BLIND SOURCE SEPARATION TECHNIQUE USED IN FOREST IMAGES ANALYSIS

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Abstract

With the purpose of forest remote sensing images analysis, this method utilizes a Blind Source Separation technique, named Robust Second Order Blind Identification. In orthogonalization stage, a Robust orthogonalization is performed which ensures that positive definite covariance matrix is not sensitive to the additive noise.

The separation process considers the periodical spatial distribution of vegetation as source, namely the coverage along the forest plantation position. Consequently, the spectrum of vegetation was estimated as the mixture ratio of the source.

This technique allows recognizing the qualitative change of vegetation from the estimated spectra and quantitative one from the coverage.

Key words: blind source separation, robust ortogonalization, forest images, spectrum, vegetation, soil, coverage.

INTRODUCTION

The artificial installation of forest vegetation on the land in the national forest stock, which were covered with single regeneration cuttings (clear cuttings), is one of the priority objectives of the National Forest Administration. The introduction into the economic-forest circuit of some plots of land with relatively extreme conditions of vegetation, called degraded lands, can be achieved by artificial installing of forest vegetation on them.

A preliminary step to this end is the process of identifying and mapping of these areas, known as perimeters of improvement, a step which can be done by using spectral reflectance of the existing underlying surfaces in the work area. Based on the spectral response obtained from the analysis of forest remote sensing images (forest orthophotomap), like the one in Figure 1, the technical solutions regarding the artificial installation works of forest vegetation (phytomeliorations) can be substantiated.

Fig. 1. Forest remote sensing image (forest orthophotomap).

In the remote sensing images, many materials contribute to the value of a pixel, so that the pixel value is a mixture that produces a mixed spectrum.

Blind Source Separation technique consists in retrieving the source signals without resorting to any a priori information about mixing; it exploits only the information carried by the received signals themselves.

This processing method estimates the spectra and the coverage by applying the Blind Source Separation technique to the forest remote sensing images for recognizing fine structure vegetation change on forest plantation. This technique allows separation the change of vegetation into qualitative one due to ecological characteristics such as the chlorophyll quantity from the estimated spectra and quantitative one from the coverage.

Some methods extract the spectra from the observed mixed spectra by considering the spectrum against wavelength as independent component. In the purpose of the component elements separation this processing method adopts the idea proposed by N.Kosaka and Y.Kosugi in (Kosaka N. et al., 2003) to consider the periodical spatial distribution of crops, namely the coverage along the surface position as the independent component, so that the spectrum of crops is estimated as the mixture ratio of the independent component.

Also, this method allows the separation in the presence of the fluctuation of vegetation coverage and additive Gaussian noise, such as thermal noise of the sensors and atmospheric noise, in the real data.

MATERIAL AND METHOD

A formula of the general atmospheric model for transmission of radiation is described in (MODTRANS Report, 1996). It contains three terms, the surface radiation, the atmospheric radiation and the scattered light including that by the earth surface:

$$\begin{aligned} I_v = & \underbrace{\varepsilon_e B_v(T_e)\, e^{-(\tau_1/\mu)}}_{surface\ radiation} + \underbrace{\int_{\tau}^{\tau_1} \varepsilon_a B_v(T_a)\, e^{-(t/\mu)} \frac{dt}{\mu}}_{atmospheric\ radiation} + \\ & + \underbrace{\int_{\tau}^{\tau_1} \left[k \int_0^{2\pi} \int_{-1}^{1} P_v(\mu', \phi')\, L_v(\tau, \mu', \phi')\, d\mu' d\phi' \right] e^{-(t/\mu)} \frac{dt}{\mu}}_{scattered\ light\ by\ the\ earth\ surface} \end{aligned} \tag{1}$$

where I_v represents the radiance observed by a satellite. The used parameters are described in (MODTRANS Report, 1996). When the observed scene is very close to the camera, the solid angle of the observation is very weak, the term corresponding to the reflection of the sky light is very weak as well and negligible, without affecting the pertinence of the model. The resulted model includes the two terms, namely surface radiation and atmospheric radiation.

