Category Decomposition Method Based on Matched Filter for Un-Mixing of Mixed Pixels Acquired with Spaceborne Based Hyperspectral Radiometers

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***Abstract*—Category decomposition method based on matched filter for un-mixing of mixed pixels: mixels which are acquired with spaceborne based hyperspectral radiometers is proposed. Through simulation studies with simulated mixed pixels which are created with spectral reflectance data derived from USGS spectral library as well as actual airborne based hyperspectral radiometer imagery data, it is found that the proposed method works well with acceptable decomposition accuracy.**

***Keywords*—category decomposition; hyperspectral radiometer; mixed pixel; un-mixing; matched filter;**

I. INTRODUCTION

Hyperspectrometer in the visible to near infrared wavelength regions are developed and used for general purposes of earth observation missions such as Agriculture, Mineralogy, Surveillance, Physics, Chemical Imaging, Environment, in particular, for mineral resources explorations and agricultural monitoring [1]-[15]. Hyperspectormeter allows estimate atmospheric continuants by using absorption characteristics of the atmospheric continuants because spectral bandwidth of the hyperspectrometer is quit narrow like an atmospheric sounders onboard earth observation satellites [16].

Remote sensing is the practice of deriving information about the earth land and water surfaces using images acquired from an overhead perspective, using electromagnetic radiation in one or more regions of the electromagnetic spectrum, reflected or emitted from the earth surface. In particular, hyperspectral sensor (for instance, T.Lillesand et al., 1994 [17]) that covers from visible to short wave infrared wavelength region has many continuation spectrum bands (G.Vane, et al., 1993 [18], J.B.Adams, et al., 1986 [19]). Not only one single ground cover target but also two or more targets (category) are contained in the instantaneous field of view of the sensor. It is generally called as mixed pixel (Mixel) (K.Arai, 1991 [20]).

Un-mixing is the technique of presuming the category kind that constitutes the mixel, and its mixing ratio (N.Keshava, et al., 2002 [21]). There are two models for the Mixel, a linear and a nonlinear model (S.Liangrocapart et al., 1998 [22], K. Arai et al., 1992 [23]). The spectrum feature of the pixel that consists of one category is called a pure pixel (also it is called an end-member). Un-mixing is performed based on the linear or the nonlinear models (C.C.Borel et al., 1994 [24]). It is as which a linear model disregards the interaction between end-members, and a nonlinear model considers the multiple reflection and scattering which depends on the geometric relations among the sun, a ground cover target, and a sensor (K.Arai et al., 2002 [25]). There are linear model based un-mixing methods that based on (1) a maximum likelihood method (J.J.Settle, 1996 [26], M.Matsumoto, et al., 1991 [27]), (2) a least square method with constraints (C.I.Chang, 2003 [28], K.Arai et al., 1995 [29]), (3) a spectrum feature matching (A.S.Mazer, 1988 [30]), (4) a partial space projective technique (C.Chang, et al., 1998 [31], K.Arai et al., 2002 [32]), (5) a rectangular partial space method (J.C.Harsanyi et al., 1994 [33]), etc. The least square method with a constraint presumes a mixing ratio vector based on an end-member's spectrum feature vector by the generalized inverse matrix or the least-squares method which makes convex combination conditions a constraint. The spectrum feature matching searches and selects two or more spectrum features out of a plenty of spectrum features in a spectral database. It is the spectral feature matching method in consideration of those mixing ratios, and the spectrum feature of the Mixel in concern.

Further studies are required for appropriate end-member determination, improvement of accuracy, reduction of processing time, etc. for un-mixing methods. This paper mainly focuses on improvement of un-mixing accuracy, estimation accuracy of mixing ratio. The methods based on a partial space projective technique (C.Chang, et al., 1998 [31], K.Arai et al., 2002 [34]), and a rectangular partial space method (J.C.Harsanyi et al., 1994 [33]) may make the spectrum feature of a desirable category conspicuous, they map and combine the spectrum feature of the Mixel with sub-space which is made to intersect perpendicularly with the other spectrum feature. It also can perform dimensionality reduction. Moreover, the un-mixing technique based on an orthogonal subspace method has comparatively good un-mixing accuracy, and is used abundantly. Furthermore, it is equivalent to the un-mixing based on a maximum likelihood method, and this is also equivalent to the method of least square. An independent component analysis method (ICA) decomposes given Mixel into a highly independent component in the spectrum feature space in alignment (L.Parra, et al., 2000 [35]). Namely, it is determined that a mixing ratio can express the spectrum feature of Mixel by taking into consideration an end-member's spectrum feature and its variation. The statistic model about a component is considered and presumption of a statistic model and the ratio of each component are presumed by unsupervised learning. Therefore, it is the method of using the independent component analysis with constraints. Moreover, since the orthogonal subspace method becomes ideally independent in the spectrum feature after projection, it is also equivalent to ICA. From the above reason, this paper shall examine the un-mixing based on the orthogonal subspace method. The subspace method with learning process is already proposed as the image classification technique (Oja Erkki, 1983 [36]). The basic idea for that is the following. If the axis of coordinates of the subspace in the orthogonal subspace method is rotated, then classification accuracy will be improved to find an appropriate angle for a high classification performance, and then the spectrum feature of a pixel is mapped and classified into the orthogonal subspace of this optimal axis-of-coordinates angle.

