HYPERSPECTRAL IMAGE CLASSIFICATION BASED ON SPECTRAL MIXTURE ANALYSIS FOR CROP TYPE DETERMINATION

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ABSTRACT

For the application of agricultural area, remote sensing techniques were studied and applied for its advantages for continuous and quantitative monitoring. Especially, hyperspectral images have been studied for the precise agriculture since they provide chemical and physical information of vegetation. In this study, we analyzed crop types using hyperspectral image data collected by a ground scanner. Spectral mixture analysis, which is widely used for processing hyperspectral images, was adopted for the crop discrimination. Endmember extraction algorithms used in this study were N-FINDR, Vertex Component Analysis (VCA), and Simplex Identification via variable Splitting and Augmented Lagrangian (SISAL), and classification was processed using fully constrained linear spectral unmixing (FCLSU). This study presents the application of spectral mixture analysis for hyperspectral scanner data at canopy level and optimal endmember extraction algorithms for different crop types for precise agriculture.

Index Terms— Hyperspectral images, spectral mixture analysis, classification, crop types

1. INTRODUCTION

Remote sensing techniques are the key method of agricultural area to control extensive crop fields and track the crop conditions in changing environments. Among the remote sensing data, hyperspectral image data provides fine spectral resolutions in visible, near infrared, and shortwave infrared wavelength region and can offer abundant spectral information of crop and vegetation. For this reason, previous studies on vegetation analysis using hyperspectral images were performed in many years.

Spectral mixture analysis have been studied for hyperspectral data processing for its applications for process of precise spectral information and considering mixed pixel assumption. Many researchers developed different algorithms based on spectral mixture analysis, but studies on their performances on various hyperspectral data is limited [2]. Some studies performed vegetation analysis based on spectral mixture analysis was performed using the hyperspectral data collected by satellite data with low-spatial-resolution [4]. Other than satellites, hyperspectral images can be collected airborne and ground scanner now.

For the effective analysis for agriculture analysis, we performed crop type determination using hyperspectral image collected at canopy level by ground scanner. Crop types were defined in two cases to estimate the effects of vegetation color and crop species for classification results. Spectral mixture analysis algorithms, such as N-FINDR, VCA, and SISAL algorithms were used for endmember extraction, and abundance maps were estimated by FCLSU for crop type determination. Classification results were evaluated comparing with reference data of the hyperspectral image.

2. METHOD

To determine crop types using hyperspectral images, unmixing based algorithms were implemented to estimate endmember without ground spectrometer data. Brief explanations on N-FINDR, VCA, and SISAL algorithms and classification process for crop types by analyzing abundance maps will be presented in this section.

2.1. N-FINDR

N-FINDR is based on the fact that in spectral dimensions, the volume defined by a simplex formed by the purest pixels is larger than any other volume defined by any other combination of pixels.

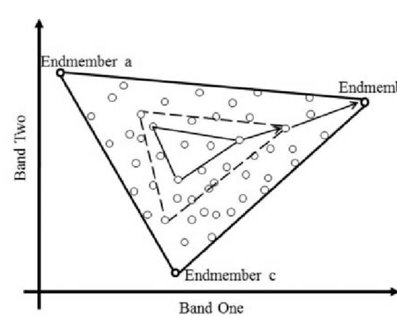

Fig. 1. Simplex for N-FINDR algorithm to estimate endmembers

$$E = \begin{bmatrix} 1 & 1 & \cdots & 1 \\ e_a & e_b & \cdots & e_i \end{bmatrix}$$

$$V(E) = \frac{1}{(l-1)!} abs(|E|)$$

This algorithm estimates endmembers e_i by finding the set of pixels defining the largest volume by inflating a simplex inside the data [5].

2.2. VCA

VCA iteratively projects data onto a direction orthogonal to the subspace spanned by the endmembers already determined in previous stages. The extreme of the projection are selected as a new endmember, and it continues finding endmembers until it extracts all the endmembers in an image. The initial endmember is extracted using singular value decomposition (SVD). It also has an assumption that pure pixels are existed in an image [3].

