# OPTIMAL HYPERSPECTRAL CLASSIFICATION FOR PADDY FIELD WITH SEMISUPERVISED SELF-LEARNING

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## ABSTRACT

Monitoring and management of paddy fields are one of key elements for not only stable production but also ensuring national food security. Classification of growth stage with remote sensing data is expected to be a highly effective solution, which can capture large area in one time observation. In general cases, a pixel-based classification is one of the most attractive choices. However, acquiring enough number of field survey plots for the classification is not easy from the aspect of consumed time and cost. This problem can impact negatively on the accuracy of classification map. In this paper, we propose semisupervised classification method considering characteristic of paddy field in order to provide an optimal classification map with hyperspectral data.

***Index Terms—*** Hyperspectral, semisupervised classification, growth stage, sparse discrimination analysis, paddy

## 1. INTRODUCTION

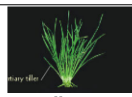
Remote sensing in precision agriculture is one of strong support tools for crop monitoring and management. From stable production by individual farmers to national food security in government level, the accurate monitoring and management are very useful. Especially remote sensing data enables us to know the condition in large area in one time observation. There are many researches for monitoring crop conditions with multispectral data, which have limitations in providing accurate estimates. This limitation has motivated to use hyperspectral data for the crop monitoring. Hyper spectral data has rich spectral information which is strong tools for classification of land use, growth stage, etc. In the near future, some organizations plan to launch spaceborne hyperspectral sensors, such as HISUI by Japan Space Systems and EnMAP by DLR.

Our main target of this study is to provide growth stage maps with high accurate classification performance, using hyperspectral data. In the past more than 20 years, there were many researches on crop monitoring using hyperspectral data [1]. Statistical techniques with hyperspectral data for agriculture might be classified in some categories; predictive spectral indices with only two to four narrow bands [2], chemometric analysis such as partial least squares, principal components analysis, etc., machine learning techniques [3] such as support vector machine, neural network, etc. Especially, this machine learning techniques provides good performance. However, accurate crop forecasting models need enough amounts of training samples. In many cases, there is a concern about the small-sample-size problem with high-dimensional data due to limitation of field samples. This problem can be caused of the complexity of prediction models, resulting in the poor performance caused by model overfitting. The importance of crop forecasting under the limitation of the training data are shown in the report of GEOSS [4]. In this study, we used the sparse regularization method which has high generalization capability and can select limited and important bands for classification in order to solve the ill-posed problem [5]. Moreover, focusing on the characteristics of reflectance in the paddy field, not only spatial information but also semisupervised classification techniques are used in our classification scheme for improving the performance.

## 2. SURVEY AREA AND DATA SET

The study area is located in Karawang which is well known as major granaries in West Java area. Dual and triple cropping of rice is common trend in these areas. Airborne hyperspectral data were acquired on 13th July 2011 and field survey for training data of classification in the study area was conducted on June to July 2011. The airborne hyperspectral sensor, HyMAP, has 126 bands (450nm - 2480nm) with 4.2 m/pixel. All the field survey points are located in those captured remote sensing image. However, some survey plots locating under clouds in HyMAP images were eliminated in this study. Therefore, total number of survey plots used in this study is 78 quadrats. Growth stage of each quadrat is classified in 9 classes, which is define by International Rice Research Institute (IRRI). Table 1 shows the details information about the defined growth stage. Since not enough number of quadrat in some growth stage such as vegetative early, reproductive mid, mature grain were obtained in the field survey, we focus on high accurate classification for remaining 6 classes.

**Table 1.** Growth stage defined by IRRI

| | early | mid | late |
|---|---|---|---|
| Vegetative |  Seeding |  Tillering |  Stem elongation |
| Reproductive |  Panicle initiation to booting |  Heading |  Flowering |
| Ripening |  Milk grain |  Dough grain |  Mature grain |

## 3. METHODOLOGY

Total processing scheme of this study is shown in Fig. 1. Our proposed methodology consists of four parts described in the following sections.

