

A STUDY ON SPATIAL FEATURE EXTRACTION IN THE CLASSIFICATION OF HIGH RESOLUTION SATELLITE IMAGERY

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ABSTRACT: It is well known that combining spatial and spectral information can improve land use classification from satellite imagery. High spatial resolution classification has a limitation when only using the spectral information due to the complex spatial arrangement of features and spectral heterogeneity within each class. Therefore, extracting the spatial information is one of the most important steps in high resolution satellite image classification.

In this paper, we propose a new spatial feature extraction method. The extracted features are integrated with spectral bands to improve overall classification accuracy. The classification is achieved by applying a Support Vector Machines classifier. In order to evaluate the proposed feature extraction method, we applied our approach to KOMPSAT-2 data and compared the result with the other methods.

KEY WORDS: High Resolution Image Classification, Spatial Features, SSI, SVM

1. INTRODUCTION

With the recent commercial availability of high resolution multispectral remote sensing imagery from satellites, it has become possible to identify small scale features such as individual roads and buildings in urban environments (Shackelford and Davis, 2003). Such small scale features could not be recognized using low resolution images due to poor spatial feature detection opportunities. Therefore, methods for the classification of roads, buildings and other land cover types in urban environments, employing high resolution satellite images, are of great interest. However, due to the complex spatial arrangement of features and spectral heterogeneity within each class, conventional spectral classification methods are inadequate for this purpose (Myint et al., 2004). In order to overcome this drawback, there are many methods of combining spatial feature information with spectral information (Pakorn, 2005). Spatial analytical approaches can be categorized into spatial features extracted by moving windows or elements and a spatial classifier based on contextual decision criteria with consideration of neighboring pixels inside the classifier (Dell'Acoya et al., 2004). This paper focuses on extracting spatial features based on a region-growing algorithm to enhance the accuracy of classification. A Support Vector Machine (SVM) is employed as the classifier because it is an appropriate method of high resolution multispectral image classification. Pixel Shape Index (PSI), which is a generally used method of extracting spatial features, is used for comparison.

2. RELATED WORK

Several effective spatial feature extraction methods have been proposed. Wavelet Transform (WT) methods are used to extract texture features (Myint et al., 2004). WT allows the extraction of different texture features at different scales, thus providing a useful alternative approach to spatial feature analysis in high resolution images. The Gray Level Co-occurrence Matrix (GLCM) method can introduce spatial information into a spectral classification, in which an image gray value is transformed into a co-occurrence matrix space and various output images are calculated, adopting different spatial measures (Zhang, 1999). Shackelford and Davis (2003) proposed the Length-Width Extraction Algorithm (LWEA), to extract the length and width of spectrally similar connected groups of pixels. Pixel Shape Index (PSI) adds an extension to LWEA (Zhang et al., 2006). PSI extracts features in a pixel-by-pixel manner, whereby each pixel is allocated a feature value based on the spectral similarity of its neighboring pixels. PSI sums the grey similarity distance of all the radiating lines to describe the structure around each central pixel.

3. SEGMENT SIZE INDEX

PSI encounters a limitation in certain situations. Pixels in the same feature can be allocated different values according to the feature's shape. Figure 1 illustrates this problem. Pixels A and B are belong to same feature ("doughnut" shape at left, "L" shape at right), but are nevertheless allocated different values.

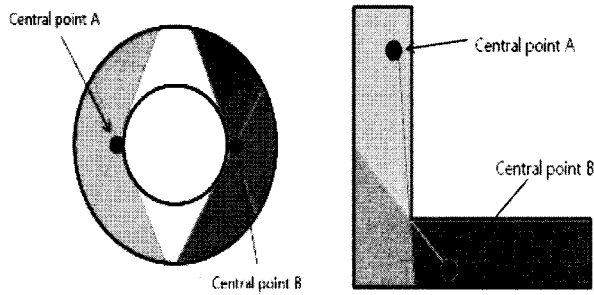


Figure 1. Drawback of PSI

To overcome this issue with PSI's radial approach, we suggest an area based feature extraction algorithm, Segment Size Index (SSI). To extract features using the SSI algorithm, first we carry out region-growing based image segmentation using principal component analysis (PC1). Region-growing approaches exploit the important fact that pixels which are close together have similar gray values, starting with a single pixel and adding new pixels gradually. After segmentation, each segment is allocated the number of pixels in the segment. For example, the pixels within a large sized segment are allocated a large value. Compared to PSI, SSI is a simple and fast method of extracting spatial features. The SSI algorithm is summarized by the pseudocode shown in Figure 2.

