Identification of Materials in Hyperspectral Images Using a Convolutional Neural Network Based Autoencoder

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Introduction

Hyperspectral images are used to identify materials, objects, and chemical processes in a scene. Each pixel in a hyperspectral image is a spectral profile that characterizes the intensity of light at that pixel as a function of wavelength. Since material has unique spectra, hyperspectral images are often used to identify the presence and relative abundances of materials in a scene. However, identifying which materials can be found in a scene is often a slow and difficult process. The goal of this project is to use an autoencoder to identify the dominant materials found in a hyperspectral image in an unsupervised manner.

Objective

To use machine learning to compress hyperspectral images into their three primary component materials and find the corresponding spectra, identifying the material.

Methods

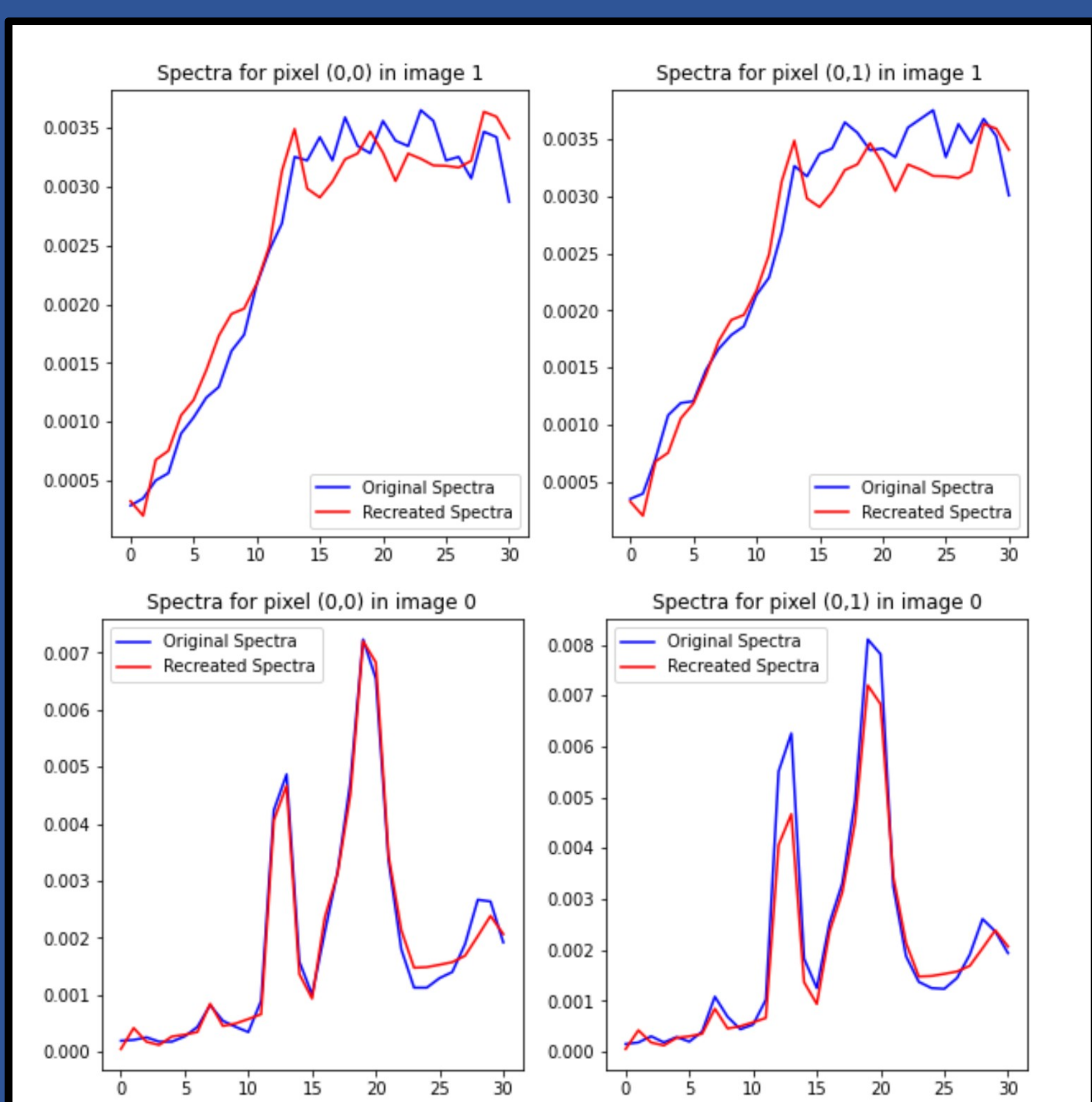
Our method relies on the interesting observation that the spectral complexity of most scenes can be well approximated with three material and two lighting spectra [3]. As a result, it was assumed that the hyperspectral images had three main materials, with each material being represented by a unique spectra, and a material map [4]. The light sources were not considered in this initial study. Given this, the hyperspectral image h(x, y, λ) can be represented by the following equation:

