Evaluating Apparatus for the ICA-Aided Mixel Analysis of Periodical Hyperspectral Images

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Abstract: In the images obtained from high altitude, several materials are mixed in one pixel and observed as a mixel. It makes difficult to separate the value of pure materials from obtained data. As mixel analysis, various techniques using Independent Component Analysis (ICA) and wavelet analysis, etc, were proposed.

In this study, we applied to the ICA technique to real data collected by hyperspectral line sensor. Real data came under the influence of several effects regarded as basin on the convolution. We show that combining the ICA method with deconvolution improve it's estimation ability.

Keywords: ICA, Deconvolution, Hyperspectral Line Sensor.

1. Introduction

In recent years, with the lunch of the commercial high resolution satellites, it is expected to utilize the resultant images in various fields such as agriculture, environment, disaster prevention and so on. However, in satellites and aircraft images, obtained from high altitude, several materials are mixed over to be observed as a "mixel", making it difficult to separate the value of pure materials. As mixel analysis, various techniques using ICA or wavelet, etc were proposed. Kosaka et al. proposed a technique to recognize the variety and the growth stage of crops simultaneously, by applying ICA to periodical mixed spectrum observed in agricultural land [1].

We tried to apply this ICA technique to real observed data. Real data came influence of several effects, like atmospheric scattering, adjacent effect and so on. Therefore, it is not so easy to estimate independent component from real observed data. We regarded these effects as basin on the convolution. Therefore, we carried out the deconvolution before applying the ICA method.

2. Method

In this section, we described about the method used for estimating the independent component from mixed hyperspectral data.

1) Deconvolution

Deconvolution is commonly used for image restoration. There are many algorithms for deconvolution e.g. Richardson-Lucy algorithm, using regularized filter, wiener filter, blind deconvolution, etc. [2,3,4]. In this study we used deconvolution in accordance with Richardson-Lucy algorithm and regularized filter.

2) Independent Component Analysis

ICA is one of the solution methods of the blind source separation problem, and is the technique to estimate original source **s** and mixing ratio **A** simultaneously from the observed signal **z**. With the definition of mixed signal $\mathbf{z} = (z_1, \dots, z_k)^T$, and the mixing matrix **A**, consisting of k rows by 1 columns with element a_{ij}, the original signal $\mathbf{s} = (s_1, \dots, s_l)^T$ satisfies,

$$\mathbf{z} = \mathbf{A} \cdot \mathbf{s} + \mathbf{n} + \mathbf{z_0}, \quad \sum_{j=1}^{l} a_{ij} = 1, \tag{1}$$

where **n** is the additive noise. In order to apply the ICA technique, following assumptions have to be satisfied, (A) the mixed signal is a linear sum of original signals, (B) the probability density distribution of original signals are non-Gaussian, (C) the original signals are statistically independent each other. We used the package of FastICA in MATLAB [5].

3. Experiment

First, we show the specific of the sensor used in this study, and then we illustrated the experiment using this sensor.

1) Equipment

In this study, we used a imaging spectrograph, ImSpector V10, made by Specim Co. to collect the hyperspectral data. The specification of ImSpector V10 is shown in Table 1. More detailed information about this system is described in [6].

Table 1 Specification of hyperspectral sensor.

Spectral range	400 - 1000 nm ±5%
Band number	121 band
Spectral resolution half-power bandwidth geometrical resolution	 3 nm 0.8 nm / pixel
Frame rate	30 frames / sec
Dynamic range	10 bits

2) Experiment using Airborne Data

In this subsection, we used real data acquired using the sensor mounted on an aircraft. The observation is conducted about at noon in July 16, 2003. A small part of observed data is shown in Fig. 1, and used region is shown in the yellow rectangle. Then, we show the field image of this region in the Fig. 2.

The observation parameters were flight altitude of 800 m and 260 km/h. The spatial resolution was about 71 cm/pixel, and Interval between rice plants was about 34 cm.

Since the object region is narrow, it is not possible that the data of the sufficient quantity is acquired by continuing. Therefore, we used 30 points per line and connected the data of 7 lines. We show the observed data at 650 nm in Fig. 3. Then, we applied ICA for observed data after deconvolution. Figs. 4 and 5 shows coverage pattern calculated according to aperture ratio and estimated independent components. However, The independent component could not be well estimated, since the discontinuity exists for the periodicity in connecting points illustrated with dotted line in Figs. 3 and 5.

Fig. 1. True color image and target region

Fig. 2. Field photo of the target region

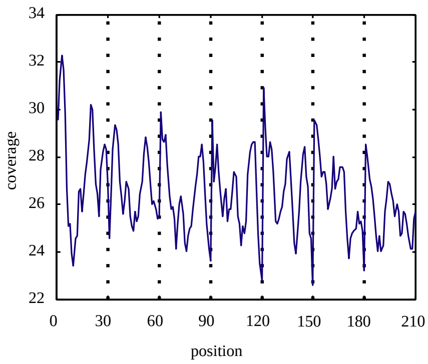

Fig. 3 Observed data

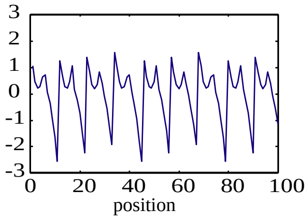

Fig. 4 Calculated pattern

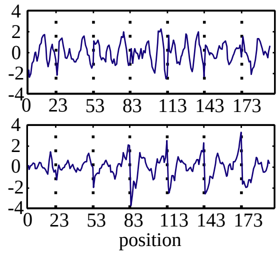

Fig.5 Estimated pattern

3) Experiment in the laboratory

First, we generated a stripe pattern with constant periodicity and printed it on a sheet of white paper. Generated pattern is shown in Fig. 6. Wv and Ws is the width of each region, and Wp is diameter of Instantaneous Field of View (IFOV) of each pixel. Then, we scanned it by the monitoring system in the direction of perpendicular to the stripe. Figs. 7 and 8 shows observed and preprocessed data. We applied the ICA technique with and without deconvolution to the preprocessed data. The estimated signals and histograms by each method are shown in Figs. 9 and 10.

