A NOVEL APPROACH FOR HYPERSPECTRAL UNMIXING BASED ON NONNEGATIVE MATRIX FACTORIZATION

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1. INTRODUCTION

Decomposition of mixed pixels has become an important problem of hyperspectral imagery for its application in identification and detection of ground targets [1]. The Nonnegative Matrix Factorization (NMF) algorithm [2][3] has been applied to hyperspectral unmixing in recent years, for its advantages that can ensure the nonnegativity of results and automate the adjustment of step-length [4][5]. Due to the obvious nonconvexity of the objective function of NMF, the algorithm has a large amount of local minima. An effective solution for this problem is to introduce constraints according to the characteristics of hyperspectral images.

In this paper, we propose a new approach, Abundance Separation and Smoothness NMF (ASSNMF), by introducing two constraints, abundance separation constraint and abundance smoothness constraint, into the multiplicative NMF algorithm. These two constraints are considered in spectral and spatial domains respectively, and are useful for improving the performance of NMF algorithm.

2. THE PROPOSED ALGORITHM

For hyperspectral images, abundance separation is an important property. Usually, every ground object presents dominance in a specific region of the entire area, and it is hard to find the relationship among these regions of different endmembers. That is to say, each endmember has its own distributive situation, and the distributions of different endmembers have weak correlation. We introduce a constraint named "abundance separation" into NMF to obtain results which satisfy this requirement. From the information theory point of view, the abundances of one endmember can be regarded as a random signal, what we need to do is to minimize the correlative information, or maximize the probability distance among them. We developed the separation constraint based on the K-L divergence [6] and Spectral Information Divergence (SID) [7]. K-L divergence is a widely-used measure for signal similarity in information theory. Unfortunately, the logarithm function used in K-L divergence has an infinite value range, which will bring uncertainty and may cause divergence of the iteration algorithm. Thus, the K-L divergence is improved to be more suitable for a NMF iteration algorithm, in order to enhance its stability. Here the improved function is called "separation function", rather than "divergence", because its physical meaning has been changed.

Another important characteristic of hyperspectral images is the abundance smoothness. Because of the low spatial resolution of sensors, usually we cannot find very small details from hyperspectral imagery, although these details do exist on the ground. The result is that, abundances usually vary slowly and abrupt changing rarely appears. The characteristic is called "abundance smoothness" and is introduced to NMF algorithm. Differences between every pixel and its surrounding pixels are used here to measure the smoothness quantitatively. There already exist some algorithms using the property of smoothness, such as PSNMFSC. The difference is that, for every element in an abundance matrix, a series of surrounding elements are considered in our approach, while in PSNMFSC, only adjacent elements are considered. Thus the smoothness constraint proposed here can utilize information in the data more completely. The smoothness used in the proposed approach is based on linear transform and simplify the computation, which is another superiority compared with PSNMFSC.

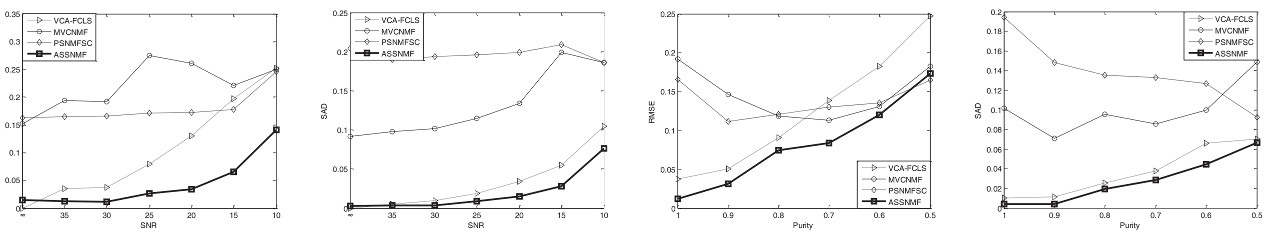
By introducing the two constraints into the traditional objective function of NMF, we obtain the proposed ASSNMF.

3. EXPERIMENTAL RESULTS

We use synthetic data to compare the performance of our algorithm with several other unmixing approaches, including VCA [8] followed by FCLS [9] (VCA-FCLS), MVCNMF [4], and PSNMFSC [5].

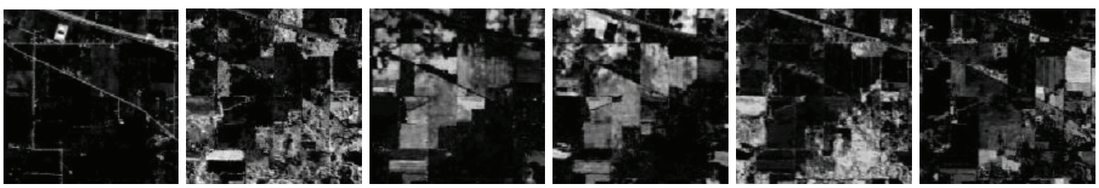
We evaluate algorithms mentioned above using two experiments, and one of which changes the noise level to test anti-noise capability of these algorithms. The other experiment changes the mixing degree of endmembers for comparing the performance in condition where pure pixels are lost. The results of the two experiments are shown in Fig. 1. It is obvious that our algorithm gives the best result.

We also use a real hyperspectral image to evaluate our approach. It is a farm area in the State of Indiana, captured by Airborne Visible/Infrared Imaging Spectrometer (AVIRIS). This data set has been studied much for development of hyperspectral unmixing and classification algorithms. Purdue University has already given a field survey report about this area [10]. Figure 2 shows the unmixing result. Six endmembers, man-made lands, wheat, corn, soybean, vegetation, and haystack are obtained. The result coincides with the ground truth provided in the field survey report very well [10].



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

Fig. 1. Performance comparison of different algorithms. (a) RMSE to SNR, (b) SAD to SNR, (c) RMSE to purity, (d) SAD to purity.



(a) (b) (c) (d) (e) (f)

Fig. 2. Experiment with real hyperspectral data. (a) man-made lands, (b) wheat, (c) corn, (d) soybean, (e) vegetation, (f) haystack.

4. CONCLUSION

In this paper, we proposed a new approach based on NMF for hyperspectral unmixing. Our algorithm overcomes the shortcoming of local minima by introducing additional constraints including abundance separation and smoothness into NMF. The separation constraint is improved based on K-L divergence, while the smoothness constraint is based on linear transform and can denote the overall relationship of pixels in images. Experiments with synthetic data and real data confirm the validity, anti-noise capability, and adaptability of the proposed approach, even for highly mixed data.

5. REFERENCES

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