The following section describes the proposed category decomposition with matched filter method followed by some experiments. Then conclusion is described together with some discussions.

II. Proposed Method

A. Conventional Un-Mixing Method

Hyper-spectral data represented by vector Y can be expressed as follows:

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ . \\ . \\ y_n \end{bmatrix} = \begin{bmatrix} m_1 \\ m_2 \\ . \\ m_m \end{bmatrix} \begin{bmatrix} z_{11} & z_{12} & . & . & z_{1n} \\ z_{21} & . & . & . & z_{2n} \\ . & . & . & . & . \\ . & . & . & . & . \\ z_{m1} & . & . & . & z_{mn} \end{bmatrix} = mZ \quad (1)$$

where m denotes mixing ratio vector of each ground cover target no.1 to m, while Z denotes the spectral characteristics of the ground cover target such that if the inverse matrix of Z is existing then the mixing ratio vector can be estimated as follows,

$$m = YZ^{-1} \quad (2)$$

It is, however, not always true that the inverse matrix exists. In order to solve this problem, regularization techniques with constraints, a prior information, etc., have been proposed. One of those is the generalized inverse matrix, or so called "Moore-Penrose" inverse matrix that is derived from Singular Value Decomposition (SVD). If Y is expressed with SVD as follows:

$$X = u^t Yv \quad (3)$$

where u and v are orthogonal vectors, then the Moore-Penrose generalized inverse matrix Y^+ is expressed by the following equation:

$$Y^+ = v^t Yu \quad (4)$$

Therefore, if u and v can be calculated then the generalized inverse matrix can also be calculated. This method is referred to the conventional SVD based method hereafter.

However, the number of spectral bands, n is more than 200 for hyperspectral imaging sensors, so that a time-consuming matrix calculation is required. In order to overcome this situation, the subspace method (SSM) is introduced.

If an n-dimensional observation data Y is mapped into an n-dimensional feature space of X, in general, then the square of the norm of Y is mapped to that of X as follows:

$$\| p_i X \|^2 = X^t p_i p_i X = X^t p_i X \quad (5)$$

where p_i denotes the orthogonal mapping matrix so that $p_i X$ can be mapped from X to the subspace. Thus the mixing ratio of ground cover target, j, can be estimated with the following equation:

$$\sqrt{X^t p_i X} = \sum_{j=1}^{n} m_j \sqrt{X_j^t p_j X_j} \quad (6)$$

If the dominant dimensions are selected from the subspace, then SSM can also reduce the dimensionality of the feature space. It may be said that the first three dimensions would cover more than 90% of the whole information, following the subspace method of conversion of orthogonal mapping. This can reduce time-consuming computations for the matrix calculations. By using the probability density function of the mapped observation vector, un-mixing can be done without any time-consuming calculation. The subspace method is closely related to the well known PCA (Principal Component Analysis) analysis which allows convert feature space coordinate into the principal coordinate system using rotation of coordinate system. In this case the original feature space, X, is mapped into the subspace, u. On the other hand, the proposed subspace method adjust the rotation angle to concentrate the information content, the rotation angle is adjusted through an iterative learning process. The most appropriate rotation angle is determined by category by category. Generally, PCA determines an appropriate rotation angle in the sense of average means. On the other hand, the proposed method takes separability between all the combinations of categories

By using the definition of length which is expressed with the equation (5),

$$(p_1 X_1)^t p_1 X = (p_1 X_1)^t (m_1 p_1 X_i + ... + m_m p_1 X_m)$$
..
$$(p_m X_m)^t p_m X = (p_m X_m)^t (m_1 p_m X_1 + ... + m_m p_m X_m) \quad (7)$$

then,

$$\| p_1 X \| \cos\alpha^1 = m_1 \| p_1 X_1 \| \cos\alpha_{1,1}^1 + ... + m_m \| p_1 X_m \| \cos\alpha_{1,m}^1$$
.
$$\| p_m X \| \cos\alpha^m = m_m \| p_m X_1 \| \cos\alpha_{m,1}^m + ... + m_m \| p_m X_m \| \cos\alpha_{m,m}^m$$
(8)

where X_i denotes feature vector of category i while X denotes unknown vector which has to be estimated its mixing ratio. Feature vector X_i of category i can be mapped onto subspace $p_i X_i$. The angle between its coordinate, $p_i X_i$ and orthogonal transformation of $p_k X_k$ is $\alpha^i_{,i,k}$. Thus mixing ratio, m_i can be estimated.