A light beam gets attenuated due to scattering by atmospheric particles. Mie's law (McCartney E.J., 1976) gives the following representation of the radiance of an object observed:

$$I_{SR}(\lambda, x) = I_o(\lambda) \cdot e^{-\beta(\lambda)\,x} = I_0(\lambda)\, R(\lambda)\, T(x) \qquad (2)$$

where λ is the wavelength, β is the scattering coefficient, I_o is the object radiance, I_0 is the sky radiance, $R = I_o/I_0$.is the reflection coefficient and $T = e^{-\beta(\lambda)\,x}$ is the transmission coefficient.

The scattering of sky light is due to particles from atmosphere. The radiance at the observer after attenuation of the scattered light due to the aerosol particles between the scene and the observer is given by:

$$I_{AR}(\lambda, x) = I_0(\lambda)\beta(\lambda)\int_0^x e^{-\beta(\lambda)\,x}dx = I_0(\lambda)\left(1 - e^{-\beta(\lambda)\,x}\right) \qquad (3)$$

Assuming that the observation is made in a day with clear sky, we chosed to use a simple description that yields the properties of an actually model but only takes care of the surface radiation phenomen.

The geometry of the observation in the forest plantation is depicted in Figure 2.

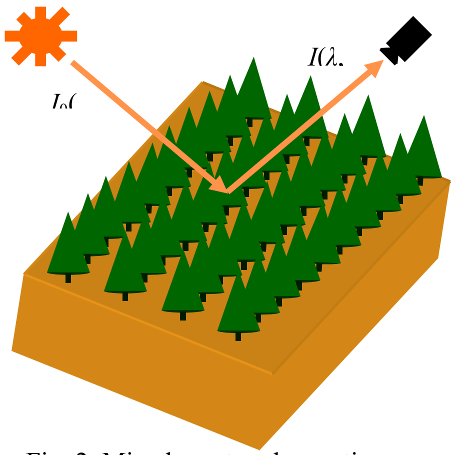


Fig. 2. Mixed spectra observation.

When into a pixel there are only vegetation and soil it can write the following relation:

$$T_v(x)+T_s(x)=1 \qquad (4)$$

In this case, the mixed spectra observed by sensor, at wavelength λ and position x, are composed of two terms as:

$$I(\lambda, x)=I_0(\lambda)[R_v(\lambda)T_v(x)+R_s(\lambda)T_s(x)] \qquad (5)$$

where $R_v(\lambda)$ and $T_v(x)$ are the spectra respectively the coverage of vegetation, $R_s(\lambda)$ and $T_s(x)$ are the spectra respectively the coverage of soil and $I_0(\lambda)$ is the intensity of incident light.

By replacing $T_s(x)$ from equation (4) into equation (5) the problem is reduced to the one channel estimation for the dependency on $T_v(x)$, according to following relation:

$$I(\lambda, x)=I_0(\lambda)[(R_v(\lambda)-R_s(\lambda))T_v(x)+R_s(\lambda)] \quad (6)$$

The thermal noise of the sensor is considered as additive Gaussian noise. In a limited narrow area of a vegetation field the atmospheric condition is approximately uniform. Consequently, the atmospheric noise for each vegetation field can be approximated as an additive Gaussian noise.

For real observations it can suppose additive Gaussian noise and consider fluctuations in vegetation coverage term because the size of each vegetation coverage might be irregular. Consequently, the mixed spectra observed become:

$$I(\lambda, x)=I_0(\lambda)[(R_v(\lambda)-R_s(\lambda))(T_v(x)+\Delta T_v(x))+R_s(\lambda)]+R_n(\lambda)T_n(x) \quad (7)$$

where $R_n(\lambda)$ and $T_n(x)$ are the amplitude respectively periodical pattern of the noise and $\Delta T_v(x)$ is the fluctuation of the vegetation coverage.

The periodicity of the coverage according to the position x for vegetation and soil is presented in Figure 3.

