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A Geometric Matched Filter for Hyperspectral Target Detection and Partial Unmixing

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***Abstract*—In this paper, a new geometric matched filter is proposed by combining the standard matched filter with concepts of convex geometry. The purpose of the method is twofold: for subpixel target detection and for partial unmixing of a hyperspectral image. In standard matched filtering, the filter is designed based on the background statistics of the entire image, which works fine for rare targets but fails when the target is frequently present throughout the whole image. In the presented method, the background is restricted to pixels that have a zero contribution to the target spectrum. These background pixels are identified based on the simplex formed by the target and other relevant endmembers of the dataset. Experiments are conducted for the specific case of targets which are frequently present in an image. The presented method is shown to outperform standard matched filtering and orthogonal subspace projection for target detection, and for the estimation of the target abundances.**

***Index Terms*—Hyperspectral, Partial Unmixing, Target Detection, Matched Filter**

I. Introduction

Hyperspectral imagery characterizes ground cover materials based on their spectral reflectance. The limited spatial resolution of hyperspectral images however causes pixels to contain mixtures of different materials. In mixed pixels, the spectrum is a combination of the constituent materials (endmembers) present in the scene [1]. Spectral unmixing techniques decompose the pixels spectrum into its constituent materials and calculate the fractional presence (abundances) of each material. In the linear mixing model, the spectra of mixed pixels are assumed to be a linear combination of endmembers and the weights represent the relative abundances of each material within the pixel.

A complete spectral unmixing of hyperspectral data may not always be possible or required. In subpixel target detection, the aim is to detect whether a particular target spectrum is present within the pixels spectrum, without having to know the target's specific relative contribution [2]. Sometimes, a partial unmixing i.e. the determination of the relative contribution of one or a few target spectra is aimed for [3].

To date, various algorithms have been developed for unmixing-based target detection and partial unmixing. In particular, subspace-based target detection methods project the data onto the subspace orthogonal to the background. The background subspace can be estimated in a structured manner, in which the background is modeled using endmembers. In [4], an orthogonal subspace projection (OSP) method was proposed for this purpose. In [5], it was shown that OSP is identical to full (unconstrained) unmixing. On the other hand, in a stochastic approach, no background modeling is applied. In [3], a Matched Filter (MF) detector was proposed in which the background is estimated from the eigenvectors of the data correlation matrix, or from the singular vector of the data matrix. This was further elaborated in [6]. In [7], k-means clustering was used to improve the matched filter detection process. Recently, in [8], a feasibility measure was added to reduce false alarms. In [9], an analytical comparison between the model-based and the statistical approach was performed. In [10], a hybrid target detector was proposed that combines the statistical and model-based approaches. Sometimes, the target abundance values are to be estimated as well. In [11], an overview of subspace-based partial unmixing methods is given. In [12], it was shown that, under certain conditions, the whitened version of matched filtering, constrained energy minimization, delivers fractional abundances.

A problem with the background-based detection methods is that target-signal components may be included in the background estimation, causing target leakage. One of the causes of this problem is an overestimation of the dimensionality of the background subspace. The effect of the dimensionality is studied in [13] and [14] for the MF and in [15] for OSP. In [16], sparse representations were applied to reduce the dimensionality effects. A local estimation of the background was proposed in [17].

Other recent topics that were treated in the literature are the problem of false alarm mitigation [18], target variability [19], nonlinear kernel-based target detection [20] and sparsity in target detection [21]. For a recent signal processing oriented overview of the state of the art on hyperspectral target detection, see [2] and [22].

Background subspace methods are likely to only work when 'rare' targets are aimed for, i.e. having a contribution to only a very small subset of the pixels. When a target is more frequently present in the data cube, the background statistics is wrongly influenced by the target contribution, again causing target leakage. In this paper, we regard the problem of 'frequent target' detection in data with many pixels containing the target, albeit with low abundances, as may be the case in e.g. mineral detection. To mitigate the dependency on the

particular number and choice of endmembers in the model-based approaches and the target influence on the background statistics in the stochastic approaches, we present a new hybrid target detection method combining spectral unmixing and matched filtering, making use of convex geometry concepts.