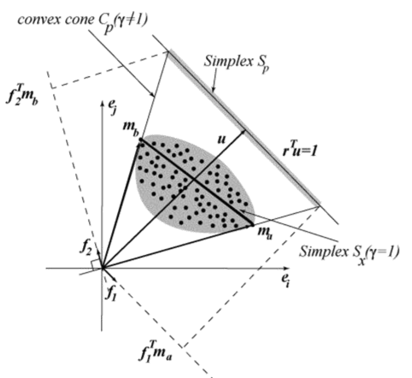

Fig. 2. Example of VCA algorithm [3]

2.3. SISAL

SISAL finds the endmembers that minimizes the volume of the simplex, and the spectral vector may lie outside the true data simplex to resolve the problems of noise as below figure.

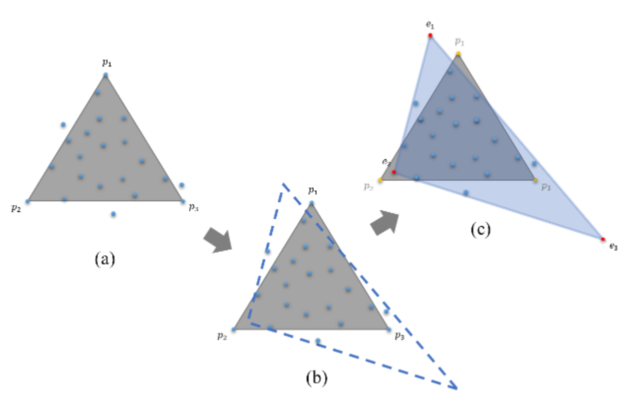

Fig. 3. Example of SISAL algorithm

SISAL allows violations to the positivity constraint and uses augmented Lagrangian method for effective computation [2]. Below figure presents the example of the process for SISAL algorithm. Red points on Fig. 3. (c) are the final extracted endmembers having minimized volume of the simplex.

2.4. Classification using extracted endmembers

With the estimated endmembers, abundance maps for individual endmembers were estimated by FCLSU [1], and crop cover type was defined by maximum abundance estimates for each pixels. The crop discrimination results using three different endmember algorithms were compared with the classification result of manually collected endmembers, and accuracy values were estimated using a reference data.

3. DATA AND PREPROCESSING

For the determination of young crop types, hyperspectral image data at canopy level was collected by a SPECIM hyperspectral scanner (PS-FW-11-V10E). Radiometric calibration was performed using a dark reference and 18% white reference, and noise bands were removed. Study data was a subset of 100×100 pixels with the targets of green crops. The preprocessed data has 960 bands with 0.6 nm of spectral width in 400-1020 nm range.

Crop type determination was performed in two cases. In dataset 1, classes were divided by red and green crops. Green lettuce, perilla leaf, and corn were classified into class #1, and red lettuce was classified into class #2. In dataset 2, classes were defined in crop species. Green and red lettuces were classified into class #1, and perilla leaf and corn were classified into class #2 and #3, respectively.

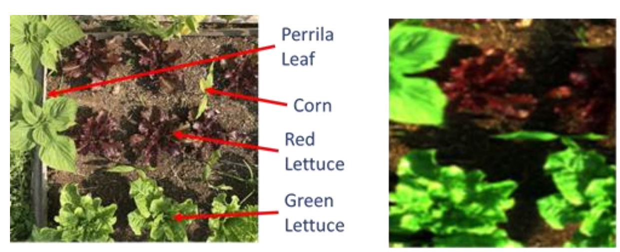

Fig. 4. Study site of the ground scanner hyperspectral image (left) and hyperspectral image in RGB channel (right)

4. RESULTS

Endmember extraction was performed by N-FINDR, VCA, and SISAL, and six endmembers were initially extracted and merged into class #1, class #2, and unclassified (black). Maximum number of iteration of N-FINDR was 10000, and delta value of FCLSU was 1/10000 in this study.

