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# Advanced Method for Small-Size Targets Detection in Hyperspectral Image

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***ABSTRACT***

The advanced method for subpixel detection of small-size targets on hyperspectral image is described. The method is based on matched filtering model with the succeeding correction of determined pixel fractions. Correction consists of two stages. First one is a statistical adjustment for actual set of targets/backgrounds in a scene and second one is a pixel-wise consideration of radiometric separability of spectra. The proposed advanced method provides more exact subpixel detection of small-size targets in hyperspectral image.

***Key Words*.** Hyperspectral imagery, matched filtering, subpixel target detection, pixel fraction.

**Introduction.** The hyperspectral imagery possibilities to detect subpixel targets are based on spectra's fine structure analysis. It is especially important for distinction of targets similar to natural backgrounds [1]. The special methods and algorithms need for processing of tremendous data amount in hyperspectral images. In particular, an immediate visual interpretation of hyperspectral imagery is inefficient because the three-dimensional color representation delivers only a small part of the full spectral information which is contained in hyperspectral image. Direct interpreting features such as a shape and details are, as a rule, inaccessible owing to insufficient spatial resolution.

The minimum size of target which can be detected on the image by routine classification is determined by the geometrical detailing i.e. a ground sample distance (GSD) on the land surface. At the same time there is an inverse relation between providing GSD and number of imaging spectral bands in the known multispectral systems of remote sensing. The larger size of GSD in hyperspectral imagery leads to a possibility of several different targets capture inside one pixel. It causes identification errors.

**Problem.** Pixel fractions of the target spectra which contain in current pixel have to be result of subpixel detection of small-sized objects in hyperspectral image. At that the target spectra can be several, i.e. more than one. Herewith it is considered that only target spectra – the spectral reflectance of target covers – are known. Other spectra within scene remain unknowns.

For ensuring acceptable level of reliability of target detection by their spectral reflectance the accuracy of the quantitative determining of pixel fractions of target spectra should be as high as possible compared to the best known methods [2].

Thus, the purpose of the paper is improvement of a method for subpixel detection of small-size targets in hyperspectral image.

**State-of-the-art.** One of features of hyperspectral images a possibility of targets resolving even inside pixel if their exact spectral signatures are available. This process is called as subpixel detection [3].

Methods for subpixel detection are used to determine a detected target fraction in each pixel of the hyperspectral image. In case of high spectral contrast between target and background the detection of target which occupy some percent of the pixel area is possible [4]. Methods for subpixel detection include the linear unmixing and the matched filtering.

The *linear unmixing* is based on representation of a spectrum in any pixel by result of mixing of several spectra. Mixing in this context is understood as weighing of spectra of all covers within pixel. Weights of each spectrum are proportional to fractions of the pixel area with this covers [5].

If spectra of all covers in scene are known, then their fractions within each pixel can be calculated by spectrum of this pixel. Unmixing is carried out by solving of the $m$ linear equations for each pixel where $m$ is number of spectral samples in the hyperspectral image. In order for the system of these equations to be solved, it is necessary that $m$ is more than total number of spectra.

For this reason unmixing is possible on hyperspectral data and almost is never applied to usual multispectral imagery. The output of the linear unmixing is a set of spatial distributions of pixel fractions for each of input spectra.

The *matched filtering* is a method for selection from the image only the target spectra chosen by the user. Unlike the linear unmixing, it isn't obligatory that all occurred spectra are known therefore the matched filtering is often called also as partial unmixing.

Originally the matched filtering was developed for selection of rather rare targets in a scene, for example artificial. For rather widespread targets the results of the matched filtering require the some correction.

The matched filtering allocates in the input image the pixels, close to a target spectrum, and suppresses a response from all other spectra which are considered as the complex unknown background [6]. As with the linear unmixing, the output of the matched filtering is a target spectrum fraction inside pixel. The potential problem of the matched filtering consists in determining the similarity threshold between examined and target spectrum.