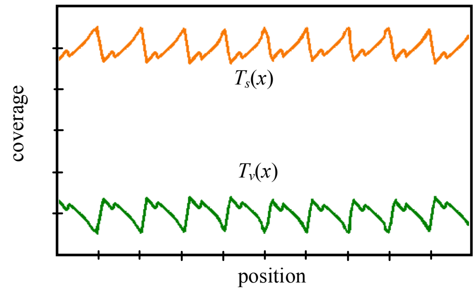


Fig. 3. The periodicity of the coverage

From Johns Hopkins University Spectral Library (http://asterweb.jpl.nasa.gov/speclib/) was adopted the spectrum of Conifer for vegetation spectrum and the spectrum of Loam for soil spectrum. These spectra are represented in Figure 4.

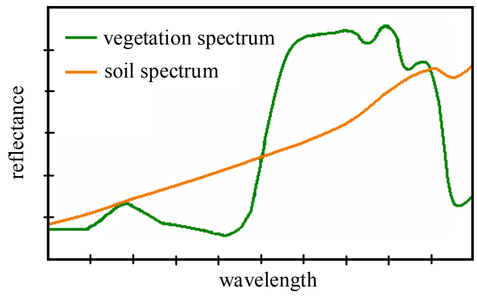


Fig. 4. Vegetation and soil spectra.

Below is presented the problem formulation of the forest images analysis by a Blind Source Separation technique designed for separating the observed mixed signals from multiple sources into original signals.

In many practical problems the processed data are multidimensional observations, that has the form:

$$\boldsymbol{x}(k) = \boldsymbol{A}\,\boldsymbol{s}(k) + \boldsymbol{n}(k) + c \quad (8)$$

where the N-dimensional vector $\boldsymbol{x}(k) = [x_1(k), x_2(k),\ldots, x_N(k)]^T$ is an instantaneous linear mixture of source signals, the M-dimensional vector $\boldsymbol{s}(k) = [s_1(k), s_2(k), \ldots, s_M(k)]^T$ contains the source signals sampled at $1\le k\le K$, $\boldsymbol{n}(k)=[n_1(k), n_2(k), \ldots, n_N(k)]^T$ is the additive noise vector that is assumed to be statistically independent of source signals and the matrix $\boldsymbol{A}$ called mixing matrix is the transfer function between sources and sensors. The source signals $s_i(k)$, $1 \le i \le M$ ($M < N$), are assumed independent, and additive noises $n_i(k)$, $1 \le i \le N$, can be spatially correlated but temporally white.

From the relations (7) and (8) results the following equation:

$$I_0(\lambda)[(R_v(\lambda)-R_s(\lambda))(T_v(x)+\Delta T_v(x))+R_s(\lambda)]+R_n(\lambda)T_n(x)=\boldsymbol{A}\ \boldsymbol{s}(k) + \boldsymbol{n}(k) + c \quad (9)$$

According to the suggestion of N.Kosaka and Y.Kosugi presented in (Kosaka N. et al., 2003), it can write the following relations:

$$\begin{aligned} &\boldsymbol{A}\ \boldsymbol{s}(k)=I_0(\lambda)[(R_v(\lambda)-R_s(\lambda))(T_v(x)+\Delta T_v(x))] \\ &\boldsymbol{n}(k)=R_n(\lambda)T_n(x) \\ &c=I_0(\lambda)R_s(\lambda) \end{aligned} \quad (10)$$

To obtain source signals from observations we utilize Blind Source Separation technique entitled *Robust Second Order Blind Identification*, described in the next section.

ROBUST SECOND ORDER BLIND IDENTIFICATION (RSOBI)

This algorithm was described by A.Cichocki in (Cichocki A. et al., 2002) on the foundation of *Second Order Blind Identification* algorithm, developed first by A.Belouchrani in (Belouchrani A. et al., 1997). This one consists of an orthogonalization stage fallowed by a unitary transform.

Orthogonalization stage is performed by *Robust orthogonalization* algorithm described by A. Cichocki in (Cichocki A. et al., 2002). For preselected delays (p_1, p_2, ... , p_J) one estimates a set of symmetric delayed covariance matrices of sensor signals:

$$\tilde{\boldsymbol{R}}_x(p_j) = \frac{\boldsymbol{R}_x(p_J) + \boldsymbol{R}_x^T(p_J)}{2}, \ j = 1,..., J \quad (11)$$

where $\boldsymbol{R}_x(p)$ is the delayed covariance matrix of the observation vector computed as:

$$\boldsymbol{R}_x(p) = E\left[\boldsymbol{x}(k)\boldsymbol{x}^T(k-p)\right] = \frac{1}{K}\sum_{k=1}^{K}\boldsymbol{x}(k)\ \boldsymbol{x}^T(k-p) \quad (12)$$

and one constructs an NxNJ matrix:

$$\boldsymbol{R} = [\tilde{\boldsymbol{R}}_x(p_1)\ , \dots ,\ \tilde{\boldsymbol{R}}_x(p_J)] \quad (13)$$

