SUBPIXEL TARGET DETECTION IN HYPERSPECTRAL IMAGES WITH LOCAL MATCHED FILTERING IN SLIC SUPERPIXELS

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ABSTRACT
In subpixel-target detection in hyperspectral images, there is well-documented current interest for identifying preferred background covariance matrix estimates to be used in the formation of matched-filter detectors. The traditional approach suggests global covariance matrix estimates, calculated upon all the image pixels, while several recent works suggest locally formed matched filters within image segments. In this work, we propose for the first time local matched filters from background covariance matrices calculated within SLIC-superpixels of the image. Our simulation studies illustrate that the proposed SLIC-based matched-filter (SLIC-MF) detector attains performance superior to that of contemporary alternatives that employ different, globally or locally estimated, background statistics.

Index Terms— Clustering, hyperspectral images, image segmentation, matched-filtering, subpixel-target detection.

1. INTRODUCTION
Due to its many important civil, military, and environmental remote-sensing applications, target detection in hyperspectral images has enjoyed in the past decade extensive research interest [1]. Examples of such applications include, among others, detection of specific terrestrial features such as vegetation and minerals, terrain classification in planetary exploration, and detection of military vehicles for defense and intelligence [1, 2].

Depending on the availability of the hyperspectral signature of the sought-after subpixel target, subpixel-target detectors can be divided in two major categories: anomaly detectors and target-matched detectors [2]. On the one hand, anomaly detectors utilize no target-spectrum knowledge and, thus, cannot distinguish between targets of interest and the other rarely appearing objects. On the other hand, target-matched detectors exploit assumed knowledge of the target spectral signature and, thus, attain higher detection performance. In this paper, we focus on the latter case and adopt the common linear mixture model (LMM) [3], by which the observed spectrum of a pixel is a linear combination of the spectral signature of local background endmembers and the known target signature.

Popular target-matched detectors include adaptive coherence estimator (ACE) [4], matched filter (MF) [2], normalized matched filter (NMF) [1], Kelly’s detector (Kelly) [5], and constrained energy minimization (CEM) [6], to name a few. Importantly, all above detectors rely on the spectral mean and covariance matrix of the background scene, statistics that can only be calculated by the detector from the image in hand. Therefore, there has been recently recorded in the literature an increasing interest for identifying methods for successful calculation of background statistics [7]. According to the standard, traditional approach, background statistics are calculated from all the image pixels and the single detector formed upon these statistics (global filtering) is applied on the entire image. However, in cases, significantly superior performance has been reported when background statistics are calculated locally within image regions defined by spectral-similarity-based segmentation methods, such as histogram segmentation [8, 9].

In this paper, we modify simple linear iterative clustering (SLIC) [10] to operate on all bands of the hyperspectral image (originally SLIC was defined to operate on CIELAB color space) and propose SLIC-MF: a local matched-filter detector, calculated and operating within background-coherent regions formed by SLIC segmentation. In contrast to segmentation methods employed by existing local filtering approaches, SLIC segmentation places weighted emphasis on both spectral similarity and spatial proximity. Thus, the formed segments are not only spectrally coherent, but also spatially restrained. Our simulation studies illustrate that the proposed matched-filters outperform in probability of target detection the global matched filtering, as well as state-of-the-art local filtering counterparts.

2. SIGNAL MODEL AND DETECTION PRELIMINARIES
We consider an image of dimensions \( H \times W \) pixels. According to the popular linear mixture model (LMM) [3], the mea-
ured reflectance L-band spectrum of a pixel, \( x \), is expressed as a linear combination of the target spectral signature \( s \) and \( K \) background endmembers \( \{s_k\}_{k \in \{1, \ldots, K\}} \) as

\[
x = as + \sum_{k=1}^{K} a_k s_k + n \in \mathbb{R}^{L \times 1}
\]

where \( a \) is the target fill-factor, \( a_k \) is the fill-factor for the \( k \)-th background endmember, and \( n \) accounts for zero-mean additive Gaussian noise. The fill-factors of the target and background endmembers satisfy the non-negativity and additivity properties \( a \geq 0, a_k \geq 0 \), and \( a + \sum_{k=1}^{K} a_k = 1 \). Evidently, for background-only pixels, \( a = 0 \).