B. Matched Filter

Hyper-spectral radiometer has more than one hundred spectral channels. Therefore, it requires, in general, a huge computer resources for category decomposition, or un-mixing which is composed with huge element size of matrix calculus. On the other hand, there is a matched filter which allows extract specific object which has a specific spectral feature from mixed spectral characteristics of object. In this section, background theory of matched filter is introduced. If the specific spectral feature is known a prior basis, then the matched filter can be used for category decomposition. In other word, if there is intensive ground cover material, mixing ratio of the material in the mixed pixel in concern can be estimated with the proposed matched filter.

In the time domain, output signal $y[n]$ is expressed as equation (1),

$$y[n] = \sum_{k=-\infty}^{\infty} h[n-k]x[k]. \tag{1}$$

where x and h denotes input signal and impulse response function of the system. Input signal consists of signal and noise as shown in equation (2).

$$x = s + v. \tag{2}$$

where v denotes noise and noise power is expressed as equation (3).

$$R_v = E\{vv^{\mathrm{H}}\} \tag{3}$$

where H denotes complex conjugate. Then output can be represented as equation (4)

$$y = \sum_{k=-\infty}^{\infty} h^*[k]x[k] = h^{\mathrm{H}}x = h^{\mathrm{H}}s + h^{\mathrm{H}}v = y_s + y_v. \tag{4}$$

The signal-to-noise ratio SNR is expressed as equation (5)

$$\mathrm{SNR} = \frac{|y_s|^2}{E\{|y_v|^2\}}. \tag{5}$$

Signal component can be expressed as equation (6).

$$|y_s|^2 = {y_s}^{\mathrm{H}} y_s = h^{\mathrm{H}} s s^{\mathrm{H}} h. \tag{6}$$

Nose component, on the other hand, is expressed with equation (7).

$$E\{|y_v|^2\} = E\{{y_v}^{\mathrm{H}} y_v\} = E\{h^{\mathrm{H}} v v^{\mathrm{H}} h\} = h^{\mathrm{H}} R_v h. \tag{7}$$

Thus signal-to-noise ratio becomes the following equation,

$$\mathrm{SNR} = \frac{h^{\mathrm{H}} s s^{\mathrm{H}} h}{h^{\mathrm{H}} R_v h}. \tag{8}$$

Assuming the following equation,

$$h^{\mathrm{H}} R_v h = 1 \tag{9}$$

Then cost function can be expressed with the following equation using Lagrange multiplier, λ,

$$\mathcal{L} = h^{\mathrm{H}} s s^{\mathrm{H}} h + \lambda(1 - h^{\mathrm{H}} R_v h) \tag{10}$$

From equation (10), the following equations are derived,

$$\nabla_{h^*}\mathcal{L} = s s^{\mathrm{H}} h - \lambda R_v h = 0 \tag{11}$$

$$(s s^{\mathrm{H}}) h = \lambda R_v h \tag{12}$$

This is well known as a generalized eigen value problem.

$$h^{\mathrm{H}}(s s^{\mathrm{H}}) h = \lambda h^{\mathrm{H}} R_v h. \tag{13}$$

Since ss^{H} is of unit rank, it has only one nonzero eigen value. Therefore, it can be shown that this eigen value equals

$$\lambda_{\max} = s^{\mathrm{H}} R_v^{-1} s, \tag{14}$$

which is yielding the following optimal matched filter

$$h = \frac{1}{\sqrt{s^{\mathrm{H}} R_v^{-1} s}} R_v^{-1} s. \tag{15}$$

C. Un-Mixing Method

The mixed pixel: Mixel in concern is assumed to be composed with several ground cover materials. Figure 1 shows mathematical model of the Mixel. Namely, the Mixel is composed with more than two spectral characteristics are combine together depending on their mixing ratios. Using spectral characteristic of ground cover material in concern, it is possible to extract same spectral characteristic from the combined spectral characteristics using matched filter.

Two types of noises, colored and white noise are added to the pure pixel of spectral characteristics.