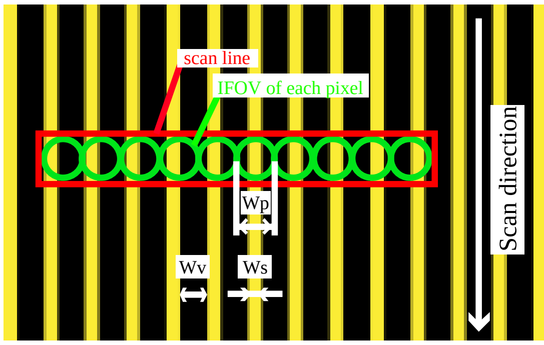

Fig. 6 Generated periodical pattern

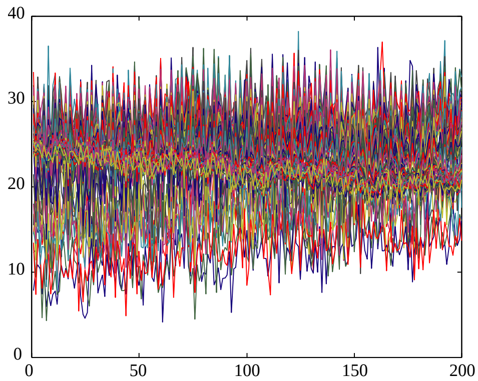

Fig. 7 Observed data

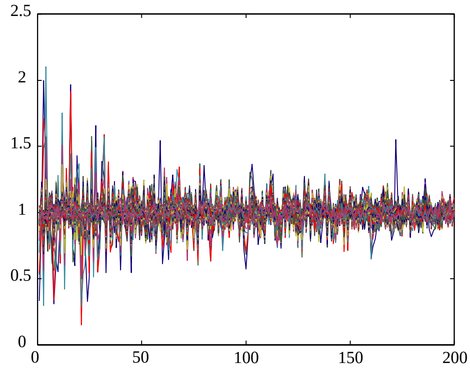

Fig. 8. Preprocessed data

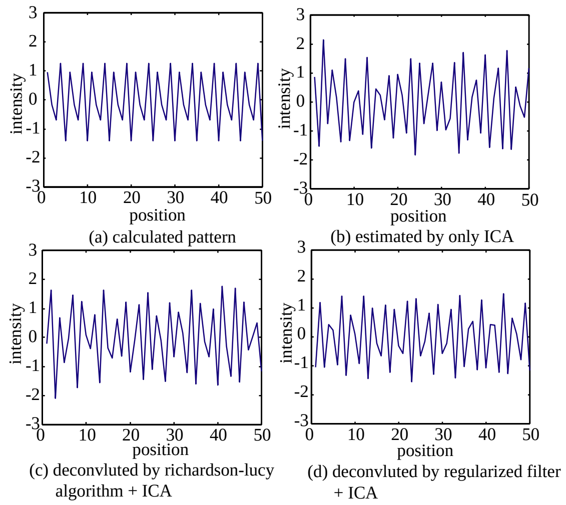

Fig. 9 Calculated pattern and estimated pattern

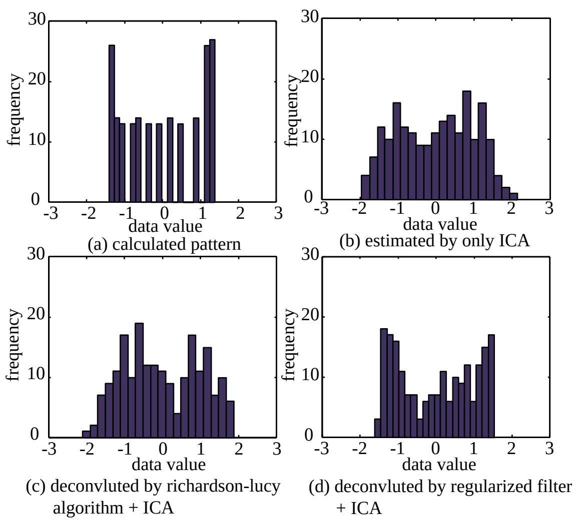

Fig. 10 Histograms of signals in Fig. 7

Fig. 8 shows that the result based on ICA-aided deconvolution method are better estimated than that based only on ICA. Fig. 9 shows same trend, but it also shows that deconvolution based on regularized filter and ICA method produces better result than other method.

4. Conclusion

As a result of the experiment, some problems in handling the airborne data were revealed. First, if the observation region is narrow, it is difficult to take sufficient data from one line. Therefore, some preprocessing is necessary in the connecting point of the data of the different line where the periodical pattern is discontinuity.

In the experiment in the laboratory, the possibility in which estimation performance of the periodical pattern was improved by using ICA jointly with the deconvolution was confirmed.

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