EVALUATION ON EQUATION MODELS BASED ON NONNEGATIVE MATRIX FACTORIZATION FOR HYPERSPECTRAL IMAGE FUSION WITH A MULTISPECTRAL IMAGE

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ABSTRACT

The precise spectral information and continuous spectrum of hyperspectral images allow to identify materials of the earth by their reflectance for detailed analysis of remote sensing data. Due to the physical limitation of sensor systems, hyperspectral images usually have lower spatial resolution than panchromatic and multispectral images. Therefore, image fusion techniques of hyperspectral images with additional images having higher spatial resolution are studied to enhance the performance of hyperspectral image analysis. A number of hyperspectral fusion algorithms adopted spectral unmixing technique, which estimates the materials, called endmembers, in a hyperspectral image and the fraction of each endmembers, within a pixel. Recently, nonnegative matrix factorization (NMF) has been studied in various fields, such as text mining and spectral unmixing techniques, for its low complexity and ability to easily include physical constraints based on the non-negativity property, and many studies introduced image fusion, classification, and target detection techniques using hyperspectral images based on NMF. In this study, we constructed and evaluated different combinations of equations for the constrained version of NMF to optimize the spectral characteristics of hyperspectral images and the spatial information of multispectral images in the fusion results. We rearranged equations in different ways of iteration process based on coupled NMF to set the CNMF equation models and applied them to hyperspectral and multispectral images datasets. The fusion results of the suggested equation model could represent the spectral characteristics of hyperspectral images on the fusion results although hyperspectral and multispectral images were collected from different sensors.

INTRODUCTION

Hyperspectral sensors offer fine spectral resolutions less than 10 nm typically in visible to shortwave infrared and thermal wavelength region. This continuous spectrum allows to identify materials of the earth by their reflectance for detailed analysis of remote sensing data. Due to the physical limitation of sensor systems, spatial resolution of a remote sensing data becomes lower as its spectral resolution becomes higher, so hyperspectral images usually have lower spatial resolution than panchromatic and multispectral images. Therefore, image fusion techniques of hyperspectral images with additional images having higher spatial resolution are studied to enhance the performance of hyperspectral image analysis. A number of hyperspectral fusion algorithms adopted spectral unmixing technique, which estimates the materials, called endmembers, in a hyperspectral image and the fraction of each endmembers, within a pixel. Recently, nonnegative matrix factorization (NMF) has been studied in various fields, such as text mining and spectral unmixing techniques, for its low complexity and ability to easily include physical constraints based on the non-negativity property, and many studies introduced image fusion, classification, and target detection techniques using hyperspectral images based on NMF. Recently introduced unmixing-based fusion algorithm for hyperspectral and multispectral images is coupled NMF(CNMF), which iteratively unmixes them to improve the quality of the endmember spectral matrix and the abundance maps matrix (Yokoya et al, 2012). Bendoumi et al. (2012) attempted to decrease the error from the linear unmixing calculation of CNMF by reducing the iteration number. Kim et al. (2015) introduced block-based NMF, which considers the spectral difference between bands, to improve spectral information of fusion results for hyperspectral image.

In this study, we constructed and evaluated different combinations of equations for the constrained version of NMF to optimize the fusion results of hyperspectral images and the spatial information of multispectral images collected from different sensors, and compared them with existing methods. The fusion results of the suggested equation model could represent the spectral characteristics of hyperspectral images than an existing method although hyperspectral and multispectral images were collected from different sensors.