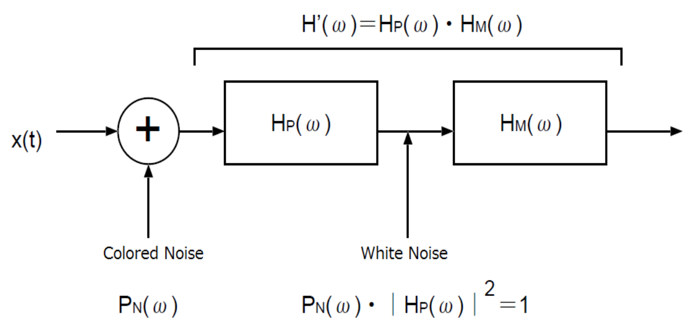
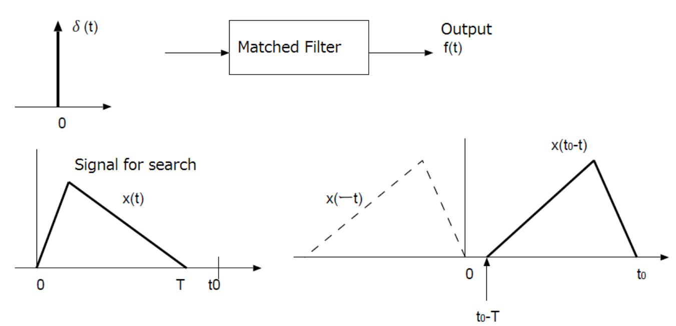
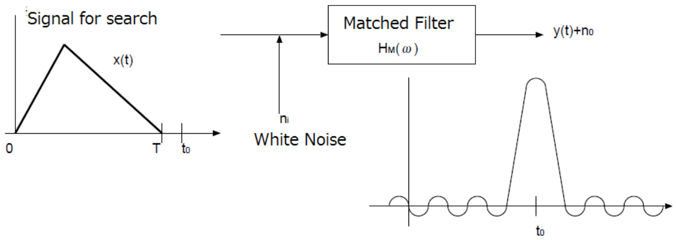


Fig. 1. Spectral characteristic of Mixel model

If the proposed matched filter is applied to the Mixel data with a assumed spectral feature of pure pixel in concern, then mixing ratio can be estimated as shown in Figure 2.



(a)Frequency domain



(b)Time domain

Fig. 2. Mixing ratio estimation from the Mixels by using the specific spectral feature of the assumed ground cover materials in concern

Matched filter can be applied in frequency and time domains. Using Fourier transformation, the proposed un-mixing method based on matched filter can be expressed in both time and frequency domains as shown in Figure 3.

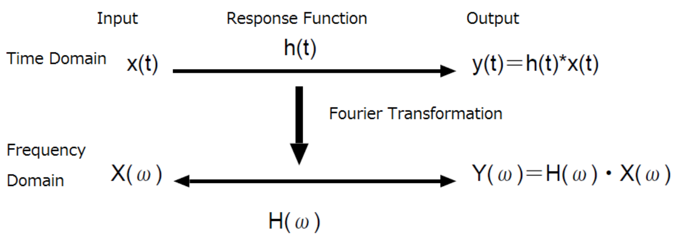
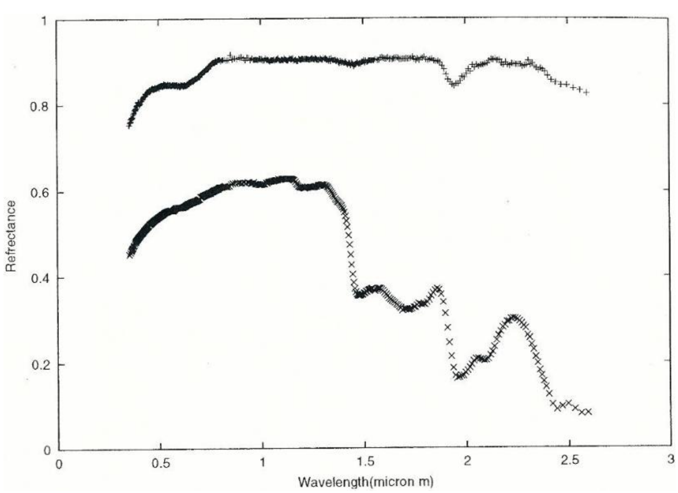


Fig. 3. Proposed un-mixing method based on matched filter which is expressed in both time and frequency domains

