A GENERALIZED LINEAR MIXING MODEL FOR HYPERSPECTRAL IMAGERY

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1. INTRODUCTION

The Linear Mixing Model (LMM) [1, and references within] is a well-known and useful method for hyperspectral data analysis. For physical reasons, the spectrum corresponding to a single pixel in a hyperspectral scene can be modeled (to first order) as a linear combination of the various materials within the given pixel. The main assumption of the LMM is that there exists a *global* set of spectra that can be used to decompose every pixel in the scene. These spectra are generally known as the endmembers for the scene, and intuitively represent the major material classes within the image. In mathematical terms, we consider each image spectrum $\mathbf{v}$ as a vector in some n-dimensional space, where n is the number of spectral bands for the image. The LMM may then be written as

$$\mathbf{v} = \sum_{\mathbf{i}=1}^{\mathbf{k}} \alpha_{\mathbf{i}} \mathbf{E}_{\mathbf{i}} + \mathbf{N}$$

where $\mathbf{E}_{\mathbf{i}}$ represent the n-dimensional endmember vectors, k is the number of different endmembers, and $\mathbf{N}$ is an n-dimensional vector representing noise and modeling error. The scalars $\alpha_{\mathbf{i}}$ are known as the abundance (or mixing) coefficients, and represent the amount of the corresponding endmember that is present in a given pixel.

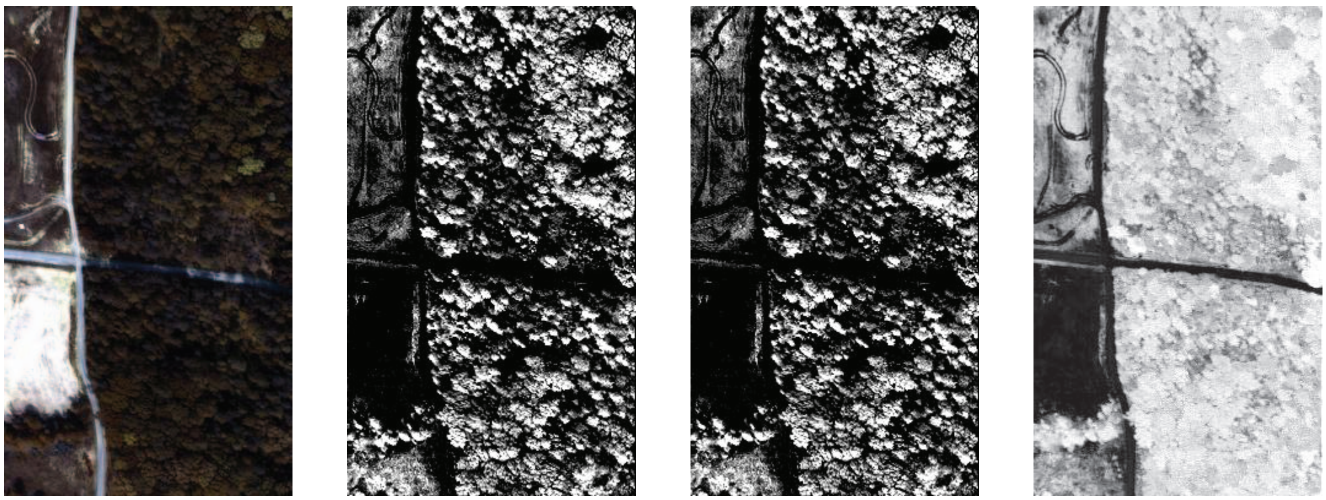
2. THE GENERALIZED LINEAR MIXING MODEL

An implicit assumption in the LMM is that each of the constituents or classes within a given scene may be modeled using only a single endmember vector, which does not change for the different scene spectra. Unfortunately, however, this assumption is generally not valid when dealing with real-world data. This is due to the fact that the representatives of a given class tend to exhibit a fair amount of intra-class variation. For example, consider the scene in Fig.1(a). This scene contains a large field of grass on the left, and a large forest on the right. Although the various vegetation spectra within the scene will have spectra that are similar, there will also be some differences between the various pixels (healthy vs. dry grass, soil content, etc.). In the context of the LMM, this means that there is no single 'vegetation endmember' that is able to model every grass pixel within the scene. In practice, the only way for the LMM to account for this variation is to create multiple endmembers for the given class, as shown in Fig. 1(b) and (c).

To account for this variation, we have introduced [2] a new method for linear mixing that we call the generalized linear mixing model (GLMM). In the GLMM, the concept of an endmember vector is generalized to an endmember affine subspace; each distinct physical component in a given hyperspectral image will correspond to one endmember subspace. The dimensionality of each subspace will generally vary, and is determined by the intra-class variation seen in a given material. Once the endmember subspaces have been determined, the scene may be 'demixed' (abundance coefficients estimated) using a new 2-step procedure. Each coefficient now represents a general *class* of materials, as shown in Fig. 1(d).

3. TARGET DETECTION

The GLM model can be extended to a target detection scheme through the use of Physically Derived Signature Spaces (PDSS). The PDSS model uses physics-based modeling to convert a library reflectance signature into an at-sensor radiance. By varying the atmospheric parameters, a number of different radiance spectra (each corresponding to a particular atmosphere) are produced. It has been shown [3] that these spectra can be modeled using a low-dimensional subspace. In terms of the GLMM, the target PDSS simply becomes an endmember subspace. After demixing, any pixel containing the target material should have a relatively large endmember abundance, while all other pixels should be dark (Fig. 2), allowing for easy determination of the target pixels.



(a) (b) (c) (d)

Figure 1. Fraction Planes. (a) Original Image. (b) and (c) Traditional LMM vegetation endmembers. (d) GLMM vegetation class

(a) (b)

Figure 2. Target Detection. Results from GLMSS / PDSS target detection algorithm, using the image in Fig. 1(a).

11. REFERENCES

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