METHODS

Spectral unmixing is the procedure by which the measured spectrum of a mixed pixel is decomposed into a collection of constituent spectra, or endmembers, and a set of corresponding fractions, or abundances, that indicate the proportion of each endmember present in the pixel (Keshava, 2003). For the spectral unmixing, the linear model is generally recognized as an acceptable model for many real-world scenarios. Let HI_{ki} denotes the matrix containing digital numbers of a hyperspectral image at spectral band k and pixel i, and it can be represented as $HI_{ki} = [HI_{1i}, HI_{2i}, HI_{ki}, \cdots, HI_{bni}]$, where bn is the total band number of HI. The linear spectral unmixing model is defined by

$$HS_i = \sum_{e=1}^{en} EM_e \times ABUN_{ei} + v_i \qquad (1)$$

where each EM_e is an endmember spectrum vector, and en is the total number of endmembers. The EM has the spectral information of the specific material e in entire bands, and $ABUN_{ei}$ denotes the ratio of material EM at pixel i. The abundance vector at pixel i is described by$ABUN_{ei} = [ABUN_{1i}, ABUN_{2i}, ABUN_{ei}, \cdots ABUN_{eni}]$, and v_i is noise. The hyperspectral image, HI, can be also defined by an endmember matrix and an abundance map as following.

$$HI = EM \times ABUN + v \qquad (2)$$

Using the spectral unmixing approach, an endmember set and an abundance map can be updated using NMF and multiplicative update rules (Berry et al., 2007). It can be defined by the following equations:

$$EM \leftarrow EM.* (IMG \cdot F^T)./(EM \cdot ABUN \cdot ABUN^T) \qquad (3)$$

$$ABUN \leftarrow ABUN.* (EM^T \cdot IMG)./(EM^T \cdot EM \cdot ABUN) \qquad (4)$$

where IMG is an image data, such as HI and MI, a multispectral image with higher spatial resolution, $ABUN^T$ and EM^T denote the transposition of matrices $ABUN$ and EM, respectively, and .* and ./ represent elementwise matrix multiplication and division, respectively (Berry et al., 2007; Liu et al., 2011).

CNMF introduced by Yokoya et al. (2012) adopted the sensor model to iteratively process the NMF with two data sets. The sensor model presents the relationship of a HI, MI, and a fused image with high spectral resolution and high spatial resolution, FI. The sensor model relationship can be determined as following.

$$MI = (FI \times P) + E_s \quad (5)$$

$$HI = (R \times FI) + E_r \quad (6)$$

P is the spatial spread transform matrix and represents the transform of the point spread function from HI to MI. R is the spectral response transform matrix and represents the transform of the spectral response function from the MI to the HI. E_s and E_r are the residuals (Yokoya et al., 2012). Then, an image with low spatial resolution can be spatially enhanced using estimated the EM from HI and the $ABUN$ from MI using the sensor model.

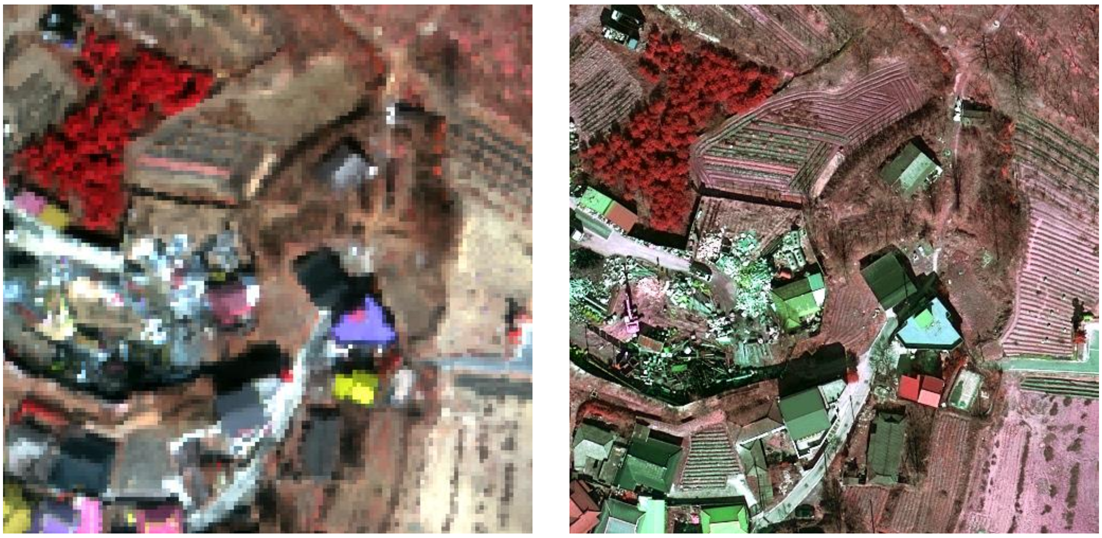
However, the sensor model of equations (5) and (6) is based on the assumption of image data collected from same sensor system with same physical and atmospheric conditions. In this study, we constructed and evaluated different combinations of equations for the constrained version of NMF to optimize the fusion results of hyperspectral images and the spatial information of multispectral images collected from different sensors, and compared them with existing methods. We rearranged equations in different ways in iteration process based on CNMF. The original CNMF converted $\mathrm{E}M$ of HI to $\mathrm{E}M$ of MI using equation (6), but it was not valid if the images were collected from different sensors for different atmospheric and radiometric conditions. So, we suggested to use $ABUN$ instead of $\mathrm{E}M$ for estimating $ABUN$ from MI through NMF iteration, and it will reduce the spectral distortion caused from estimating $\mathrm{E}M$ of MI from $\mathrm{E}M$ of HI.

