Exploring effect of segmentation scale on orient-based crop identification using HJ CCD data in Northeast China

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Abstract. Crop identification and acreage estimation with remote sensing were the main issues for crop production estimation. Object-oriented classification has been involved in crop extraction from high spatial resolution images. However, different imagery segmentation scales for object-oriented classification always yield quite different crop identification accuracy. In this paper, multi-scale image segmentation was conducted to carry out crop identification using HJ CCD imagery in Red Star Farm in Heilongjiang province. Corn, soybean and wheat were identified as the final crop classes. Crop identification features at different segmentation scale were generated. Crop separability based on different feature-combinations was evaluated using class separation distance. Nearest Neighbour classifier (NN) was then used for crop identification. The results showed that the best segmentation scale was 8, and the overall crop identification accuracy was about 0.969 at that scale.

1. Introduction

Crop identification and acreage estimation with remote sensing are one of the two key aspects for crop production estimation except crop yield estimation. Object-oriented classification technique is an effective approach for thematic information extraction from high spatial resolution remote sensing data, and has been widely used for automatic land use or land cover mapping using remotely sensed images (LULC) \cite{1}. Many studies showed that object-oriented classification had obtained good results in crop identification.

Image segmentation is a key process in object-oriented classification and affects the accuracy of the classification at much degree. In fact, it’s the scale of image segmentation, which plays an important role in segmentation, and then influence the final classification accuracy. Many studies have focused on the segmentation scale of object-oriented classification in land use and land cover mapping or crop identification.

In this paper, a multi-scale segmentation schema was conducted to evaluate the separability between different crops at different scale using a HJ-1 CCD image in Northeast China, and then used to identify corn, soybean and wheat. The purposes of the study are as follows: 1) to analysis the effect of segmentation scale for crop identification in Northeast China; 2) to investigate the best crop

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identification accuracy with one date HJ CCD imagery in the study area; and then 3) to design a schema for crop mapping in Northeast China using HJ CCD images.

2. Study area and data collection

2.1. Study area
The study area is located in a modern farm, named Red Star Farm (127°47’ E, 48°21’ N), in Heilongjiang province (Figure 1). The average annual precipitation is 556 mm, and the annual effective temperature is 2250 °C. The land area is 37100 hectares in total with 19200 hectares arable. The average field-size of crop field is about 30 ha. Corn, soybean and spring wheat dominates the main grain crops in this area.

![Figure 1. Study area and the HJ-1 CCD image collected.](image)

2.2. Data collection

2.2.1. Remotely sensed imagery
A HJ-1/CCD multispectral imagery, provided by China Centre for Resources Satellite Data and Application, was used in this study. HJ-1 satellite constellation is launched for environmental monitoring and disaster mitigation by Chinese government. The CCD sensor has 4 spectral bands (blue, green, red, and near infrared) from the spectral range of 430nm to 900nm with 30m spatial resolution. The image swath is 360 kilometers and its revisit-period is about 4 days. HJ-1 CCD has showed satisfied abilities in large-scale land use/cover, crop mapping or other application due to its wide-swath covering ability [2].

The HJ CCD imagery was collected on August 11, 2011, when corn is in booting stage, and soybean is in flowering stage. The quality of imagery is satisfied. Data preprocessing included radiation correction, orthographic correction and study area clipping, had been implemented (Figure 1).

2.2.2. Field data
Ground survey was implemented to achieve crop samples using GPS instruments. The random sampling approach was used to collect spectral training set for the classification.

3. Methods
Image segmentation represents a fundamental first-step in object based image analysis [3]. In this study, the HJ CCD imagery was segmented at a series of scales, and the separabilities between different crops were evaluated for different feature-combinations. The best combination, with maximum separability, then was used to carry out image classification at every scale. Finally, the accuracy of classification was evaluated using Kappa coefficient.

3.1. Multi-scale segmentation
The segmentation of HJ CCD image at different scales was performed using the multi-scale segmentation tools with eCognition Developer 8 [4]. In this software, multi-scale segmentation is a semi-automatic process. Users can customize partition parameters, including segmentation scale, shape factor, compactness factor. All these parameters determined the size and shape of the objects in segmentation image together. Among them, the selection of an appropriate value for the “scale” parameter was considered as the most important step, as this value controlled the relative size of the objects, which has a direct effect on the accuracy of the classification [5-7]. In this study, a series of segmentation images were generated with the scale value 20, 15, 10, 9, 8, 7, and 6, where shape factor was set as 0.2 and compactness factor was set as 0.5.

3.2. Separability distance evaluation
Statistical separability is usually used to estimate classification error with different feature combinations [8]. Usually, statistical separability can be measured by the distance between classes. Separability distance is one of the statistical separability measurements in pattern recognition, and has been widely used for feature extraction and clustering analysis.

Separability distance $J_d(x)$ is defined as follow [9]:

$$J_d(x) = \frac{1}{2} \sum_{j=1}^{c} P_j \sum_{i=1}^{c} P_i \left\| m_i - m_j \right\|^2 - r_i - r_j$$

where $c$ is the number of the classes, $P_i, P_j$ are prior probability, $\left\| m_i - m_j \right\|^2$ is the mean vector distance between $\omega_i$ and $\omega_j$, $r_i, r_j$ is the mean radius of class, $n_i$ is sample number, $x_k(i)$ is D dimensions feature vector of class $\omega_i$, $m_i$ is mean vector of samples set $i$.