In this paper, we focus on matched-filtering target detection. With the assumption that the background-plus-noise component in the coherence region of \( x \), \( v = \sum_{k=1}^{K} a_k s_k + w \), is distributed by \( \mathcal{N}(m, C) \), for some mean \( m \in \mathbb{R}^{L} \) and a covariance matrix \( C \in \mathbb{R}^{L \times L} \), the matched filter is known to take the form \( [1] \)

\[
W_{MF} = \frac{C^{-1}(s-m)}{\sqrt{(s-m)^{\top}C^{-1}(s-m)}}
\]

Then, target presence decision for \( x \) is made upon the filter output \( y_{MF}(x) = W_{MF}^\top(x - m) \). Evidently, background statistics \( m \) and \( C \) play a pivotal role in the formation of \( y_{MF}(x) \). Traditionally, \( C \) and \( m \) are calculated upon all the pixels of the given image (global statistics). Improvement on this global matched filter is sometimes sought by excluding the pixels identified as anomalies by means of a standard anomaly detector [11]. However, arguably, due to the spatially non-stationary nature of the background in scene, global-statistics based matched filters do not always attain satisfactory detection performance. In the past few years, several algorithms have been proposed for improved statistical background modeling [7]. The majority of such algorithms seek to calculate background statistics and form matched filters individually within image-segmentation derived coherence regions [9, 12].

3. PROPOSED METHOD

3.1. Local Matched Filtering

In this work we propose for the first time to form the matched-filter for each pixel based on the background statistics of the SLIC superpixel [10] wherein it lies. That is, let the image be segmented by SLIC in regions \( X_1, X_2, \ldots, X_N \), consisting of \( c_1, c_2, \ldots, c_N \) pixels, respectively. The proposed method calculates for region \( X_n \) the background statistics

\[
m_n = \frac{1}{c_n} \sum_{p \in X_n} p
\]

\[
C_n = \frac{1}{c_n} \sum_{p \in X_n} (p - m_n)(p - m_n)^\top
\]

and, accordingly, the individual (local) matched filter

\[
W_{MF,n} = \frac{C_n^{-1}(s - m_n)}{\sqrt{(s - m_n)^\top C_n^{-1}(s - m_n)}}.
\]

Proposed algorithm SLIC-MF for subpixel-target detection

1: Segment image using SLIC [10] with parameters \( G, M, P \);
2: Obtain segments \( X_1, X_2, \ldots, X_N \);
3: \( m_n \leftarrow \frac{1}{|X_n|} \sum_{p \in X_n} p \)
4: \( C_n \leftarrow \frac{1}{|X_n|} \sum_{p \in X_n} (p - m_n)(p - m_n)^\top \)
5: \( w_n \leftarrow \sqrt{(s - m_n)^\top C_n^{-1}(s - m_n)} \)
6: for \( i = 1 : |X_n| \)
7: \( x \leftarrow [X_n]_i ; y_{MF} \leftarrow w_n^\top(x - m_n) \)
8: if \( y_{MF} > \eta \)
9: detect positive
10: else
11: detect negative

Fig. 1: Proposed algorithm for matched-filter subpixel target detection from SLIC superpixel statistics.

Then, for every pixel \( x \in X_n \) we detect

\[
y_{MF,n}(x) = w_n^\top(x - m_n) \geq \eta.
\]

Apparently, for \( C_n^{-1} \) to be defined, it requires \( c_n > L \). For the case that \( c_n < L \), we employ in (3) instead of the singular \( C_n \) the diagonally loaded full rank \( C_n + \delta I_L \), for some small \( \delta > 0 \).

3.2. Proposed Superpixel Segmentation

In this work, we modify the SLIC algorithm, presented in [10], to operate on all image bands (initially SLIC was defined to operate on CIELAB color space). The algorithm initializes selecting \( N \) equally spaced pixels in the image as cluster centers (\( G \) pixels between two neighboring centers). Then, it assigns each pixel of the image to one of the \( N \) clusters by simple nearest-center selection. For identifying the nearest center, our modified SLIC defines spatio-spectral pixel distance as follows: consider pixel \( x_i \in \mathbb{R}^{L \times 1} \) with coordinates \( (x_i, y_i) \) and pixel \( x_j \in \mathbb{R}^{L \times 1} \) with coordinates \( (x_j, y_j) \); the spatio-spectral distance of \( x_i \) from \( x_j \) is given by

\[
d_{SLIC}(x_i, x_j) = \sqrt{d_{SPEC}^2 + \left(\frac{M}{G}\right)^2 d_{SPAT}^2}, \text{ where (5)}
\]

\[
d_{SPEC}(x_i, x_j) = \|x_i - x_j\|_2; \text{ (6)}
\]

\[
d_{SPAT}(x_i, x_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}; \text{ (7)}
\]

and \( M \) is the user-selected parameter that accounts for the compactness of superpixels. Then, after assigning all pixels to some original clusters, new centers are found, and the algorithm proceeds with \( k \)-means iterations that employ the distance measure defined above. By tuning \( M \) and \( G \), different image segmentations are generated. In particular, the
higher the value of $G$ is, the larger the initial superpixels. On the other hand, by increasing the regularization parameter $M$ the algorithm places more emphasis on the spatial distance $d_{SPAT}$, leading to more regular “grid-like” superpixels in the output. Finally, the algorithm conducts post-processing by which it merges superpixels that comprise less than $P$ pixels to their neighboring superpixels ($P$ is the third, user selected parameter of the algorithm). At the end of the presented SLIC iterations, the image has been divided into $N$ superpixels/segments $X_1, X_2, \ldots, X_N$.