Then it is performed a singular values decomposition of matrix $\boldsymbol{R}$:

$$\boldsymbol{R} = \boldsymbol{Q}\,\boldsymbol{\Sigma}\boldsymbol{Z}^T \quad (14)$$

where NxN matrix $\boldsymbol{Q} = [\boldsymbol{Q}_s\ \boldsymbol{Q}_n]$ (with NxM matrix $\boldsymbol{Q}_s=[\boldsymbol{q}_1\ldots\boldsymbol{q}_M\ ]$) and NJxNJ matrix $\boldsymbol{Z}$ are orthogonal, and $\boldsymbol{\Sigma}$ is an MxNJ matrix whose left M columns contain $diag[\sigma_1, \sigma_2, ... , \sigma_M]$ (with non increasing singular values) and whose right NJ-M columns are zero. For a non-zero initial vector of parameters $\boldsymbol{\alpha} = [\alpha_1, \alpha_2 ,..., \alpha_J]^T$ one computes the linear combination:

$$\overline{\boldsymbol{R}} = \sum_{j=1}^{J}\alpha_j\ \boldsymbol{Q}_s^{\ T}\ \tilde{\boldsymbol{R}}_x(p_j)\boldsymbol{Q}_s = \sum_{j=1}^{J}\alpha_j\boldsymbol{R}_j \quad (15)$$

One performs the eigenvalues decomposition of $\overline{\boldsymbol{R}}$ and one checks if $\overline{\boldsymbol{R}}$ is positive definite. If $\overline{\boldsymbol{R}}$ isn't positive definite one chooses an eigenvector $\boldsymbol{v}$ corresponding to the smallest eigenvalue of $\overline{\boldsymbol{R}}$ and one updates $\boldsymbol{\alpha}$ by $\boldsymbol{\alpha}+\boldsymbol{\delta}$, where

$$\boldsymbol{\delta} = \frac{\left[\boldsymbol{v}^T\boldsymbol{R}_1\boldsymbol{v}\ \dots\ \boldsymbol{v}^T\boldsymbol{R}_J\boldsymbol{v}\right]^T}{\left\|\left[\boldsymbol{v}^T\boldsymbol{R}_1\boldsymbol{v}\ \dots\ \boldsymbol{v}^T\boldsymbol{R}_J\boldsymbol{v}\right]\right\|} \quad (16)$$

and with new vector $\boldsymbol{\alpha}$ one returns to compute the linear combination $\overline{\boldsymbol{R}}$. Otherwise, one performs the eigenvalues decomposition of symmetric positive definite matrix:

$$\overline{\boldsymbol{R}}_x(\boldsymbol{\alpha}) = \sum_{j=1}^{J} \alpha_j \tilde{\boldsymbol{R}}(p_j) \tag{17}$$

as follows:

$$\overline{\boldsymbol{R}}_x(\boldsymbol{\alpha}) = \boldsymbol{V}^T \boldsymbol{\Lambda}\, \boldsymbol{V} \tag{18}$$

where $\boldsymbol{\alpha}$ is the set of parameters α_i after the algorithm achieves convergence positive definiteness of the matrix $\overline{\boldsymbol{R}}$, NxM matrix $\boldsymbol{V} = [\boldsymbol{v}_1, \boldsymbol{v}_2, \ldots, \boldsymbol{v}_M]$ contains the eigenvectors corresponding to the largest M eigenvalues of $\overline{\boldsymbol{R}}$, and $\boldsymbol{\Lambda} = diag[\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_M]$ contains the eigenvalues arranged in decreasing order. The *Robust orthogonalization* transformation is realized by a linear transformation with matrix $\boldsymbol{W}$:

$$\boldsymbol{y}(k) = \boldsymbol{W}\,\boldsymbol{x}(k) \tag{19}$$

where the matrix $\boldsymbol{W}$ has the form:

$$\boldsymbol{W} = \boldsymbol{\Lambda}^{-0,5}\, \boldsymbol{V}^T \tag{20}$$

The covariance matrices of the observed vector can be rewritten as:

$$\boldsymbol{R}_x(p) = \boldsymbol{A}\, \boldsymbol{R}_s(p)\, \boldsymbol{A}^T \tag{21}$$