where is is the spectra corresponding to the r-th material map, and ≥ 0 being the r-th material map.

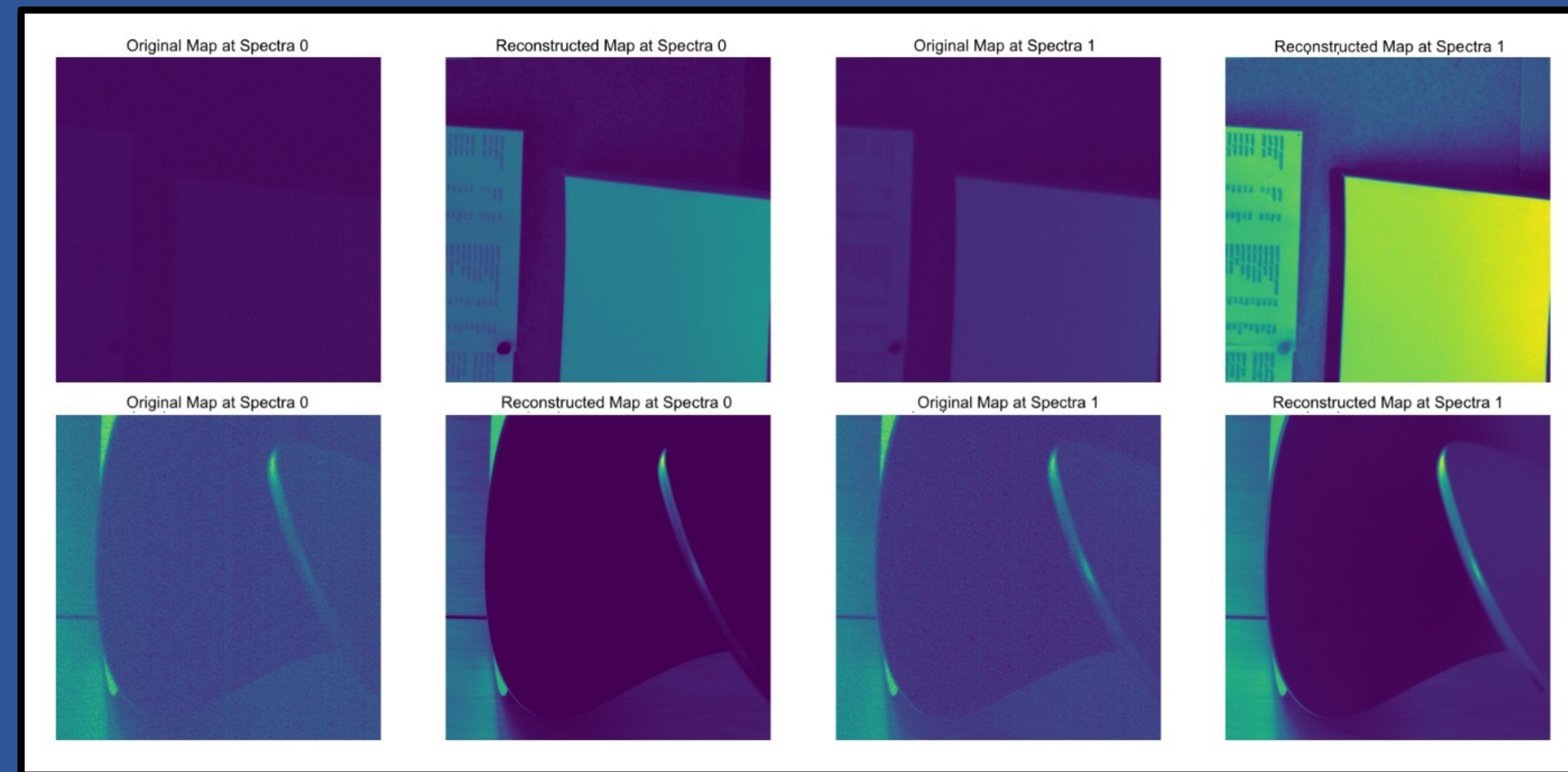
Since most datasets do not have ground truth material spectra and maps, we designed an unsupervised approach for estimating them. Specifically, we train an autoencoder [5] for hyperspectral images that is endowed with some key properties. First, the decoder is designed to implement the above equation, which attributes physical meaning to the outputs of the encoder. Second, the encoder is designed to output the three spectral profiles, subsequently, the material map is estimated at each pixel under the assumption that the spectrum at any given pixel lies in the conic hull of the material spectra. Third, we train the autoencoder end-to-end and the network learns to recognize the three dominant materials. The dataset used to train our autoencoder was sourced from the Harvard Real World Hyperspectral Images Database [1]. The autoencoder was designed with Keras [2].