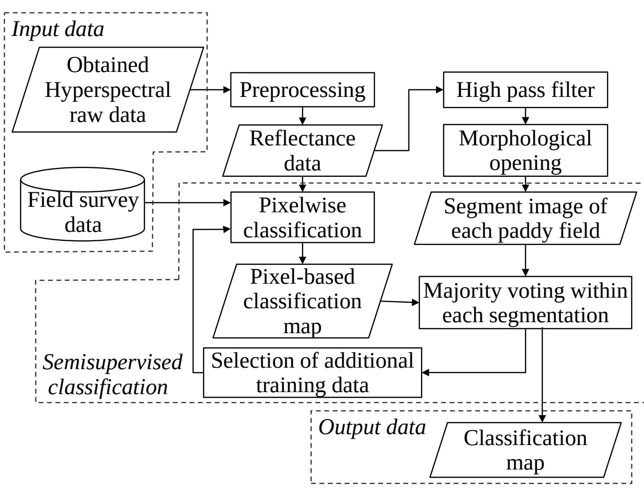



Fig. 1. Processing scheme

### 3.1. Preprocessing

In order to convert radiance data to reflectance data considering atmospheric effects, atmospheric correction is applied to the obtained HyMAP data with ATCOR-4. Moreover, we select 86 bands of the corrected HyMAP data by eliminating 40 bands which are low S/N bands and absorption bands of $O_2$, $H_2O$ and $CO_2$.

### 3.2. Pixelwise classification

In this research, sparse linear discriminant analysis (SDA) [5], which is a classification method using sparse regularization technique, is applied to the hyperspectral data for the classification of growth stage. Sparse regularization has the generalization capability and can select limited and important bands for the classification during the process. In this study, we compare the generalization capability between SDA and SVM as a typical classification method.

### 3.3. Post classification

*3.3.1. Segmentation of each paddy field*

In general, the growth stage is almost the same inside each segment. This can be confirmed from the results of field survey data. Therefore, the segmentation of each paddy field has an important role for classification, especially under the condition that the number of field survey plots is limited. In this study, we focus on the specific reflectance distribution of paddy field which consists of a square shaped flat reflectance region and a line shaped road. Spectral difference between these two elements is exist. In order to detect this spectral difference and the reflectance flatness of paddy field, high pass filter is adapted to the hyperspectral data. Furthermore, morphological opening with some typical squared disks sizes is used for keeping only the squared shaped objects similar to paddy field shapes. After that, watershed segmentation is applied to the morphological processed image in order to provide optimal segmentation fitted to shapes of individual paddy field.

*3.3.2. Majority voting within each segment*

In each segment, multiple classes from pixelwise classification may be combined. As we mentioned before, since the growth stage inside each segment is almost same in general, we apply the majority voting method to decide an optimal class. On the other hand, non-segmented regions are not applied the majority voting.

### 3.4. Semisupervised self-learning with segmentation map

Under the condition that the number of training data is not enough for classification with high robustness, increasing the training data in processing scheme is one of the key to improve the accuracy and robustness. In order to solve this problem, some studies conducted semisupervised classification method, especially semisupervised self-learning in which additional training data are decided by using neighbors of labeled samples and pixelwise classification map [6]. In this study, we focus on segmentation of paddy field and the results of the majority voting. During the process of majority voting within each segment, if almost all the classifiers agree, we can decide that the results of majority voting provides a corresponding class label with high reliability to the segment. On the other hand, if most of the classifiers don't agree, the results of majority voting may not be enough reliable. In the high reliable case, the minority classes can be identified as wrong results derived from luck of optimal training data. Therefore, these pixels having minority classes are added to training data of the pixelwise classification with a correct label which is a major class in the segment in order to reinforce performance of the classification. This process can increase the training data with high reliability. Fig. 2 shows the graphical examples.