Because the source signals have unit variance and are assumed to be uncorrelated, the covariance matrix of the sources vector equals the unit matrix:

$$\boldsymbol{R}_s(0) = E[\boldsymbol{s}(k)\, \boldsymbol{s}^T(k)] = \boldsymbol{I} \tag{22}$$

Consequently, $\boldsymbol{R}_s(p)=E[\boldsymbol{s}(k)\, \boldsymbol{s}^T(k - p)]$ are non-zero distinct diagonal matrices, and it follows that:

$$\boldsymbol{R}_x(0) = \boldsymbol{A}\, \boldsymbol{A}^T \tag{23}$$

The components of the orthogonalized vector $\boldsymbol{y}(k)$ are mutually uncorrelated and they have unit variance. The orthogonalized covariance matrices are given by:

$$\boldsymbol{R}_y(0) = \frac{1}{K}\sum_{k=1}^{K} \boldsymbol{y}(k)\, \boldsymbol{y}^T(k) = \boldsymbol{W}\, \boldsymbol{R}_x(0)\, \boldsymbol{W}^T = \boldsymbol{I} \tag{24}$$

$$\boldsymbol{R}_y(p) = \frac{1}{K}\sum_{k=1}^{K} \boldsymbol{y}(k)\, \boldsymbol{y}^T(k-p) = \boldsymbol{W}\, \boldsymbol{R}_x(p)\, \boldsymbol{W}^T, p \neq 0 \tag{25}$$

From equations (24) and (25) it results:

$$\boldsymbol{R}_y(0) = \boldsymbol{W}\boldsymbol{A}\, \boldsymbol{A}^T\, \boldsymbol{W}^T = \boldsymbol{W}\boldsymbol{A}\, (\boldsymbol{W}\boldsymbol{A})^T = \boldsymbol{I} \tag{26}$$

Thus, it follows that $\boldsymbol{U} = \boldsymbol{W}\boldsymbol{A}$ is an N x N unitary matrix. Consequently, the determination of M x N mixing matrix $\boldsymbol{A}$ is reduced to that of a unitary N x N matrix $\boldsymbol{U}$. From equations (22) and (26) it results:

$$\boldsymbol{R}_y(p) = \boldsymbol{W}\boldsymbol{A}\, \boldsymbol{R}_s(p)\, \boldsymbol{A}^T\, \boldsymbol{W}^T = \boldsymbol{W}\boldsymbol{A}\, \boldsymbol{R}_s(p)\, (\boldsymbol{W}\boldsymbol{A})^T, p \neq 0 \tag{27}$$

Since $\boldsymbol{R}_s(p)$ is diagonal, any orthogonalized covariance matrix $\boldsymbol{R}_y(p)$ with $p \neq 0$ is diagonalized by the unitary transform $\boldsymbol{U}$.

A.Belouchrani pointed out in (Belouchrani A. et al., 1997) that the unitary matrix $\boldsymbol{U}$ is retrieved by jointly diagonalizing a set of delayed covariance matrices. This matrix jointly diagonalizes the set $M_{\boldsymbol{R}}=\{\boldsymbol{R}_y(p)|p=1,\ldots, P\}$ when the next criterion is minimized:

$$C(M_R, \boldsymbol{U}) = \sum_{p=1}^{P} off\left(\boldsymbol{U}^T\, \boldsymbol{R}_y(p)\, \boldsymbol{U}\right) \tag{28}$$

where *off* operator is defined as:

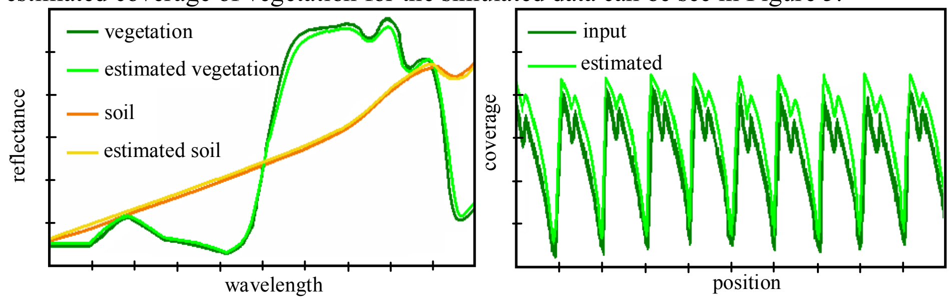
$$off\,(M) = \sum_{1 \leq i \neq j \leq N} |Mij|^2 \tag{29}$$

The unitary matrix $\boldsymbol{U}$ is computed as product of Givens rotations, see (Belouchrani A. et al., 1997). When the unitary matrix $\boldsymbol{U}$ is obtained, the mixing matrix is estimated by $\boldsymbol{A}=\boldsymbol{W}^{+}\cdot\boldsymbol{U}$ and the unmixing matrix is then given by $\boldsymbol{U}^T\, \boldsymbol{W}$, where + denotes the pseudo-inverse.

EXPERIMENTAL RESULTS

The presented algorithm has been applied first on the simulated data of vegetation coverage from the considerate forest plantation pattern and second on the data from the real forest plantation.

After the separation of the probability distribution the estimated spectra and the estimated coverage of vegetation for the simulated data can be see in Figure 5.

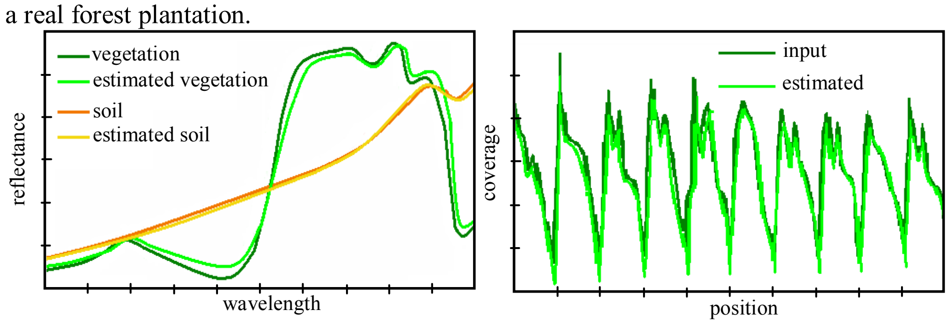


a) Spectra b) Coverage of vegetation

Figure 5. Results of simulated data.

The accuracy of the estimated results was evaluated objectively by mean square error.

Figure 6 displays the estimated spectra and the estimated coverage of vegetation for a real forest plantation.



a) Spectra b) Coverage of vegetation

Fig. 6. Results of real data.

CONCLUSIONS

For a qualitative and quantitative analysis of the forest remote sensing images this method use a Blind Source Separation technique. The probability distributions were separated by considering the periodical spatial distribution of vegetation as sources, namely the coverage along the forest plantation position. Therefore, the spectrum of vegetation was estimated as the mixture ratio of the source.

The separation process was realized by *Robust Second Order Blind Identification* algorithm. In orthogonalization stage, a *Robust orthogonalization* was performed which ensures that positive definite covariance matrix is not sensitive to the additive noise.

In the case of source signals with distinct spectra (different autocorrelation functions), one can use the delayed covariance matrices in the estimation process of the orthogonal mixing matrix. Other times it is rather difficult to determine a priori a single time lag p for which the diagonal matrix, used in the estimation process of the orthogonal mixing matrix, to have distinct diagonal elements. In these cases, one uses the Joint Approximative Diagonalization (JAD), that reduces the probability of un-identifiability of a mixing matrix caused by an unfortunate choice of time lag p.

The proposed method provides estimated spectra and coverage of vegetation with a good accuracy having the mean square error of 3.3% in the simulated case and 9.7% in the real data case, which confirm the feasibility of the separation process.

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