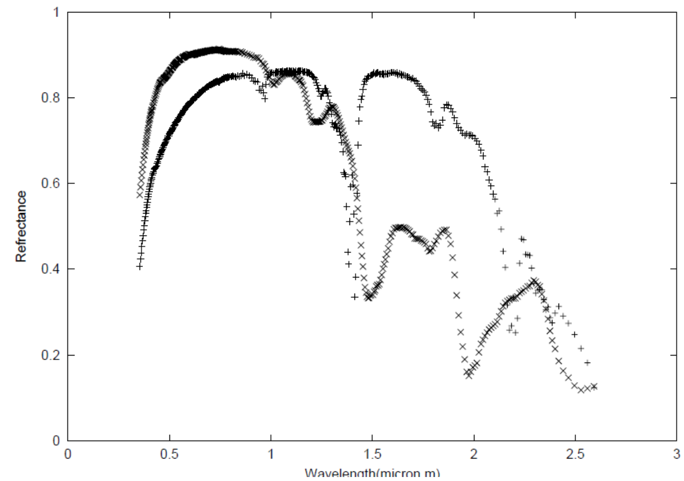
III. EXPERIMENTS AND SIMULATIONS

A. Simulation Method

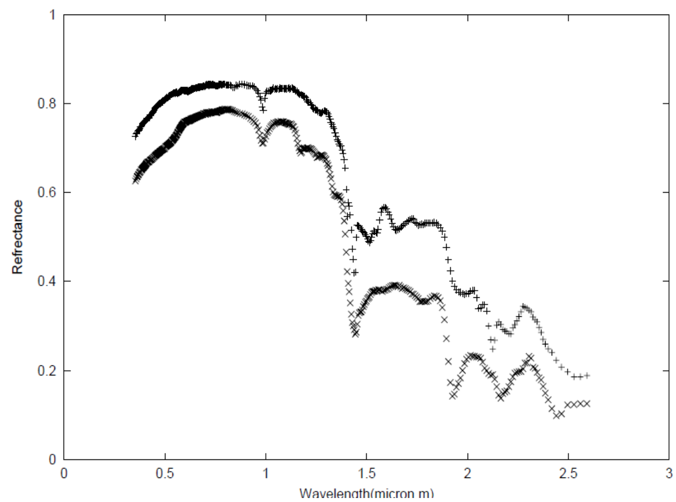
From the Unites State of America Geological Survey: USGS web site so called “Spectral Library”, spectral characteristics (surface reflectance) can be retrieved for huge number of ground cover materials. In the library, two ground cover materials which show a good correlation between both spectral characteristics are chosen. Also two ground cover materials which show a poor correlation between both are selected. Moreover, ground cover materials which show a middle level of correlation are used. These are shown in Figure 4. 437 spectral channels ranged from 500 nm to 2500 nm of wavelength region of spectral characteristics are used.



(a)Poor Correlation (R=0.0009)



(b)Middle Level of Correlation (R=0.5)



(a)Best Correlation (R=0.99)

Fig. 4. Examples of the selected two ground cover materials of spectral characteristics which show a good a middle level and a poor correlation between both spectral characteristics

Using these spectral characteristics, un-mixing by means of the proposed matched filter based un-mixing method is attempted with changing mixing ratio as well as additive noises.

Root Mean Square Error: RMSE between designated and estimated mixing ratios is evaluated. The RMSE is evaluated for both the conventional SVD based method and the proposed method.

B. Simulation Results

Evaluated RMSE for both the conventional and the proposed methods are shown in Figure 5 as function of cross correlation between spectral characteristics extracted from the USGS spectral library. In this case, Mixels are created with two ground cover materials.

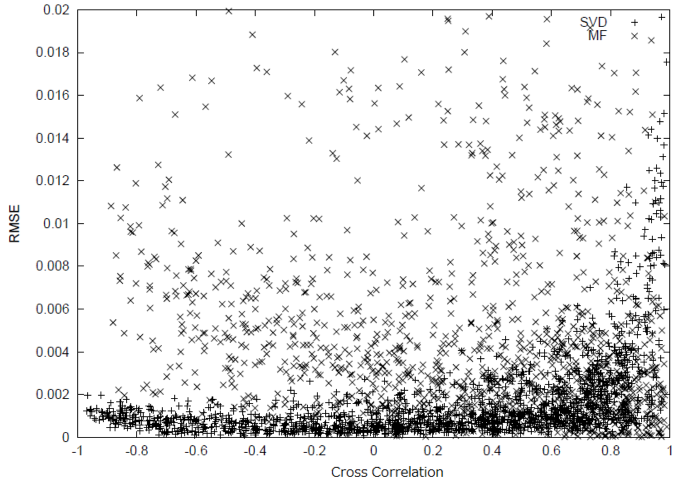


Fig. 5. Evaluated RMSE for both the conventional and the proposed methods as function of cross correlation between spectral characteristics extracted from the USGS spectral library

As shown in Figure 5, it is clear that RMSE for the proposed method is always smaller than that of the conventional method.

RMSE is also depending on the number of material of the Mixels used for simulation studies. Figure 6 shows RMSE as function of the number of ground cover materials of which the Mixels used are composed.

RMSE for the conventional un-mixing method varied greatly in comparison to that of the proposed method and is greater than that of the proposed method. It is concluded that there is a poor relation between RMSE and the number of ground cover materials of which the Mixels used for simulation. RMSE depends on the complexity of spectral characteristics of the ground cover materials and also depends on the correlation among the materials. RMSE is not function of the number of materials. Therefore, RMSE of the conventional method varied a lot comparing to the proposed method. The proposed method extracts the spectral characteristics from the mixed spectral characteristics so that RMSE is not varied too much.