First, we model the background by a number of endmembers, obtained e.g. from an unsupervised endmember extraction method. Then, using the geometry of the simplex spanned by these endmembers, a number of pixels that have zero abundance values for the target are determined and used for the background estimation in a matched filter. In the experimental section, we show that indeed the proposed method is robust against the specific choice and number of endmembers as compared to OSP. It is shown that as opposed to MF, the method performs well for rare targets as well as for non-rare targets. Moreover, the method obtains more accurate target fractions. In the next section, the methodology is explained, followed by the experiments and discussion in section 3.

II. Methodology

Consider a hyperspectral image with d spectral bands and a known target spectrum $\mathbf{t_s}$. The aim of the proposed method is to identify the target signature in the presence of a mixed background, where we assume that the target is frequently present. A pixels spectrum can then be modeled as:

$$\mathbf{x} = \gamma \cdot \mathbf{t_s} + \mathbf{b} \tag{1}$$

where γ is the targets abundance value and $\mathbf{b}$ represents the background. Usually, target detection is defined by as a binary hypothesis testing problem for testing the null hypothesis $H_0 : \gamma = 0$ versus the alternative hypothesis $H_1 : \gamma > 0$.

Methods to solve this problem differ in the way that the background is modeled.

A. Orthogonal Subspace Projection (OSP)

In OSP, it is assumed that the background can be explained by a linear mixture model (LMM), so that the model becomes

$$\mathbf{x} = \gamma \cdot \mathbf{t_s} + \sum_{i=1}^{p} a_i \mathbf{e_i} + \epsilon \tag{2}$$

where $\mathbf{e_i}$ are the p endmembers $\{\mathbf{e_1}, \mathbf{e_2}, ..., \mathbf{e_p}\}$ ($p < d$), the coefficients a_i represents the abundances for each endmember and ϵ is additive noise.

In OSP, the spectra are projected onto the subspace orthogonal to the background, using the projection operator $P^{\perp} = \mathbf{I} - \hat{\mathbf{E}}(\hat{\mathbf{E}^{\mathbf{T}}}\hat{\mathbf{E}})^{-1}\hat{\mathbf{E}^{\mathbf{T}}}$, where $\hat{\mathbf{E}}$ is the matrix of endmembers excluding the target. The OSP detector is then given as the least-squares estimator of γ in model (2).

$$OSP(\mathbf{x}) = \frac{\mathbf{x^T} P^{\perp} \mathbf{t_s}}{\mathbf{t_s^T} P^{\perp} \mathbf{t_s}} \gtrless_{H_0}^{H_1} \tau_{OSP} \tag{3}$$

where τ_{OSP} is a threshold. The detector performance is commonly measured by means of a Receiver Operating Characteristic (ROC) curve, by varying the threshold value and compare true positive against false positive detection rate. The denominator in equation (3) normalizes the result for a perfect target match to one. A clear disadvantage of this method is that it relies severely on the number and the specific choice of endmembers [15].

B. Matched Filter (MF)

In the case where the background is not modeled by endmembers, but statistically estimated from the data, a Matched Filter (MF) is obtained. The MF detector is obtained as the least-squares estimator of γ in model (1) [11]:

$$MF(\mathbf{x}) = \frac{\mathbf{x}^T \mathbf{C^{-1}} \mathbf{t_s}}{\mathbf{t_s}^T \mathbf{C^{-1}} \mathbf{t_s}} \gtrless_{H_0}^{H_1} \tau_{MF} \tag{4}$$

where $\mathbf{C^{-1}}$ the inverse of the covariance matrix estimated from the background. The denominator in equation (4) normalizes the result for a perfect target match to one. In practice, the mean spectrum is first subtracted from the data, making the data zero-mean. For 'rare' targets, the background covariance can be reliably estimated from all the pixels of the datacube. If the targeted material is frequently present in the image, the background will be wrongly influenced by pixels containing the target.

C. Geometric Matched Filter (GMF)

In the following, we will describe a hybrid method combining the model-based OSP and statistical based MF approaches. The LMM will be used for the identification of pixels that do not contain the target. These identified pixels will then be used to estimate the background covariance matrix in an improved matched filter.