The solution of this problem consists in statistical estimation of noise in hyperspectral image [7]. So, the matched filtering is the most suitable method for subpixel target detection in hyperspectral images.

The known algorithms for subpixel target detection in hyperspectral image are based on separation of target and background spectra [8]. Therefore the spectra of targets which should be detected are necessary before hyperspectral image analysis. For this purpose the spectra retrieval from pre-developed spectral library of typical targets and backgrounds has to be carried out [9].

The mix of a target spectrum (or few spectra) and undesirable background spectra is considered during subpixel detection [10]. Generally it is possible to separate all target and background spectra one from another with an accuracy which is depended on spectral resolution of input hyperspectral data [11].

The linear models of spectral unmixing are most often used for this purpose. Such models provide determination of weights of the known spectra in proportion to their fractions inside pixel [12]. Methods and algorithms for spectral unmixing are developed for decades [13], but there are still some difficulties in practical applications for subpixel target detection. First, the composition of all spectra which are present in scene is almost never unknown. Therefore, the methods which allow occurrence of uncertain background spectra are necessary [14]. Second, the majority of the existing methods which meet the first condition – the matched filters, don't guarantee keeping of physical restrictions for fractions of target spectra [15].

**Model.** Each $i$-th pixel of the hyperspectral image can be represented as an $x_i$ $m$-dimensional vector of spectral samples, and $j$-th target spectrum – as an $y_j$ $m$-dimensional vector, $j = 1 .. p$. Let $Y$ is a matrix of target spectra dimension of $m \times p$, and $\alpha_i = (\alpha_1, \alpha_2 .. \alpha_p)^T$ is a vector of fractions of target spectra inside $i$-th pixel. The linear model of spectral mix for $x_i$ pixel is described by the equation:

$$x_i = Y \alpha_i + z_i \tag{1}$$

where $z_i$ is a residue vector which can be considered as the additive noise.

The main limitation of unmixing (1) is to exceed the number of spectral bands in hyperspectral image over the number of spectra which are unmixed: $m \geq p$.

If all components of $Y$ matrix are known, then the problem comes down to the overdetermined linear equation system solving with constrains of NCLS (non-negatively constrained least squares), SCLS (sum-to-one constrained least squares), or both at once – FCLS (fully constrained least squares). In [16] paper the rigorous algorithm with FCLS constrains is developed.

Unfortunately, in practice the described state nearly always is idealized as the full composition of all spectra in scene of observation is a priori unknown. In such case, the model should be applied that detects one or more known target spectra, while the rest are regarded as undesirable [17].

The most perfect of such models is the TCMI (target-constrained minimum interference) matched filter proposed by Kwan et al. in [18] paper. In it the estimate of fractions sum of target spectra inside *i*-th pixel of image equals $\alpha^T x_i$, where $x_i$ is the full spectral signal in this pixel, and α is the solution of a minimization problem:

$$\begin{cases} \alpha^T y_j = \begin{cases} 1 \text{ if } j \text{ is target} \\ 0 \text{ otherwise} \end{cases} \\ j = 1..p \\ \sum_{i=1}^{n} (\alpha^T x_i)^2 \quad \rightarrow \quad \min \end{cases} \tag{2}$$

To calculate a *j*-th spectrum fraction, it is possible to apply the TCMI filter, considering some spectra as target, and the others ones as undesirable. Estimate of fractions in *i*-th pixel will be:

$$\alpha^T = (Y^T X^{-1} Y)^{-1} Y^T X^{-1} x_i \tag{3}$$

Here α is a *p*-dimensional vector.

The TCMI model can be reduced to the linear transformation of spectra matrix and following application of least squares method:

$$\alpha^T = \text{pinv}(X^{-1/2} Y)^{-1} X^{-1/2} x_i \tag{4}$$

where by pinv (·) a pseudo-inversion of matrix is denoted.