Table 1. Overall accuracy of crop type determination results for data 1 and 2

	Dataset 1 (%)	Dataset 2 (%)
Manual	**86.47**	64.67
N-FINDR	58.13	33.14
VCA	76.90	**73.98**
SISAL	**85.66**	64.11

Table 1 presents the overall accuracy of crop type determination using endmember extraction results of N-FINDR, VCA, and SISAL. These results were compared with manually collected endmember using ground truth data. Overall, determination of green and red crops using hyperspectral image and spectral mixture analysis was effective comparing to determination of crop species, dataset 2.

For dataset 1, result of SISAL presented high accuracy close to the result of manually collected endmembers. In dataset 2, classification result of VCA had the highest accuracy.

In Fig. 5 and 6, reference data and crop type determination results were presented. SISAL and manual results presented high accuracy to determine green and red crops. However, N-FINDR was not able to estimate the red lettuce, and VCA determined limited area of red lettuce in dataset 1. For the dataset 2, VCA results were more effective to discriminate lettuce and perilla leaf, comparing to other algorithms. Discriminating corn was not successful in this study since corn was in early vegetative stage and its size was small.

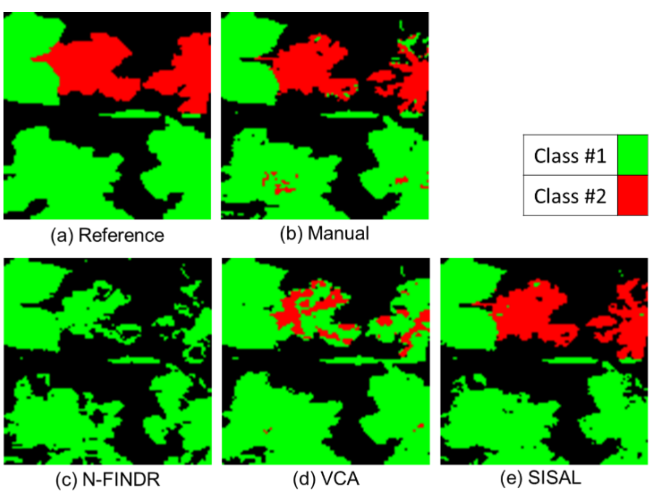

Fig. 5. Reference and crop type determination results for the dataset 1

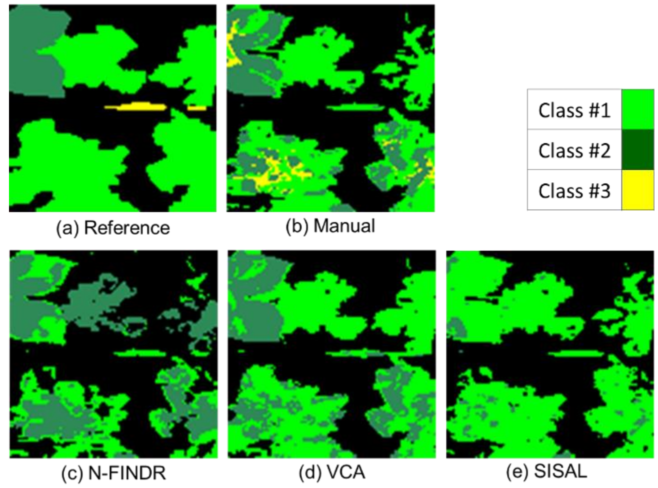

Fig. 6. Reference and crop determination results for the dataset 2

5. CONCLUSION

In this study, crop types for green/red lettuce, corn, and perilla leaf were determined based on spectral mixture analysis using hyperspectral image collected at canopy level by a ground scanner. The result of SISAL presented high accuracy close to the result of manually collected endmembers for green/red crop determination, and the VCA result had the highest accuracy for discriminating lettuce and perilla leaf. The hyperspectral image data in this study includes limited kinds of crops and image size, so we need to evaluate on more hyperspectral data to analyze the performance. Based on the studies, we will develop an optimized abundance map estimation technique for determination of crop types with higher accuracy.

6. ACKNOWLEDGEMENT

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