To present the method, we will rely on the geometric interpretation of the LMM. In geometric terms, the p endmembers form a simplex in a $(p-1)$-dimensional affine subspace of the d-dimensional data space. The first step is actually to project the data on the simplex plane, formed by the endmembers including the target endmember (this is the plane formed by the affine span of the endmembers, i.e. all linear combinations given that the coefficients sum up to one). This automatically takes care of the abundance sum-to-one constraint. It is important to notice that for high-dimensional data (as hyperspectral data is), after this projection, many data points will fall outside the actual simplex, which means that these pixels do not obey the abundance positivity constraint. In fact, this is a consequence of the curse of dimensionality. For a reasonable amount of endmembers, the volume of the simplex will be that small that it is highly improbable that a point falls inside it.

The background pixels are estimated based on this observation and the following 2 observations [23]:

- A point lying in the simplex plane, but outside the simplex, has at least one zero abundance coefficient.
- To estimate the zero abundance coefficient, the bisective cones (i.e. the planes that bisect the dihedral angles between the faces of the simplex) can be used.

First, the incenter $\mathbf{c}$ of a simplex S is defined as the intersection of all $(p-2)$-dimensional planes that bisect the dihedral angles between the faces of the simplex. It is also the center

of the largest possible hypersphere inscribed in the simplex. Let the subsimplex spanned by $\{\mathbf{e_1} \cdots, \mathbf{e_{i-1}}, \mathbf{e_{i+1}}, \cdots, \mathbf{e_p}\}$ has volume V_i. Then,

$$a_i^c = \frac{V_i}{\sum_{i=1}^{p} V_i}$$

are the abundances of the incenter $\mathbf{c}$. The Euclidean coordinates of the incenter are then given by $\mathbf{c} = \mathbf{E}\mathbf{a}^c$. If a point $\mathbf{x}$ lies in the simplex plane, then the line between $\mathbf{c}$ and $\mathbf{x}$ intersects a certain face of the simplex. The bisective cone of any simplex face is defined as the set of all the points for which the connecting line with the incenter intersects that face:

$$\mathbf{x} \in Z_i \Leftrightarrow \exists b_1, \cdots, b_p \geq 0 : \begin{cases} \mathbf{x} = \mathbf{c} + \sum_{j=1}^{p} b_j(\mathbf{e_j} - \mathbf{c}) \\ b_i = 0 \end{cases}$$

In [23], it is shown that most of the time, a point within bisective cone Z_i but outside of the simplex has an abundance value of zero for endmember $\mathbf{e_i}$. In Fig.1, this is illustrated.

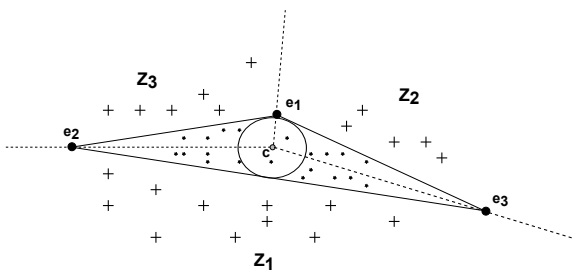


Fig. 1. 2-D simplex with 3 endmembers $(\mathbf{e_1}, \mathbf{e_2}, \mathbf{e_3})$, incenter $\mathbf{c}$ and bisective cones (Z_1, Z_2, Z_3), $\cdot$'s and $+$'s indicate points inside and outside the simplex respectively. Points in cone Z_i but outside of the simplex have zero contribution from $\mathbf{e_i}$.

Since the target is one of the endmembers, the pixels that lie in the bisective cone of the target endmember but outside of the simplex, belong to the background. Remark that pixels that lie in another bisective cone, and thus have a zero contribution from another endmember, may belong to the background as well, since they may have zero contribution from more than one endmember. These pixels can be found by removing the endmember from which they have zero contribution, and calculate the bisective cones from the reduced $(p-2)$-dimensional simplex. When the particular pixel then falls in the targets bisective cone but outside of the simplex, it can be added to the collection of background pixels. If not, the procedure can be repeated. In practise, we found that one iteration delivers sufficient background pixels to proceed.