Vector's $\alpha_i$ elements can be the negative. In order to avoid the negative values of estimates of spectra fractions it is necessary to ensure the NCLS constrains [19].

The combination of the TCMI-NCLS models consists in finding the spectra fractions in *i*-th pixel of image as critical point with respect to $\alpha_i$ in minimization problem:

$$\begin{cases} (x_i - Y\alpha_i)^T X^{-1} (x_i - Y\alpha_i) \quad \rightarrow \quad \min \\ \alpha_{ij} \geq 0 \\ j = 1..p \end{cases} \tag{5}$$

Similar to TCMI, the TCMI-NCLS model comes down to multiplication of spectra by $X^{-1/2}$ matrix and ensuring the NCLS constrains.

The significant exceeding of the pixel area over the target area should be considered as the typical case for hyperspectral imaging of small-size targets. Therefore, the pixel fraction of target spectrum will be small. In this case the NCLS constrains seem quite intrinsic, while the stronger FCLS constrains are overmuch. At the same time the NCLS constrains allow to preserve the physical nature requirements of unmixing. It is important advantage over the pure TCMI model.

So, the TCMI-NCLS model is the most suitable for small-size targets detection in hyperspectral image [20].

**Method.** Above the TCMI-NCLS (5) model was chosen as essential core of the developed method for subpixel target detection. However the accuracy of calculation of target spectra fractions provided by it significantly depends on targets and backgrounds composition in scene as well as on reliability of the close spectra separation. Therefore the TCMI-NCLS model requires the correction the kernel of which is the adjustment to specific set of target/background spectra to be detected (the first level of correction) as well as incorporation the reliability of close spectra separating (the second level of correction).

The first level of correction is based on numerous experiments and represented by regression dependence between the corrected pixel fraction *e* and initial one α. As simulation shows, the best in mean accuracy is provided by exponential type regression of:

$$e(\alpha) \approx b \times [1 - \exp(-k \times (\alpha + c)^q)] \,, \tag{6}$$

where $b$, $c$, $k$, $q$ are regression parameters.

The second level of correction should in any way consider a possibility of correct separating of close spectra in mix. This level practically is always present at classification of hyperspectral imagery [21] and can use for the preliminary estimates various informational and statistical metrics, such as information divergence [22], Bhattacharyya statistical distance [23], or spectral-topological classifier [24].

The separability of optical signals is closely related to contrast; therefore for the analysis of multidimensional optical fields the Bhattacharyya distance which is an analogue of optical contrast [25] usually is engaged. However the available practical experience of signal detection in multi- and hyperspectral images testifies that such indicator as the contrast signal-to-noise ratio (CSNR) $\psi$ provides the better efficiency and convenience [26].

Correction of pixel fractions of target spectra depending on CSNR in each pixel of hyperspectral image at a first approximation can be described by signal-dependent additive term $f(\alpha)$ taking into account the error probability $\varepsilon(\psi)$:

$$f(\alpha) = \begin{cases} \alpha - \alpha \cdot \varepsilon(\psi) & \alpha \le 0.5 \\ \alpha + (1-\alpha) \cdot \varepsilon(\psi) & \alpha > 0.5 \end{cases} \tag{7}$$

where the error probability $\varepsilon(\psi)$ is evaluated by pixel CSNR value $\psi$ as [27]:

$$\varepsilon(\psi) \cong \frac{1}{2}\left(1 - \operatorname{erf}\frac{\psi}{\sqrt{2}}\right) \tag{8}$$

Thus, three stages of calculation of target spectra pixel fractions are implemented sequentially in the developed method for subpixel detection of small-size targets in hyperspectral image. At first the matched filtering with the TCMI-NCLS model [20] which provides the initial guess of pixel fractions is carried out. Then the regression adjustment of their values by statistics collected within the hyperspectral imaging total area is conducted. And at last, the fine equalizing of the adjusted values of pixel fractions by the contrast signal-to-noise ratio in each hyperpixel of image is performed.

