensing matrix satisfies a Restricted Isometry Property (RIP) with high probability [4]. Simulations results illustrate the performance of the proposed coded apertures in the optical system are used [3].

II. CASSI IMAGE CLASSIFICATION BASED ON LEARNED DICTIONARIES

The coded aperture snapshot spectral imaging (CASSI) system [1] is a remarkable architecture that captures the spatial and spectral information of a scene in a small set of coded FPA measurements. Let $\mathbf{F} \in \mathbb{R}^{N \times N \times L}$ be the data cube representing a spectral scene, and let $\mathbf{f} = [f_1^T, f_2^T, \ldots, f_N^T]^T \in \mathbb{R}^N$ be its column vector representation, where $f_j \in \mathbb{R}^n$ is a spectral pixel, and $n = N^2L$. The set of $K$ coded FPA measurements is given by $\mathbf{y} = \mathbf{Hf} + \mathbf{w}$, where $\mathbf{H} = [H_1^T, \ldots, H_{K-1}^T]^T \in \mathbb{R}^{K \times n}$ with $V = (N + L - 1) \times N$ and $KV < n$, is the concatenation of the matrices representing the effect of the coded apertures for the $K$ shots and the dispersive element, and $\mathbf{w}$ is additive white noise in the sensing system.

Assuming that there are $P$ different classes, and a set of $N_p$ training pixels per class, then a set of $N_i = \sum_{p=1}^{P} N_p$, with $N_i > L$ samples are available to learn an overcomplete dictionary. This work uses the overcomplete ICA method proposed in [5] for learning the redundant dictionary, $\mathbf{D} \in \mathbb{R}^{L \times N_i}$, since the resulting atoms in the dictionary are quasi-orthogonal. This characteristic is key for the successful estimation of the sparse representation of the observation pixels from the CASSI sensing measurements. Given the dictionary $\mathbf{D}$, the $i^{th}$ observation pixel $f_i$ in the datacube can be expressed as $f_i = \mathbf{D}\alpha_i$, where $\alpha_i$ is a sparse vector. Using the sparse representation of the pixels, the compressive CASSI measurements are given by $\mathbf{y} = \mathbf{H} \mathbf{D} \mathbf{\hat{\alpha}} + \mathbf{w}$, where $\mathbf{H}^*$ is the optimal set of aperture codes in the CASSI obtained such that the RIP in [4] is satisfied with high probability. In addition, $\mathbf{D} = \mathbf{D} \odot \mathbf{I}$, with $\mathbf{I}$ an $N^2 \times N^2$ identity matrix, and $\odot$ the kronecker product operator.

The classifier first finds an estimate of the sparse vector $\alpha$ directly from the optimal FPA measurements $\mathbf{y}$ by solving $\alpha = \min_{\alpha} ||\alpha||_0 < T_0$ s.t. $||\mathbf{y} - \mathbf{H} \mathbf{D} \mathbf{\hat{\alpha}}||_2 < \epsilon$, where the $\ell_0$-norm accounts for the sparsity constraint, and the $\ell_2$-error norm finds the closest sparse vector to the optimal CASSI compressive measurements. Subsequently, given the estimated sparse vector, $\alpha = [\alpha_1^T, \ldots, \alpha_N^T]^T$, the classifier labels each pixel in one of the known classes as follows: $\text{Class}(f_i) = \arg \min_{\alpha} ||\alpha - \alpha_i^{(p)}||_2$; $\forall i = 1, \ldots, N^2$, $q = 1, \ldots, N_p$; where $\alpha_i^{(p)}$ is the sparse vector of the $q^{th}$ sample in the $p^{th}$ class. Figure 2 shows the performance of the proposed classifier for the AVIRIS Indian Pines image. Fig. 2-(left) depicts the classified image using the proposed classifier from only 30 shots (i.e., $\approx 15\%$ of the datacube), when Bernoulli codes (i.e., codes whose entries are from a Bernoulli distribution) and overcomplete learned dictionary are used. Fig. 2-(right) shows the classified image from 30 shots when optimal codes and an overcomplete learned dictionary are used.

REFERENCES