Using the background pixels identified by the method discussed above, the covariance matrix $\tilde{\mathbf{C}}$ of the background is estimated and the geometric matched filtering score for target endmember $\mathbf{t_s}$ is calculated as:

$$GMF(\mathbf{x}) = \frac{\mathbf{x^T}\tilde{\mathbf{C}}^{-1}\mathbf{t_s}}{\mathbf{t_s^T}\tilde{\mathbf{C}}^{-1}\mathbf{t_s}} \gtrless_{H_0}^{H_1} \tau_{GMF} \tag{5}$$

where, as in MF, the mean spectrum is first subtracted from the data. Since the covariance matrix is estimated from only the pixels that lie in the bisective cone of the target, no target leakage is introduced.

III. Experiments and Results

To demonstrate the performance of the proposed method, hyperspectral data from the AVIRIS cuprite data set, obtained over the Cuprite mining region in Nevada, USA, was used. The data is a 301×365 pixels image with 51 spectral bands in the SWIR range (1.98-2.48 μm). The proposed method is compared to standard matched filtering (MF) and orthogonal subspace projection (OSP). Remark that in the experiments, any negative outcome of OSP, MF and GMF is clipped to zero, which effectively means that the positivity constraint is enforced.

A simulated hyperspectral data cube is generated by implanting a known target spectrum (plastic) in the AVIRIS cuprite data set (as $\gamma \cdot \mathbf{t_s} + (1-\gamma) \cdot$ AVIRIS) with known fractions and at known locations. The mixed pixels are positioned in a total of 80 rectangles of size 21×21 pixels in 8 rows by 10 columns with target fractions varying from 0.20 in the first row to $0.15, 0.10, 0.08, 0.06, 0.04, 0.02, 0.01$ in the following rows. The proposed approach is applied to this dataset by combining the inserted target as an endmember along with a selection of 20 endmembers. This selection was based on an endmember extraction method (VCA) after which the obtained endmembers were identified by comparison with the USGS mineral database. To compare, Fully Constrained Least Squares Unmixing (FCLSU), OSP and MF are applied as well. To quantify the detection performance of the methods, a ROC curve is generated, in which the True Positive Rate (TPR) and False Positive Rate (FPR) are determined for different threshold values (see Fig. 2). In Fig. 3, the obtained detector outputs (where everything below the threshold is clipped to zero) are shown, for a fixed FPR of 0.07. These results

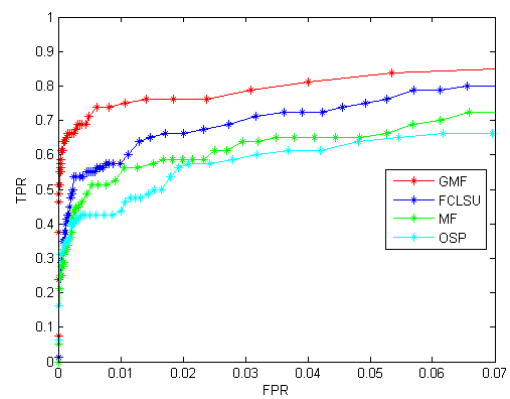


Fig. 2. ROC curve for FCLSU, OSP, MF and GMF

show that GMF outperforms the other methods for frequently present target detection.

To validate the performance of the method for partial unmixing, the average and standard deviations of the obtained target fractions (obtained as the output of the filters) from Fig. (3) are given for each row separately in Table (I). ND stands for no detection. The total MSE between the obtained and true abundance fractions is 0.0127 for GMF, 0.0135 for FCLSU, 0.0203 for OSP and 0.0217 for MF.

In a subsequent experiment, we verify that the method still works for 'rare' targets. Actually, when the size of the