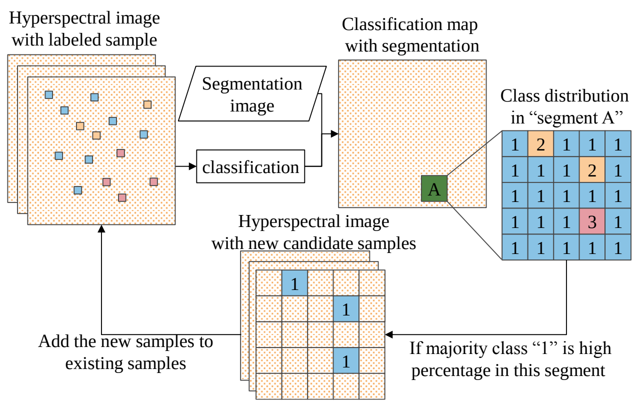



**Fig. 2.** Graphical example of self-leaning process

## 4. RESULTS AND DISCUSSION

### 4.1. Pixelwise classification

The 78 surveyed quadrats were classified in 6 classes. **Table 2** shows the number of training data in each class.

**Table 2.** Number of training samples by growth stage

| Growth stage | Vegetative | | Reproductive | | Ripening | |
|---|---|---|---|---|---|---|
| | mid | late | early | late | early | mid |
| Number | 16 | 52 | 84 | 44 | 76 | 27 |

For comparing accuracy of the classification between SDA and SVM, "Closed Test" and "Open Test" were conducted. "Closed Test" uses all the data for both training data and test data. In "Open Test", every pixel in four-fifth of all the quadrats in each class is used for training data and the every pixel in remaining one-fifth quadrats is used for test data. In this study, combination of training and test quadrats was decided randomly in 100 times.

The results of "Closed Test" and "Open Test" are shown in Table 3. From this results, SVM provides high accuracy in some classes. However, in overall accuracy, SDA provides better performance than SVM. This means SDA has enough potential in terms of generalization.

**Table 3.** Comparison between classification models

| | | Closed Test | | Open Test | |
|---|---|---|---|---|---|
| | | SVM | SDA | SVM | SDA |
| Vegetative | mid | 87.5% | 93.8% | 87.0% | 86.5% |
| | late | 59.6% | 71.2% | 56.0% | 64.9% |
| Reproductive | early | 88.1% | 95.2% | 83.1% | 80.2% |
| | late | 63.6% | 93.2% | 53.8% | 85.9% |
| Ripening | early | 93.4% | 90.8% | 92.8% | 85.3% |
| | mid | 85.2% | 92.6% | 81.5% | 76.8% |
| Overall accuracy | | 80.6% | 89.3% | 76.3% | 79.4% |

### 4.2. Semisupervised classification

Proposed segmentation method for paddy field was conducted to the hyperspectral image. In this study, considering the local condition such as typical size of paddy field and comparing individual bands, we selected 7 x 7 window size of the high pass filter and apply this filter to band 110 (center wavelength is 2,265 nm) of the hyperspectral data. Fig. 3 shows the obtained segmentation map.

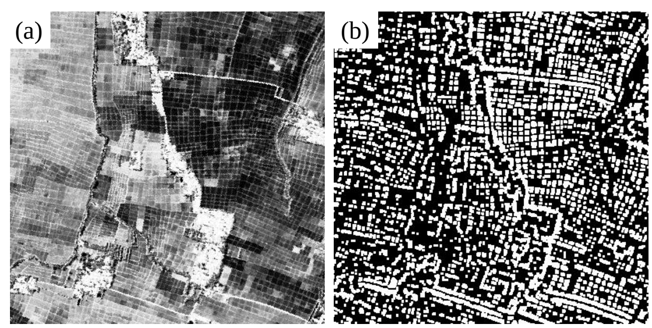



**Fig. 3.** (a) Reflectance data (band 110), (b) segmentation of paddy field

Moreover, pixel-based classification map by using SDA shown in Fig. 4(a), which shows noisy classification pattern, is improved by the majority voting with the pixelwise classification map and the segmentation map, as shown in Fig. 4(b). However, some areas in the corrected image have little consistency with neighbor pixels.