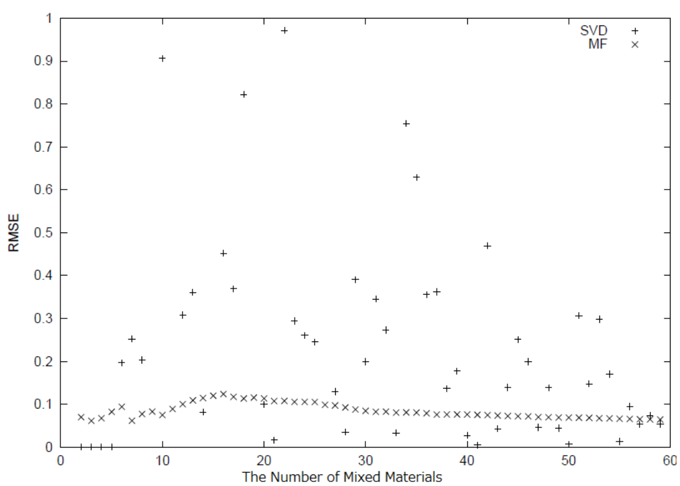


Fig. 6. Relation between the evaluated RMSE and the number of ground cover materials of mixels used for the simulation

Required computational time for un-mixing based on the proposed method, on the other hand, increases in accordance with the number of ground cover materials with which the Mixels used for simulation are composed as shown in Figure 7.

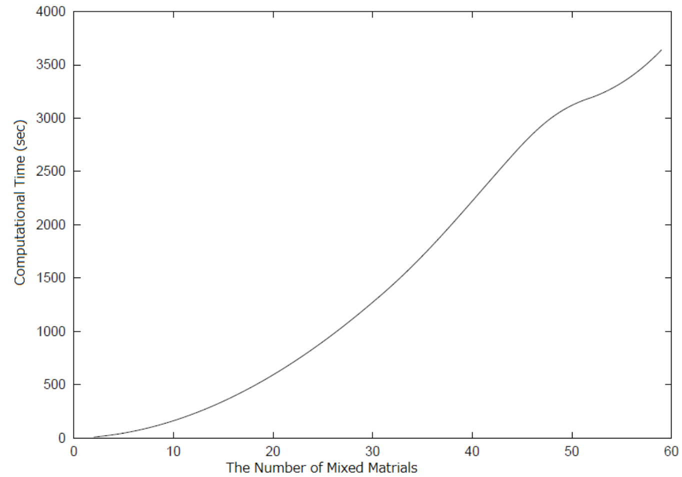


Fig. 7. Required computational time for un-mixing, on the other hand, increases in accordance with the number of ground cover materials with which the Mixels used for simulation are composed

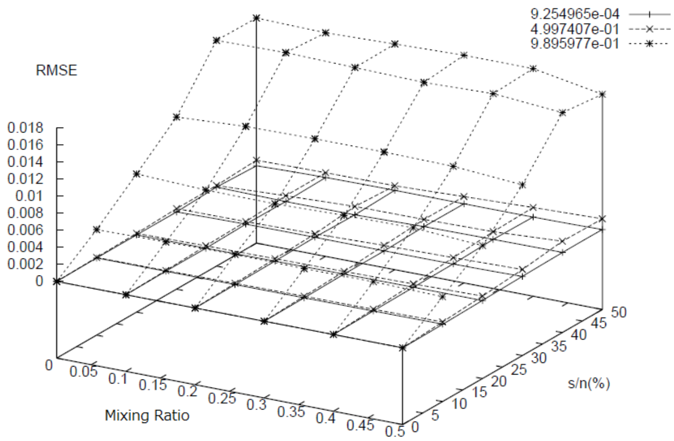
Figure 8 shows the evaluated RMSE with the parameters of mixing ratio, signal to noise ratio and cross correlation for both the conventional and the proposed un-mixing methods. Two materials are mixed together when the Mixels used for simulation is created. There are three levels of correlation coefficients between two materials. Those are 0.0009, 0.5, and 0.99.

C. Experimental Results with Actual Airborne Based Hyper Spectrometer of AVIRIS

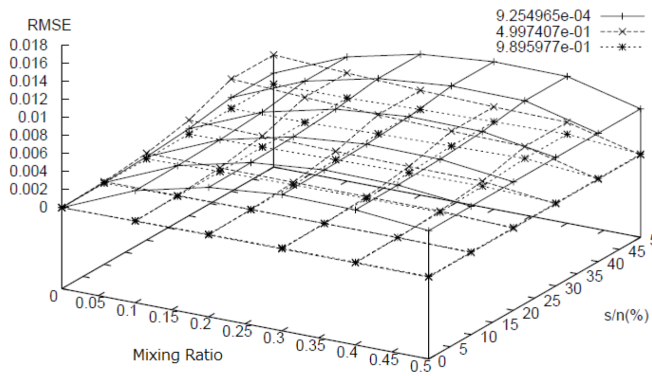
Actual hyper-spectral sensor data (AVIRIS) onboard aircraft is used for validation of the proposed method. Figure 9 shows the AVIRIS imagery data of Ivanpah playa in California, USA. The site is covered with silica Cray mostly.