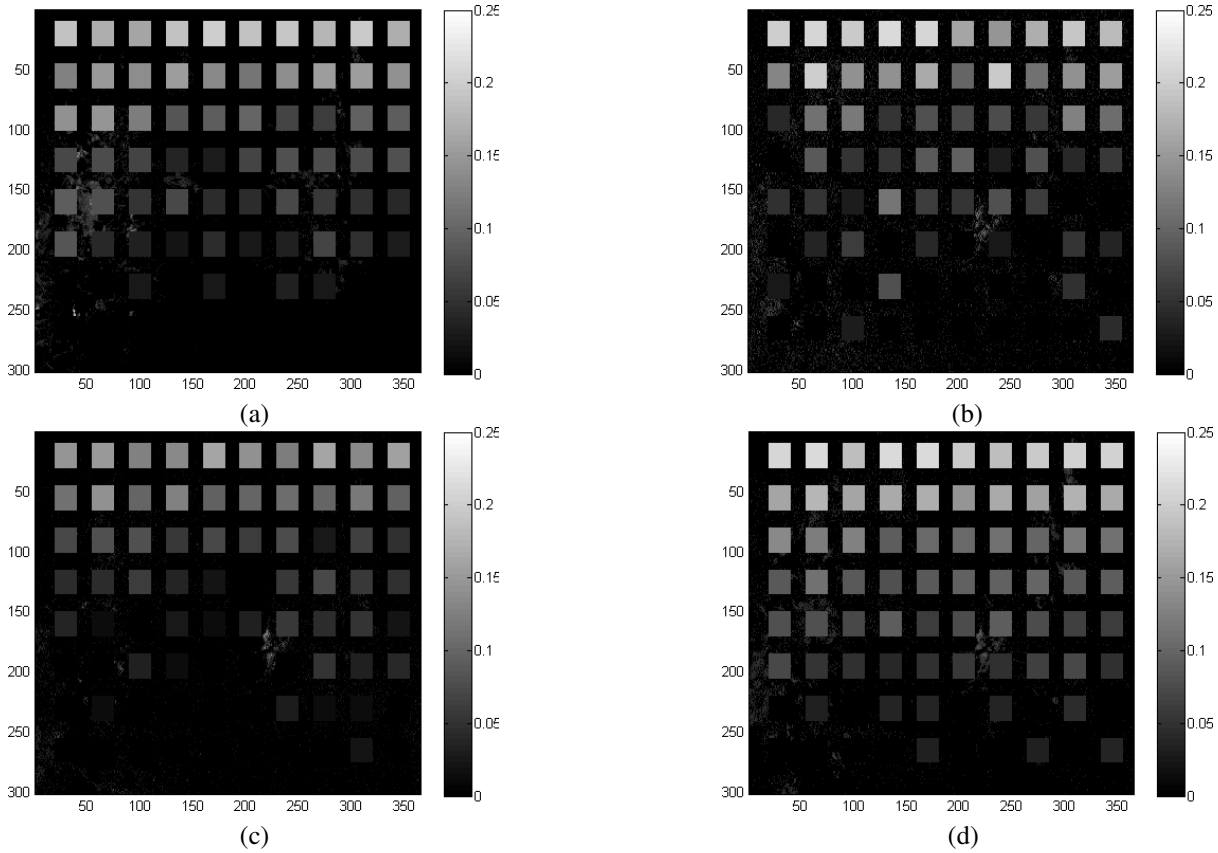


Fig. 3. (a), (b), (c), (d) : the detector output for a fixed FPR of 0.07 using FCLSU, OSP, MF and GMF respectively.