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for each pixel i
  k = 1
  if pixel i is not allocated SSI value
    repeat
      Check the neighboring pixels and add them to
      "segment i" if they are similar to i
      k = k + 1
    until no more pixels can be added
    SSI(segment i) = k
  end if
end for

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Figure 2. Pseudocode for SSI

4. EXPERIMENTS

This paper examines the feasibility of classification using SSI integrated with spectral information based on a SVM classifier. SVM is a good candidate for remote sensing image classification because it works well with a small training data set and is robust to the overfitting problem because it relies on margin maximization rather than finding a decision boundary directly from the training samples. In our experiments, we extracted the PC1 band from principal component analysis, then extracted the SSI features from the PC1 band and combined this with four multi-spectral bands. All five bands were then classified with SVM. The flowchart for this process is shown in Figure 3.

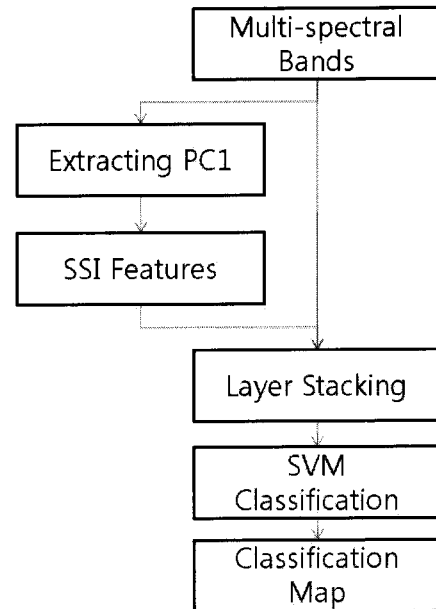


Figure 3. Flowchart of proposed approach

5. RESULTS AND DISCUSSION

To illustrate the effectiveness of SSI, we applied our algorithm to a Kompsat-2 image of Daejeon, Korea (Figure 4). The training and test datasets were mutually exclusive (Table 1). The classification result using MLC (Figure 5(a)) and SVM (Figure 5(b), (c) and (d)) with different feature indexes are shown. Table 2 shows the classification accuracies achieved.



Figure 4. Original image

Table 1. Number of Training and Test Pixels

	Training (pixel)	Test (pixel)
Tree	271	1,152
Grass	336	1,051
Water	308	1,107
Shadow	260	1,270
Road	258	1,131
Building	180	1,214
Bare Soil	198	1,153

Figures 5(a) and (b) are classified using just four spectral bands, and show that a SVM classifier provides a better classification result than MLC. Figures 5(c) and (d) show the results obtained using spectral bands with PSI and SSI spatial feature extraction respectively. Our proposed SSI algorithm appears to provide the highest classification accuracy. Using SSI significantly enhanced classification accuracies for the shadow and building classes, with an increase in class accuracy of at least 15% for the shadow class. It can also be seen that the shadow class is completely distinguished from the water class by SSI.