A psedocode of the proposed SLIC-MF target-detection algorithm is presented in Fig. 1.

4. SIMULATION STUDIES

In this section, we evaluate the proposed method on the hyperspectral image from the blind test dataset [13]. The test image contains $L = 126$ spectral bands ranging from 450nm to 2500nm, with a spectrum step varying between 4.5nm and 6.5nm. We preprocess the image by normalizing it so that the average pixel squared magnitude is 1; i.e., $\frac{1}{HW} \sum_{i=1}^{HW} \|x_i\|^2 = 1$. Then, we calculate matched filters based on global statistics, local statistics calculated in the segments of [9], [14] and local statistics calculated in the segments of the proposed modified all-spectrum SLIC. To evaluate the performance of the above detectors, we employ the method of [15] by which: (i) we form matched filters from the target-free image; (ii) we obtain the matched-filter outputs for the target-free image and perform detection; (iii) we add the target to every pixel of the image with filling factor $a$, obtain matched-filter outputs after, and perform detection. In our studies, we use the spectrum of vehicle V1 in [13] as target, applying first spectrum normalization so that $\|s\|_2 = 1$. The image scene and spectral signature of V1 are shown in Fig. 2. In all presented studies SLIC parameters defined in Section 3 are set to $G = 15$, $M = 0.2$, and $P = L = 126$, resulting to the segmentation depicted in Fig. 3.

To offer a first hint of the performance of proposed detector, in Fig. 4 we plot the histograms of $y_{MF}$ (global matched filter output) and $y_{MF,n}$ (output of proposed filter in some sample superpixel $n$) when all pixels are target-absent ($a = 0\%$) and when all pixels are target-present ($a = 0.5\%$). We observe that in sharp contrast to global matched filtering, the proposed detector discriminates emphatically the
Matched-filter response

Normalized Histogram

Global, Target absent
Global, Target present
Proposed, Target absent
Proposed, Target present

Fig. 4: Histograms of $y_{MF}$ and $y_{MF,n}$ when all pixels are target-absent ($a = 0\%$) and when all pixels are target-present ($a = 0.5\%$).

False Alarm Probability
Detection Probability

Global, $a = 0.5\%$
Local means, $a = 0.5\%$
HIST, $a = 0.5\%$
SLIC, $a = 0.5\%$
Global, $a = 0.7\%$
Local means, $a = 0.7\%$
HIST, $a = 0.7\%$
SLIC, $a = 0.7\%$

Fig. 5: ROC curves for $a = 0.5\%, 0.7\%$.

Proposed method attains PD equal to 1 for PFA as low as 0.01, while none of the other detectors attains PD 1 for PFA less than 0.9.

In Fig. 6, we study the effect of fill-factor $a$ in the performance of the proposed method, HIST [12], and LM [14], for PFA 0.1. As expected, PD increases for all methods along $a$, as the subpixel targets stand out more. Interestingly, the proposed method attains PD above 0.7 for all fill-factor values, PD greater than 0.9 for $a > 0.2\%$, and converges to PD 1 for $a > 0.7\%$. On the other hand, HIST and LM attain PD close to 0.15 for $a = 0.1\%$ and increase almost linearly along $a$, reaching PD greater than 0.7 only for $a > 0.7\%$.

5. CONCLUSIONS AND FUTURE WORK

In this paper, we propose a novel method for subpixel target detection using local statistics from SLIC superpixels of the image. Our simulation studies have shown that the proposed method outperforms significantly global matched filtering, as well as state-of-the-art local filtering counterparts. This can be arguably accredited to the fact that, in contrast to all other segmentation methods used for subpixel-target detection, SLIC segmentation places weighted emphasis on both spectral similarity and spatial proximity. To reduce the computational overhead added by the increased number of covariance matrix inversions demanded by the proposed method, in our future developments we plan to (i) combine SLIC segmentation with dimensionality reduction and band selection, (ii) adapt the matched filter of a superpixel from the ones of its neighboring superpixels, and (iii) identify image-specific maximum SLIC-superpixel size (the larger the superpixels, the smaller their number) that offers satisfactory performance.
6. REFERENCES