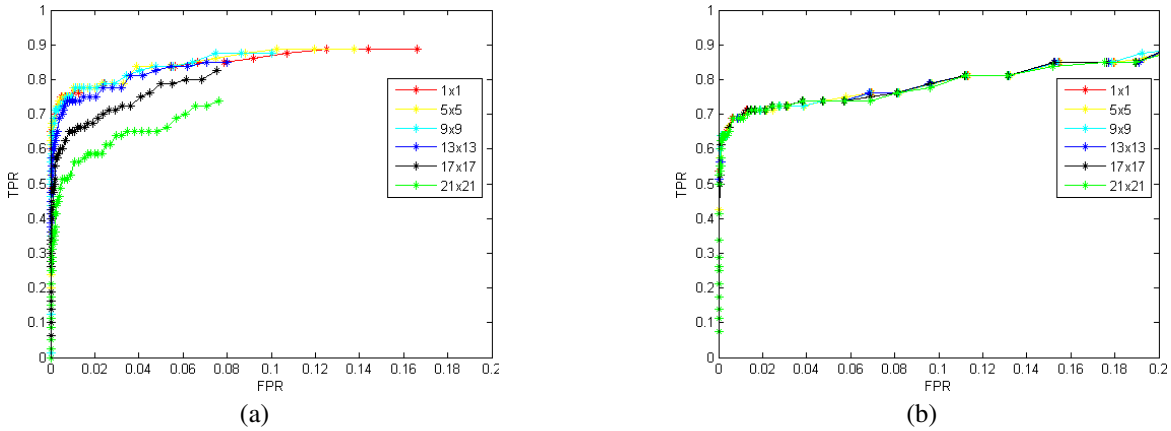


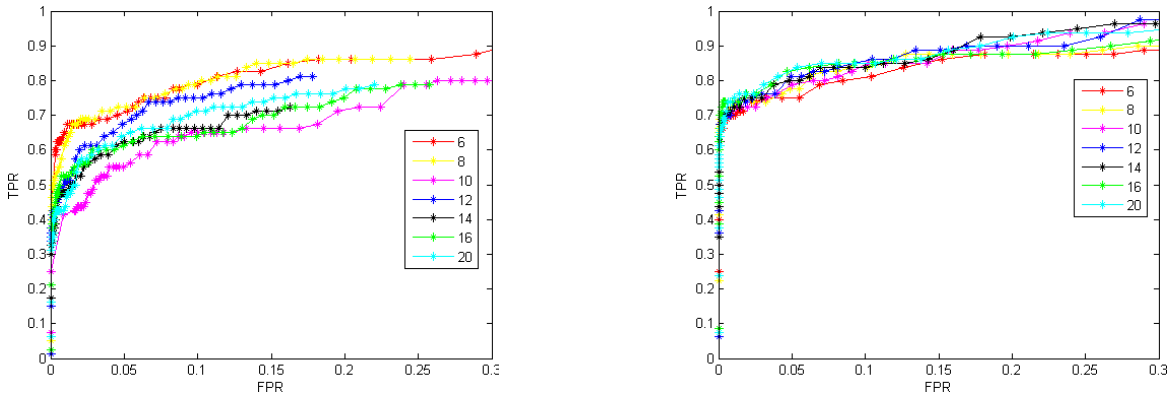
Fig. 4. ROC curve for MF (a) and GMF (b) using different target sizes

True	GMF	FCLSU	OSP	MF
.20	**0.202** (0.010)	0.184 (0.012)	0.188 (0.021)	0.144 (0.013)
.15	0.165 (0.007)	0.141 (0.012)	**0.149** (0.030)	0.109 (0.014)
.10	0.112 (0.012)	**0.100** (0.027)	0.084 (0.028)	0.062 (0.015)
.08	**0.092** (0.007)	0.066 (0.017)	0.058 (0.028)	0.043 (0.019)
.06	0.075 (0.010)	**0.060** (0.016)	0.050 (0.033)	0.030 (0.017)
.04	0.056 (0.009)	**0.043** (0.018)	0.025 (0.022)	0.014 (0.019)
.02	**0.018** (0.019)	0.010 (0.013)	0.015 (0.026)	0.007 (0.019)
.01	**0.010** (0.015)	ND	0.007 (0.015)	0.002 (0.016)

TABLE I
OBTAINED AVERAGE (STANDARD DEVIATION) ABUNDANCE VALUES FOR EACH TARGET ROW OF FIG. (3)

rectangles was reduced, the results of GMF converged to those of MF, which can be explained by the fact that for rare targets, the estimated background agrees more and more with the actual background. In order to show this, we varied the target sizes in the experiment from 1×1 to 21×21 and compared the obtained ROC curves (for GMF, 20 endmembers are applied). In Fig. 4, the obtained ROC curves for MF and GMF are shown.

In order to show that GMF is more robust than OSP against the particular choice of background model, we varied the number of applied endmembers from 5 to 20. In Fig. 5, the obtained ROC curves for OSP and GMF are shown. While the



(a) (b)

Fig. 5. ROC curve for OSP (a) and GMF (b) using different numbers of endmembers

performance of OSP varies severely with different number of endmembers, GMF performs equally well.

IV. Conclusion

In this paper, we presented a geometric matched filtering technique for targets that are frequently present in the data. The method first projects the data onto the plane of a simplex spanned by background endmembers and target. Then the background pixels are determined based on the bisective cones of the simplex. Using these background pixels, the matched filter score for the target endmember is calculated. Experiments on partial unmixing and target detection show that the proposed method outperforms the standard matched filter and orthogonal subspace projection.

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