We performed NMF iteration 1 and 2. The NMF iteration 1 estimated $ABUN$ of MI from $ABUN$ of HI, and optimize $ABUN$ of MI using equation (4). The NMF iteration 2 estimated $ABUN$ of MI from $ABUN$ of HI as the NFM iteration 1 did and process equation (3) after that to optimize $\mathrm{E}M$ of MI based on estimate $ABUN$ of MI previously. The results of the NMF iteration 1 and 2 were compared with CNMF result (Yokoya et al., 2012).

The results in this study were evaluated by comparing qualitative measurements for quality analysis, such as root mean square error (RMSE), cross correlation (CC), spectral angle mapper (SAM), Spectral Angle Mapper (SAM), *Erreur Relative Globale Adimensionnelle de Syntheses* (ERGAS), and Universal Image Quality Index (UIQI).

STUDY DATA AND SITE

In this study, we used hyperspectral image and multispectral image collected from Compact Airborne Spectrographic Imager (CASI) and Digital Mapping Camera System (DMC) sensors, respectively. The CASI developed by ITRES Research Ltd. of Canada is a visible and near infrared (VNIR) pushbroom imaging spectrometer with spectrum from 380 to 1050 nm. It provides spectral programmability to select the number of spectral bands and band widths for the user's specifications and requirements. Its ground sampling distance (GSD) range is from 0.25 m to 1.5 m, the highest spectral resolution is less than 3.5 nm at full width at half maximum (FWHM) (ITRES, 2011). The CASI image was collected over the Sejong-bo area in Sejong-Ri Yeongi-Myun Sejong-Si, Korea on 2 May 2014. Radiometric calibration, navigation data synchronization, geometric correction, and optional environmental calibration were applied to collected stripes of CASI images to obtain orthocorrected images. The Digital Mapping Camera (DMC) is the well-known digital aerial camera system of Z/I Imaging, an Intergraph. The DMC camera consists of eight synchronously operating CCD matrix based camera modules. Four panchromatic images from these cameras are used for creating a single high resolution image. Also, four parallel cameras can generate multi-spectral images (Madaini et al. 2004). DMC data provides four original spectral bands: band B1 (400 to 580 nm), band B2 (500 to 650 nm), band B3 (590 to 675 nm) and band B4 (675 to 850 nm) with panchromatic band. In this study, we used multispectral image with four bands and 8 bit images. DMC image was also collected in the Sejong-bo area in Sejong-Ri Yeongi-Myun Sejong-Si, Korea on same date of CASI image acquired. We selected a site with forest, crop fields, and urban structures, and the input data are presented on Figure 2. The specifications of CASI and DMC data are presented on Table 1.