The described three-stage model is more flexible in comparison with the TCMI-NCLS one and the more so with the pure TCMI. Therefore it is able to provide more exact subpixel detection of small-size targets in hyperspectral image.

**Results.** Testing of the developed method over the AVIRIS actual hyperspectral aerial image (Fig. 1) demonstrates its superiority over well-known methods – centered matched filter (CMF) [28], CEM and TCMI.

Fig. 1. ER-2/AVIRIS hyperspectral aerial image

Mojave (USA) power station, September 6, 2018, pseudo-natural color composite, spectral bands 36 (684 nm), 20 (550 nm), and 10 (453 nm), GSD 5.8 m

The pixel fractions accuracy of the target spectrum detection was estimated by the mean absolute error (MAE). Table 1 provides the accuracy estimates for the CMF method, joint one for CEM and TCMI methods (they are equivalent in the case of single target spectrum) and for the developed method with correction.

Table 1. The accuracy of pixel fractions of the target spectrum

| Method | Target pixel fraction MAE | False pixel fraction MAE |
|---|---|---|
| CMF | 0.149 | 0.021 |
| CEM/TCMI | 0.040 | 0.027 |
| Proposed | 0.033 | 0.014 |

As can be seen from the table 1, the proposed method provides the best performances for both target spectrum detection and false alarm compared to known methods.

**Conclusions**

The advanced method for subpixel detection of small-size targets in hyperspectral image is proposed. In addition to the core TCMI-NCLS matched filter it includes a further two-level correction chain for values adjustment of target spectra pixel fractions. At the first level of correction an adjustment to specific set of target and background spectra which are subject to detection is carried out. At the second level of correction the refinement of values of target spectra pixel fractions in each pixel of hyperspectral image is performed. The model of exponential regression is the kernel for the first level correction. The second level of correction is conducted in relation with the contrast signal-to-noise ratio in each pixel.
Fulfilled demo subpixel target detection in actual hyperspectral image shows the 17.5% increase in accuracy relative to known CEM and TCMI methods.

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# ჰიპერსპექტრალურ გამოსახულებებზე მცირეზომიანი ობიექტების აღმოჩენის გაუმჯობესებული მეთოდი

ვ. ანდრონოვი

## რეზიუმე

აღწერილია ჰიპერსპექტრალურ გამოსახულებებზე მცირეზომიანი ობიექტების სუბპიქსელური აღმოჩენისათვის გაუმჯობესებული მეთოდი. მეთოდი დაფუძნებულია შეთანხმებული გაფილტვრის მოდელზე გარკვეული პიქსელური წილების შემდგომ კორექციაზე. კორექტირება შედგება ორ სტადიიდან: სცენაში სპექტრების ობიექტების/ფონების კონკრეტული ანაკრეფის სტატისტიკური აწყობა და სპექტრების რადიომეტრიულ განყოფადობის პიქსელური აღრიცხვა. შემოთავაზებული გაუმჯობესებული მეთოდი უზრუნველყოფს ჰიპერსპექტრალურ გამოსახულებებზე მცირეზომიანი ობიექტების უფრო ზუსტ აღმოჩენას.

# Усовершенствованный метод обнаружения малоразмерных объектов на гиперспектральных изображениях

**В.В. Андронов**

## Резюме

Описан усовершенствованный метод для субпиксельного обнаружения малоразмерных объектов на гиперспектральных изображениях. Метод основан на модели согласованной фильтрации с последующей коррекцией определённых пиксельных долей. Коррекция состоит из двух стадий: статистическая настройка на конкретный набор объектов/фонов спектров в сцене и попиксельный учёт радиометрической разделимости спектров. Предложенный усовершенствованный метод обеспечивает более точное субпиксельное обнаружение малоразмерных объектов на гиперспектральных изображениях.