From the image, silica Cray of pixel is extracted at the x=54, y=479, while asphalt pixel is also extracted from the pixel location at x=81, y=405, respectively. Meanwhile, four test pixels are extracted from the pixels in the Ivanpah playa. These pixels are situated on the Root # 15 of road so that the pixels are essentially covered with asphalt. Then the mixing ratio of silica Cray and Asphalt are estimated with the proposed Matched Filter: MF based method and the conventional Singular Value Decomposition: SVD based method. Estimated mixing ratios are shown in Table 1.

Although these test pixels seem to be covered with asphalt, mixing ratio of asphalt estimated with the conventional method is not so large in comparison to that with the proposed method. On the other hand, mixing ratio of silica Cray estimated with the conventional method is relatively large in comparison to that with the proposed method. From these facts, it is concluded that the proposed MF based un-mixing method is superior to the conventional SVD based method.



(a)SVD based method



(b)Proposed matched filter based method

Fig. 8. Evaluated RMSE with the parameters of mixing ratio, signal to noise ratio and cross correlation for both the conventional and the proposed un-mixing methods

TABLE I. ESTIMATED MIXING RATIO OF SILICA CRAY AND ASPHALT ARE ESTIMATED WITH THE PROPOSED MATCHED FILTER: MF BASED METHOD AND THE CONVENTIONAL SINGULAR VALUE DECOMPOSITION: SVD BASED METHOD

Pixel	Silica Cray		Asphalt	
Location	SVD	MF	SVD	MF
Data #1 (96,402)	0.32	0.21	0.54	0.76
Data #2 (108,402)	0.36	0.22	0.40	0.73
Data #3 (128,402)	0.33	0.21	0.51	0.75
Data #4 (295,405)	0.36	0.21	0.47	0.73

Fig. 9. AVIRIS imagery data of Ivanpah playa in California, USA.

IV. CONCLUSION

Category decomposition method based on matched filter for un-mixing of mixed pixels: Mixels which are acquired with spaceborne based hyper-spectral radiometers is proposed. Through simulation studies with simulated mixed pixels which are created with spectral reflectance data derived from USGS spectral library as well as actual airborne based hyper-spectral radiometer imagery data, it is found that the proposed method works well with acceptable decomposition accuracy

Through the experiment and simulation, it is found that the proposed Matched Filter based un-mixing method is superior to the conventional Singular Value Decomposition based un-mixing method for almost all cases. In particular, the estimated mixing ratio of asphalt which has a specific spectral feature derived from the proposed method shows better performance in comparison to that from the conventional method.

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REFERENCES

[1] Lushalan Liao, Peter Jarecke, "Radiometric Performance Characterization of the Hyperion Imaging Spectrometer Instrument", Proc. Optical Science and Technology Symposium, Earth Observing Systems V, SPIE 1435, (2000)

[2] Peter Jarecke, Karen Yokoyama, "Radiometric Calibration Transfer Chain from Primary Standards to the End-to-End Hyperion Sensor", Proc. Optical Science and Technology Symposium, Earth Observing Systems V, SPIE 1435, (2000).

[3] Schurmer, J.H., Air Force Research Laboratories Technology Horizons, (2003)

[4] Ellis, J., Searching for oil seeps and oil-impacted soil with hyperspectral imagery, Earth Observation Magazine (2001).

[5] Smith, R.B. Introduction to hyperspectral imaging with TMIPS, MicroImages Tutorial Web site, (Accessed on July 14, 2012),

[6] Lacar, F.M., et al., Use of hyperspectral imagery for mapping grape varieties in the Barossa Valley, South Australia , Geoscience and remote sensing symposium (IGARSS'01) - IEEE 2001 International, vol.6 2875-2877p. doi:10.1109/IGARSS.2001.978191, (2001)

[7] Tilling, A.K., et al., Remote sensing to detect nitrogen and water stress in wheat, The Australian Society of Agronomy, (2006)

[8] Fernández Pierna, J.A., et al., 'Combination of Support Vector Machines (SVM) and Near Infrared (NIR) imaging spectroscopy for the detection of meat and bone meat (MBM) in compound feeds' Journal of Chemometrics 18 341-349 (2004)

[9] Holma, H., Thermische Hyperspektralbildgebung im langwelligen Infrarot, Photonik, (2011),

[10] Werff H. Knowledge based remote sensing of complex objects: recognition of spectral and spatial patterns resulting from natural hydrocarbon seepages, Utrecht University, ITC Dissertation 131, 138p. ISBN 90-6164-238-8 (2006),

[11] Noomen, M.F. Hyperspectral reflectance of vegetation affected by underground hydrocarbon gas seepage, Enschede, ITC 151p. ISBN 978-90-8504-671-4 (2007),.