(a) (b)

Figure 2: Input data for this study (a) CASI displayed in 801.1 nm, 643.3 nm, and 557.2 nm and (b) DMC images displayed in NIR, red, and green spectral range as RGB channel

Table 1: Specification of CASI and DMC

	CASI	DMC
Band #	48	4
Wavelength Range (nm)	350-1060 (wavelength sampling interval: 14.4nm)	400-580
		500-650
		590-675
		675-850
GSD (m)	1	0.25

Image registration and empirical calibration between the CASI and DMC images were performed to decrease the geometric and radiometric differences between two images. In the addition to that, histogram matching was performed on calibrated DMC image to eliminate negative DN values from the data, which caused error on NMF processing.

RESULTS

Figures 3 and 4 present the results of CNMF, NMF iteration 1, and NMF iteration 2, and input data. The CNMF results displayed high quality of spatial information of the study sites, but it have spectral distortions on some urban structures and roads. Both the NMF iteration 1 and 2 had slightly lower spatial quality than CNMF result, but its spectral information was close to input CASI images.

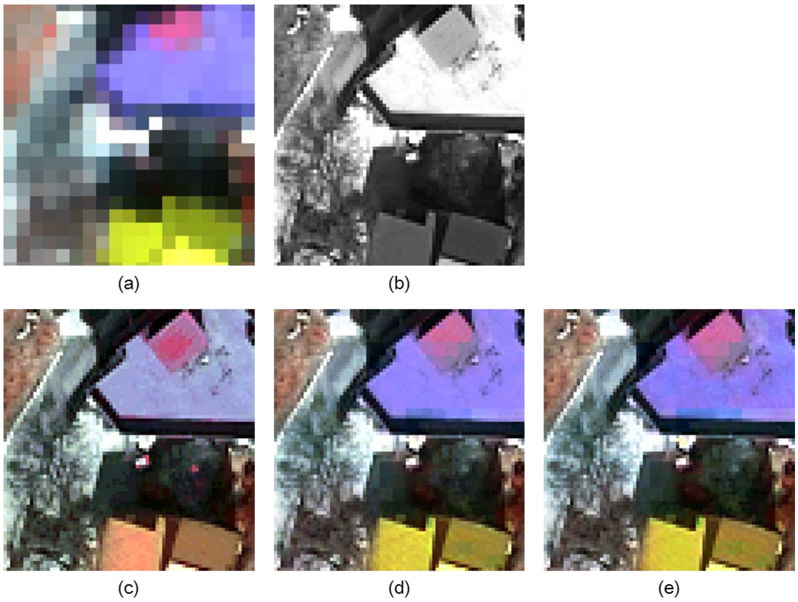


Figure 3: Comparison of input data and results displayed in 801.1 nm, 643.3 nm, and 557.2 (a) input CASI, (b) input DMC in green band, (c) CNMF result, (d) NMF iteration 1, (e) NMF iteration 2