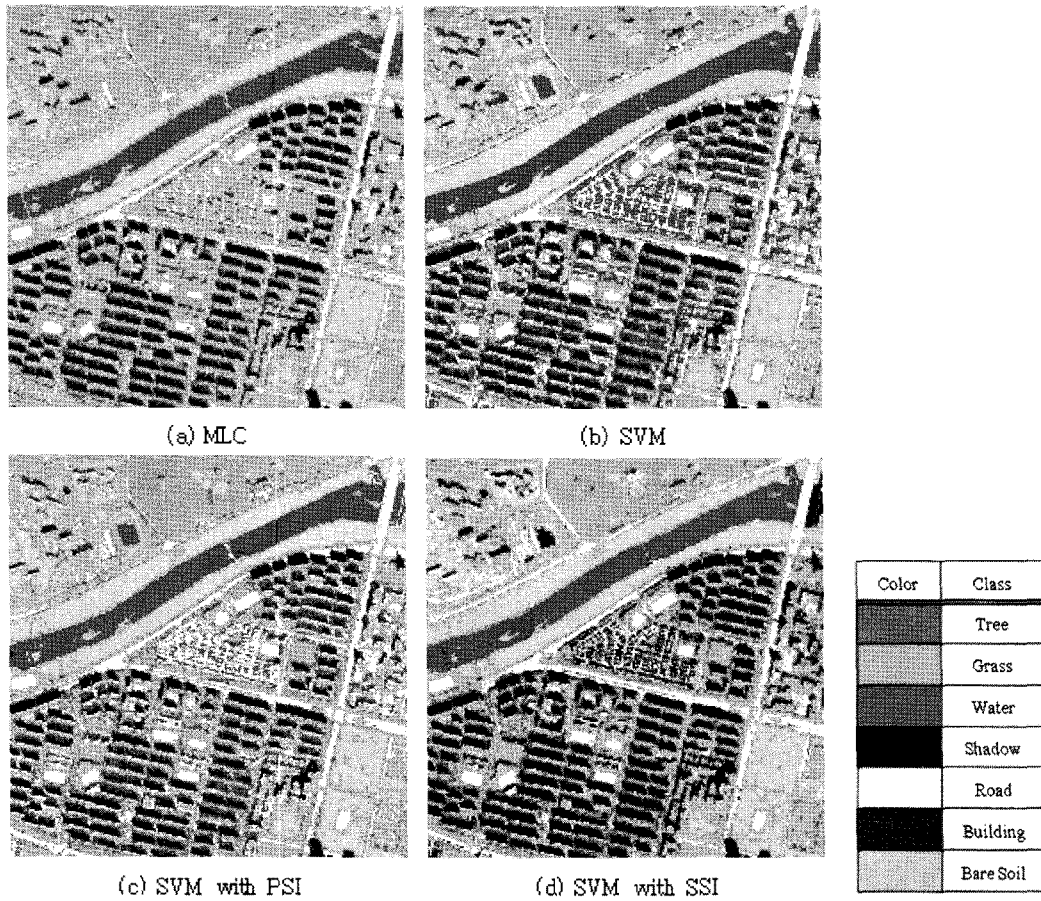


Figure 5. Classification results

Table 2. Classification accuracies

Class	MLC (%)	SVM (%)	SVM with PSI (%)	SVM with SSI (%)
Tree	96.18	97.40	99.22	99.13
Grass	99.62	99.81	99.43	98.76
Water	98.46	99.91	99.19	95.03
Shadow	87.95	78.98	83.78	99.76
Road	76.30	92.66	89.30	88.42
Building	91.43	80.81	83.53	88.96
Bare Soil	54.03	81.70	86.73	82.31
Overall Accuracy	86.14	89.76	91.29	93.19

5. CONCLUSION AND FUTURE WORK

We suggested a spatial feature extraction algorithm to be combined with spectral features in order to raise classification accuracy for high resolution satellite imagery. The SVM classifier we employed showed better results than MLC. An area-based spatial feature index, SSI, was proposed in this paper. SSI uses a simple method to effectively describe the contextual information. We demonstrated that our proposed SSI algorithm leads to a notable increase in classification accuracy over the PSI algorithm. Moreover, SSI is computationally faster than other methods. In order to verify the applicability of our approach, it will be necessary to carry out further tests using a wider range of data. We expect that using more diverse feature indexes together will be able to improve the classification accuracy. This will be investigated in our future work.

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