[12] M. Chamberland, V. Farley, A. Vallières, L. Belhumeur, A. Villemaire, J. Giroux et J. Legault, "High-Performance Field-Portable Imaging Radiometric Spectrometer Technology For Hyperspectral imaging Applications," Proc. SPIE 5994, 59940N, September 2005.

[13] Farley, V., Chamberland, M., Lagueux, P., et al., "Chemical agent detection and identification with a hyperspectral imaging infrared sensor," Proceedings of SPIE Vol. 6661, 66610L (2007).

[14] Kevin C. Gross, Kenneth C Bradley and Glen P. Perram, "Remote indentification and quantification of industrial smokestack effluents via imaging Fourier-transform spectroscopy," Environmental Sci Tech, 44, 9390-9397, 2010.

[15] Tremblay, P., Savary, S., Rolland, M., et al., "Standoff gas identification and quantification from turbulent stack plumes with an imaging Fourier-transform spectrometer," Proceedings of SPIE Vol. 7673, 76730H (2010).

[16] K.Arai, K. Yamaguchi,Atmospheric correction through estimation of atmospheric optical properties with hyperspectrometer data, Proceedings of the 46th General Assembly of Japan Society of Remote Sensing, 22, 2009.

[17] Lillesand T. and R.Kiefer, Remote Sensing and Image Interpretation, 3rd ed., John Willey & Sons, Inc., 1994.

[18] Vane G., R.Green, T.Chrien, H.Enmark, E.Hansen, and W.Porter, The airborne visible/infrared imaging spectrometer (AVIRIS), Remote Sensing of the Environment, 44, 127-143, 1993.

[19] Adams J.B., and M.O.Smith, A new analysis of rock and soil types at the viking lander 1 site, J. of Geophysical Research, 91, B8, 8098-8112, 1986.

[20] Arai K., Information extraction of inner pixel contents derived from satellite remote sensing imagery data, J. of Japanese Society for Photogrammetry and Remote Sensing, 30, 4, 30-34, 1991.

[21] Keshava N. and J.Mustard, Spectral unmixing, IEEE Signal Processing Mag., 19, 1, 44-57, 2002.

[22] Liangrocapart S. and M.Petrou, Mixed pixels classification, Proc. of the SPIE Conference on Image and Signal Processing for Remote Sensing IV, 3500, 72-83, 1998.

[23] Arai K. and Y.Terayama, Label Relaxation Using a Linear Mixture Model, International Journal of Remote Sensing, 13, 16, 3217-3227, 1992.

[24] Borel C.C. and S.A.Gerstl, Nonlinear spectral mixing models for vegetation and soil surface, Remote Sensing of the Environment, 47, 2, 403-416, 1994.

[25] Arai K. and Reiko Inagaki, Nonlinear mixel model taking into account multiple reflections between ground cover targets and the atmosphere, Proceedings of the 33rd General Conference of Remote Sensing Society of Japan, 2002.

[26] Settle J.J., On the relationship between spectral unmixing and subspace projection, IEEE Trans., Geosci. Remote Sensing, 34, 1045-1046, 1996.

[27] Matsumoto M., H. Fujiku, K.Tsuchiya and K.Arai, Unmixing by means of maximum likelihood classification, J. of Japanese Society for Photogrammetry and Remote Sensing, 30, 2, 25-34, 1991.

[28] Chang C.I., Hyperspectral Imaging: Techniques for spectral detection and classification, New York: Kluwer Academic, 2003.

[29] Arai K., Y.Terayama, Y.Ueda, and M.Moriyama, Adaptive least square method for estimation of partial cloud coverage within a pixel, International J. of Remote Sensing, 16. 12, 2197-2206, 1995.

[30] Mazer A.S., M.Martin, et. al., Image processing software for imaging spectrometry data analysis, Remote Sensing of the Environment, 24, 1, 201-210, 1988.

[31] Chang C., X.Zhao, M.L.G.Althouse, and J.J.Pan, Least squares subspace projection approach to mixed pixel classification for hyperspectral images, IEEE Trans. Geosci. Remote Sensing, 36, 3, 898-912, 1998.

[32] Arai K., H.Chen, Unmixing based on subspace method with learning process, Proceedings of the 33rd General Conference of Remote Sensing Society of Japan, 2002.

[33] Harsanyi J.C. and C.I.Chang, Hyperspectral image classification and dimensionality reduction: An orthogonal subspace projection approach, IEEE Trans. Geosci. Remote Sensing, 32, 4, 779-785, 1994.

[34] Arai K. and K.Seto, Data hiding method based on a linear transformation to the subspace, Journal of the Visualization Society of Japan, 25, 5, Suppl.No.1, 55-58, 2005.

[35] Parra L., K.R.Muller, C.Specce, A.Ziehe, and S.Sajda, Unmixing hyperspectral data, Advances in Neural Information Processing Systems, 12, 942-948, 2000.

[36] Erkki O., Subspace methods of pattern recognition, Research Studies Press Ltd., 1983.

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