To improve this phenomenon, semisupervised self-learning with the pixelwise classification map, the corrected map provided by the majority voting, and the segmentation map, is applied  For selection of the segmentation with high reliability, a threshold is necessary for ratio of pixels with a majority class to all pixels in the segment is set to 80 %. The obtained classification map is shown in Fig. 5(a), and Fig. 5(b) is the results provided by applying majority voting to the classification map. For comparison between with and without semisupervised self-learning, Fig. 5(c) and (d) show those extended images. These results show our proposed methods have better consistency with the neighbor pixels and local conditions.

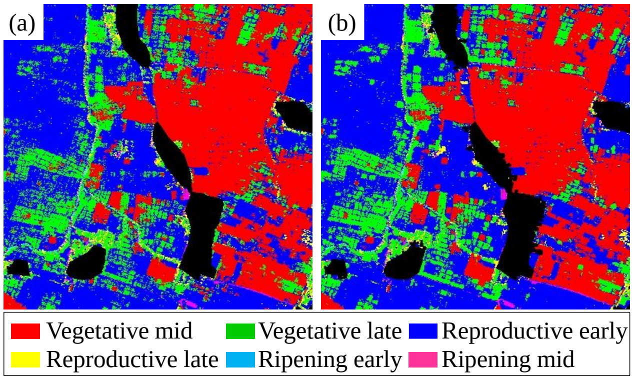



**Fig. 4.** Classification map (a) pixelwise classification, (b) applied majority voting

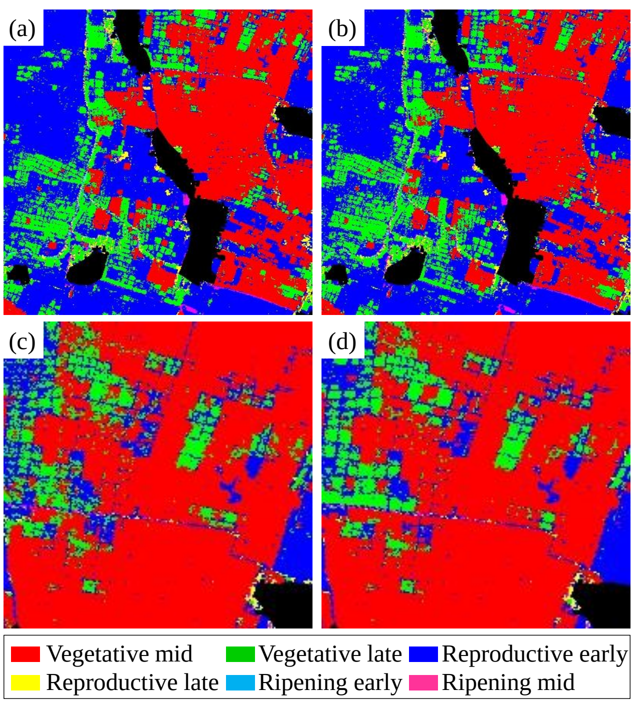



**Fig. 5.** (a) Semisupervised classification map, (b) applied majority voting, (c) an extend image of Fig. 4.(b), (d) an extended image of (b)

## 5. CONCLUSION

This paper has presented the efficiency of semisupervised self-learning for paddy field analysis with hyperspectral data. In the pixelwise classification, SDA performed high accuracy and generalization as shown in the results of "Open Test". Furthermore the post classification, such as majority voting with segmentation map, and semisupervised self-learning showed high consistency with the neighbor pixels and local conditions. The number of field survey plots as training and test data was enough for evaluation of pixelwise classification, however validating the accuracy of our proposed semisupervised classification needs more field survey plots or additional GIS data. Moreover, we understood radiometric distortion in each stripe data obtained by not only airborne hyperspectral sensor and radiometric adjustment between those stripe data during mosaic process have much impact to accuracy of classification. On the other hands, recently hyperspectral data captured by airborne or spaceborne sensor but also sensors mounted on UAV is getting to be available for research. The use of UAV has potential for making easy to collect data and decreasing the cost for survey. Our future work is to challenge the problems by using those benefits of UAV observation.

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