Results

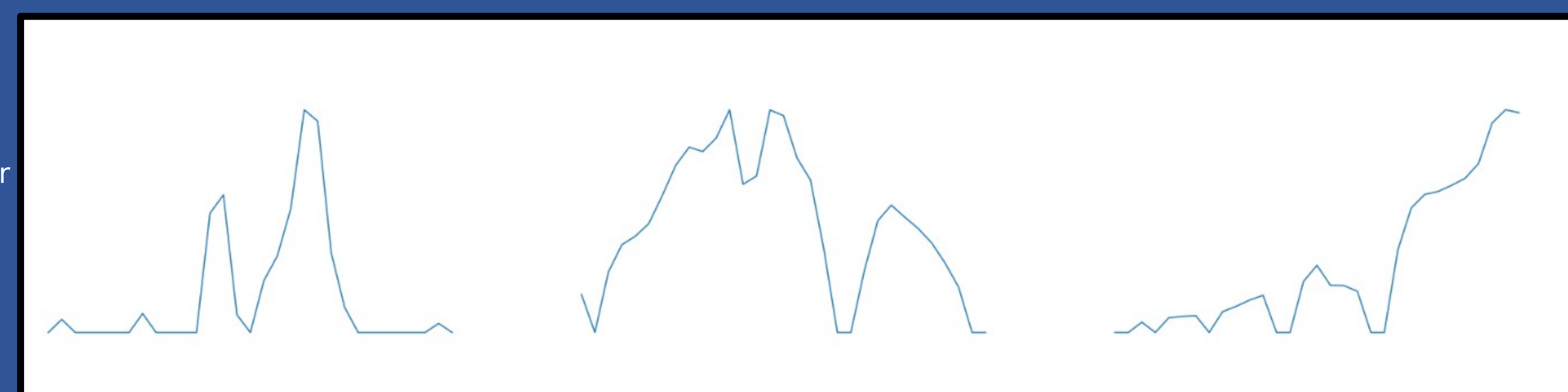
After running for 25 epochs a validation loss of 0.0130 was achieved. Loss was determined by the normalized mean squared error. As seen in the figure below, the recreated spectra for many of the pixels were quite similar to the original spectra, likely due to the spectra being optimized for over the material maps.



However as seen in the below figure, the reconstructed material maps are somewhat less similar to the original material maps, likely because the material maps are not specifically trained by the model but are rather created as a result of the trained spectra.



The trained model was then split into a decoder and and encoder. The encoder portion compressed a hyperspectral image into the spectra of its three primary materials. An image of a wooden floor generated the three spectra seen below



Future Work

Future research will investigate whether the spectra displayed are similar to materials likely to be found in the scene, improve the accuracy of the material maps, and improve the ability of the model to generalize on scenes different from the Harvard dataset.

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