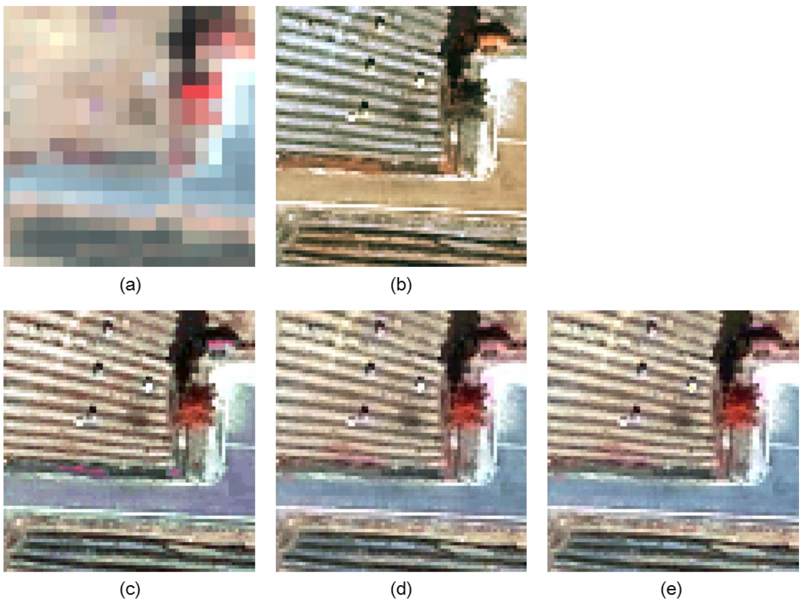


Figure 4: Comparison of input data and results displayed in 801.1 nm, 643.3 nm, and 557.2 (a) input CASI, (b) input DMC in RGB bands, (c) CNMF result, (d) NMF iteration 1, (e) NMF iteration 2

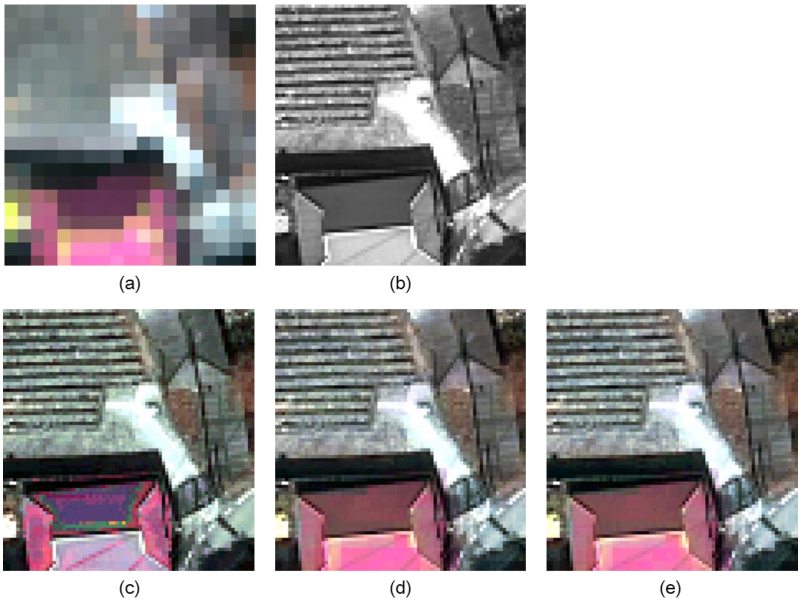


Figure 5: Comparison of input data and results displayed in 801.1 nm, 643.3 nm, and 557.2 (a) input CASI, (b) input DMC in green band, (c) CNMF result, (d) NMF iteration 1, (e) NMF iteration 2

The similarity index of CNMF also demonstrated its lower quality of spectral information than other methods. The spectral information of the NMF iteration 1 were slightly closer to CASI data, which was used as reference for similarity index calculations, than the NMF iteration 2, but there similarity index indicated their performance were close.

Table 2: Similarity Index of CNMF, modified CNMF 1, and modified CNMF 2

methods / index	CNMF	NMF iteration 1	NMF iteration 2
RMSE	370.909	**329.183**	331.044
CC	0.645	**0.729**	0.726
SAM	0.426	**0.349**	0.353
ERGAS	44.822	**11.411**	11.701
UIQI	0.633	**0.716**	0.714

CONCLUSIONS

In this study, we evaluated different combinations of equations for the constrained version of NMF to increase the spectral quality of fusion results using multi-sensor images. The result presented that using abundance maps instead of endmember set was better to estimate abundance maps from multispectral image to enhance the spatial information of hyperspectral image, which were collected from different spectral sensors. In future study, we will study on improving the conversion of abundance maps between multi-sensor images to increase the spatial quality of the NMF iteration 1 and 2.

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