3.3. Crop identification
In this study, Nearest Neighbor classifier (NN) was used to identify different crops. NN is one of the most important methods of non-parameter of pattern recognition. A significant feature of NN is that all the samples of various classes are representative points, and the samples to be classified will be clustered into the class nearest sample belongs to[10]. NN algorithm is described as following:

Suppose class $\omega_1, \omega_2, \cdots, \omega_m$, each class has $N=(i=1,2,\cdots n)$ samples, we define the distance between the sample and the class $\omega_i$ as:

$$g_i(x) = \min_{k=1,2,\cdots N_i} \left\| x - x_k^i \right\|$$

Where, $x_k^i$ means the sample $k$ of class $i$.

Criterion: if $g(x) = \min_{i=1,2,\cdots m} g_i(x)$, then $x \in \omega_i$.

4. Results and analysis
4.1. Segmentation results
Figure 2 showed the segmentation results at different partition scales. With the decrease of the segmentation scales, the image was divided into more and more objects, and the objects contained less and less pixels, reflecting more and more distinct spectral properties.
4.2. Separability analysis
The optimal separability distances were different under different feature-combinations (Table 1). We found that neither more features, nor a finer scale would result in the optimal separability distances. A combination of nine features for segmentation images at scale 8 is more satisfied for crop classification.

With the decrease of the segmentation scales, the separability distances changed as three different ways (Figure 3). The driver may involve the spectrum heterogeneity among objects, the numbers of mixed pixels and others. Here gives the three different mode of separability distance between different crops or vegetation.

(1) Stability mode. The separability distances were in subtle and nearly unchanged with segmentation scales become finer and finer. The typical crop pair was corn and soybean. That’s because they were the most common inter-planted crop pair, and their spectrum were more similar than other crop-pairs.

(2) Rise then decline mode. The separability distances were relative larger, and its profile appeared firstly rise and then decline with the decreasing of the segmentation scale. The typical crop pairs included corn-wheat, soybean-wheat and wheat-tree. These crop pairs are not common interplant-crops, and their spectrum heterogeneities were much greater. At scale 20, there exist much mixed pixels and the spectrum heterogeneity was strong, so the separability distances were small. With the reducing of segmentation scale, mixed pixels were less and spectrum heterogeneity went lower and lower, thus, separability distance got optimal at scale 15. At fine scales, the image objects were fragmentary, and spectrum heterogeneity of inter-class was stronger, so the separability distance decreased.

(3) Fluctuation mode. Separability distance profile showed fluctuation with the decrease of segmentation scale. Yet the general trend is descending. The typical crop pairs included corn-tree and soybean-tree. Because the interaction between spectrum heterogeneity and mixed pixels was very
complex. In some scales, spectrum heterogeneity was stronger than the number of mixed pixels, while in some other scales on the contrary.

**Table 1.** Feature combination separability and classification accuracy at different scale

| Feature                  | Scale | 20  | 15  | 10  | 9   | 8   | 7   | 6   |
|--------------------------|-------|-----|-----|-----|-----|-----|-----|-----|
| Nev1                     | √     | √   | √   | √   | √   | √   | √   | √   |
| mean b4                  | √     | √   | √   | √   | √   | √   | √   | √   |
| max diff                 | √     | √   | √   | √   | √   | √   | √   | √   |
| mean diff to scene b4    | √     | √   | √   | √   | √   | √   | √   | √   |
| ratio b4                 | √     | √   | √   | √   | √   | √   | √   | √   |
| ratio to scene b4        | √     | √   | √   | √   | √   | √   | √   | √   |
| min pixel value b4       | √     | √   | √   | √   | √   | √   | √   | √   |
| max pixel value b4       | √     | √   | √   | √   | √   | √   | √   | √   |
| standard deviation b4    | O     | O   | O   | O   | O   | O   | O   | O   |
| ratio to scene b2        | √     | √   | √   | √   | √   | √   | √   | √   |
| min pixel value b2       | O     | √   | √   | √   | √   | √   | √   | √   |
| max pixel value b2       | O     | √   | √   | √   | √   | √   | √   | √   |
| standard deviation b2    | O     | √   | O   | O   | O   | O   | O   | O   |

Overall separability classification:

| Scale | 0.971 | 1.108 | 1.204 | 1.21 | 1.305 | 1.205 | 1.153 |
|-------|-------|-------|-------|------|-------|-------|-------|
| 20    | 0.872 | 0.872 | 0.846 | 0.91 | 0.969 | 0.938 | 0.933 |
| 15    |       |       |       |      |       |       |       |
| 10    |       |       |       |      |       |       |       |
| 9     |       |       |       |      |       |       |       |
| 8     |       |       |       |      |       |       |       |
| 7     |       |       |       |      |       |       |       |
| 6     |       |       |       |      |       |       |       |

'√' means the feature was selected and 'O' means the feature was not selected.

**Figure 3.** Changes of the class separability distance at different segmentation scales.

**Figure 4.** Classification results.
4.3. Crop classification results
The accuracy of classifications at different scales was shown in Table 1. The classification accuracy and the separability went to maximum when segmentation scale equals 8. That is to say, the optimal segmentation scale is 8 for crop classification in the region; Figure 4 showed the best classification results at different scales. When the segmentation scale went near to the pixel-scale, "salt and pepper effect" appeared in the classification result, just like pixel-based classification.

5. Conclusion
The following conclusions can be draw:
1) The optimal segmentation scale was 8 for image segmentation for crop identification using HJ-1 CCD images with 30 meter spatial resolution.
2) The best accuracy of crop identification can reach 96% using object-orient classification with single HJ CCD imagery in northeast China.
3) For crop acreage estimation or crop mapping in northeast China, HJ-1 CCD image is certainly ideal data source.
4) The study results also showed that, the segmentation scale had nearly no effects on discrimination between corn and soybean. That meant HJ-1 CCD image classification could be used to estimate the acreage of corn and soybean at coarser segmentation scales.

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