EMPERICAL COMPARISON OF MACHINE LEARNING TECHNIQUES FOR OBJECT-BASED VEGETATION SPECIES CLASSIFICATION

Zhengrong Li [1,2], Ross Hayward [1], Yuee Liu [1], Rodney Walker [2]

[1] School of IT, Queensland University of Technology
[2] Australian Research Centre for Aerospace Automation (ARCAA)

1. INTRODUCTION

Object-based approaches have been intensively studied in high spatial resolution remote sensing image classification, which has proven to be an alternative to the pixel-based image analysis and a number of publications suggest that better results can be expected [1, 2]. In object-based image classification, image objects are used as the basic classification unit the classification is often done in the object-feature space. Therefore, the use of appropriate features and the choice of particular classification algorithms are two fundamental problems.

A variety of machine learning approaches to classification tasks are currently available, but few comparisons among different models have been done in object-based image classification. The motivation behind this paper is to develop a better understanding of the machine classification process in object-based image classification, to evaluate the performance of different machine learning algorithms in a specific application, and to compare the results not only in terms of their classification accuracy but also some other properties such as training and testing speed, and ease of use. These issues are of great importance to the application of machine classifiers in object-based image analysis.

2. AN OVERVIEW OF OBJECT SEGMENTATION AND FEATURE EXTRACTION

A typical object-based image analysis consists of a three-stage processing: image segmentation, object feature extraction, and pattern classification. Image segmentation is the process of breaking an image into regions that have some meaning with respect to image content and application[3]. Since we are going to classify the species among trees, tree crowns are the only image-objects of interest in our research. We have developed an automatic tree crown detection and delineation algorithm by utilizing spectral features in a pulse coupled neural network followed by post-processing using morphological reconstruction [4]. Although the automatic segmentation is satisfied from visual assessment, decomposition of tree clusters is occasionally poor. Since the main aim of this research is evaluate different machine classifiers, manual segmentation is used to minimize the influence of inaccuracy in segmentation. The background is removed and each tree crown is labeled with a unique label to identify the tree which is paired against individual tree species obtained from field surveys.

As trees are very similar in colour, we use texture feature descriptors to represent each tree crowns. Figure 1 illustrates tree crown delineation and object-feature extraction process (i.e. LBP histogram) from one segmented tree crown. In this paper, three widely used texture features are extracted from the segments (polygons) and then input to the classifiers: GLCM [5], Gabor wavelet features [6], and Uniform Local Binary Patterns (ULBP) [7]. The feature dimensions of GLCM, Gabor and ULBP are 8, 48, and 607 respectively.

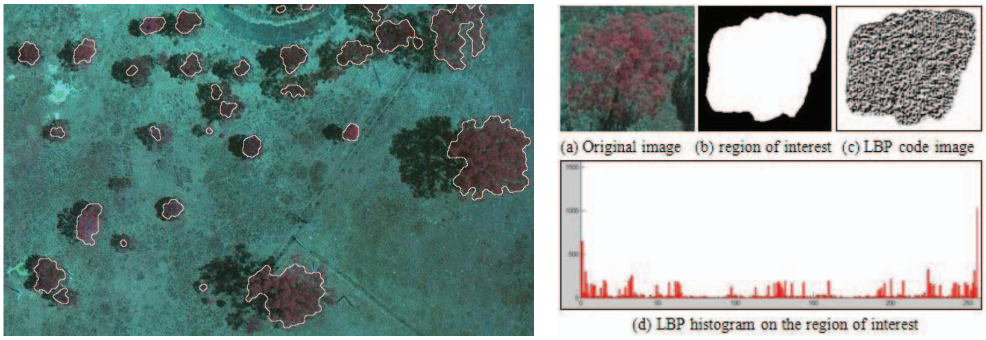

Figure 2 Example tree crown segmentation and object-feature extraction

3. MACHINE CLASSIFIERS

During the past decades, a variety of machine learning algorithms have been proposed for classification tasks. Although the potential advantages and disadvantage of these techniques have been addressed in many published work, most of them are from the theoretical view under some assumption about data distribution, characteristics of the classification task, signal-to-noise, etc. In reality, these assumptions are often hard to be verified. Therefore, a practical solution for selecting an appropriate model for a given classification task is to experimentally compare the discriminatory power of these techniques and considering the tradeoffs among the classification performance, cost and model interpretability. In this paper, we compared 7 widely used machine classifiers. Due to the space limitation, only the basic design of each model is given.

K-Means Clustering (KM): The optimal number of clusters is found by cross-validation: using a varying number of clusters, test each one and find the one with the best classification performance.

Linear Discriminant Analysis (LDA): The optimizing criterion in LDA is to maximize between-class difference while minimizing within-class difference. This is done by defining a transformation matrix. The projection to the transformation matrix achieves the maximum separation between classes.

Multilayer Perceptron Neural Networks (MLP): A full-connected, three layer, feed forward, perceptron neural network is used. A logistic (sigmoid) activation function is employed in both the hidden layer and output layer.

Radial Basis Function Networks (RBFN): A maximum of 100 neurons are allowed to be used in the model. The RBF training algorithm stops adding neurons when it detects that overfitting may occur. The radius of each RBF function (spread) is set to be 400.

Support Vector Machines (SVM): Radial Basis Function (RBF) kernel is used and “one against one” technique is employed for multi-class classification.

Single Decision Tree (SDT): The minimum size node to split is set to be 10 which means that a node group should never be split if it contains fewer than 10 rows. Initially a large tree with many levels is built and then the redundant levels are removed in the pruning phase until the tree levels are fewer than 10.

Decision Tree Forest (DTF): In the experiments, we use a maximum number of 200 trees to be constructed in the forest, and each tree can be grown to up to 50 levels (depth). In addition, a node in a tree will not split if it has fewer than 2 rows in it.

4. EXPERIMENT AND DISCUSSION

The experiment dataset used in this research were collected in rural Queensland Australia in October 2008 by a high resolution 3-CCD digital multi-spectral camera mounted on fixed wing aircraft. Figure 2 shows a mosaic of the test area generated from aerial images acquired from the trial. The spatial resolution of the captured images is about 15cm. In this research, we focus on three dominant species in our test field: *Eucalyptus tereticornis (Euc_Ter), Eucalyptus melanophloia (Euc_Mel)*, and *Corymbia tesselaris (Cor_Tes)*. Through field survey with botanist's participation, 121 trees were selected and labeled for the experiment with 64 Euc_Ter, 30 Euc_Mel and 27 Cor_Tes. The criterion is that tree crowns are big enough so that they can be visually identified from images.

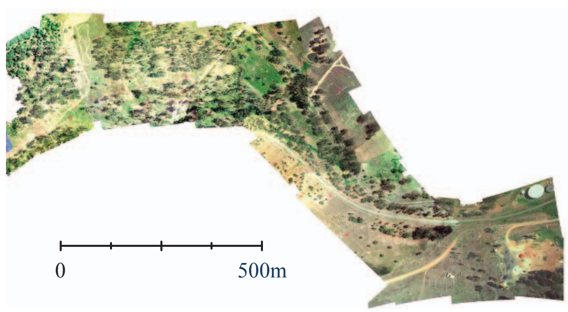

Figure 2 Experiment test site

In the experiment, we use the implementation of DTREG for the machine classifiers [8]. V-fold cross validation technique is employed, and 10 folders were selected for the cross validation. The classification models are constructed with 9/10 of the rows being used in the training, and the remaining 1/10 rows are then used to measure the accuracy of the model. As mentioned above, selecting a good model for a give classification task depends not only on discriminatory power, but also on the cost of model construction and interpretability. As the interpretability of each model is hard to measure, we focused on comparing the discriminatory power and the cost. We use classification accuracy to measure the discriminatory power of each machine classifiers. The classification accuracy is obtained by comparing the classified data and the ground truth reference data. The cost of model is measured by considering the analysis time including both training and testing process.

Table 1 summarizes the classification accuracy of each machine classifier on the three feature vectors respectively. As is shown in the experimental results, the MLP and SVM classifiers generate higher accuracy on all three features. Overall, the classification accuracies are not as good as expected. Two reasons might cause the low classification accuracy: 1) tree species are very similar in visual appearances which make it hard to discriminate them from each other; 2) the use of feature descriptors may not be optimal for the classification task.

Table 1 Comparison of the classification accuracies

Classifiers / Features	KM	LDA	RBFN	MLP	SVM	SDT	DTF
GLCM	55.37	64.46	62.81	69.42	69.42	58.68	56.20
Gabor	65.29	62.81	57.02	71.90	71.07	71.90	71.07
ULBP	69.42	50.41	52.89	72.73	71.07	66.12	71.07

Table 2 Comparison of the computational costs (in seconds)

Classifiers / Features	KM	LDA	RBFN	MLP	SVM	SDT	DTF
GLCM	2.64	0.23	43.53	2.72	22.89	0.3	0.55
Gabor	44.06	0.47	139.14	5.81	15.97	0.56	1.13
ULBP	385.97	7.41	113.19	136.41	230.93	2.53	2.31

Table 2 compares the computational cost of each machine classifier on the three feature vectors respectively. The analysis time is recorded by DTREG software under a desktop PC configuration of core duo 2.66GHz CUP and 2GB memory. Overall, LDA, SDT and DTF are very computational efficient, whereas RBFN, MLP and SVM are computational much more intensive. It is also noted that with the dimensions of feature vectors increase, the computational cost increase considerably. This indicates that feature selection and dimension reduction is necessary when the feature vectors are of high dimensions.

5. CONCLUSION

This paper evaluates the capability of machine learning techniques for object-based vegetation species classification. Severn machine classifiers were evaluated in the experiment and the performance are compared by means of classification accuracy and analysis time. The experimental results showed that the classification performance not only depends on the discriminatory power of classifiers but also the characteristics of datasets and the feature(s) selected. MLP and SVM classifiers are suggested if the computational cost is not a big issue, while tree type classifiers are when considering both classification performance and analysis time.

6. REFERENCES

[1] J. R.Jensen, "Thematic Information Extraction: Pattern Recognition," in *Introductory Digital Image Processing: A Remote Sensing Perspective (Third Edition)*: Pearson Education, 2005, pp. 337-406.

[2] Y. Liu, M. Li, L. Mao, F. Xu, and S. Huang, "Review of Remotely Sensed Imagery Classification Patterns Based on Object-oriented Image Analysis," *Chinese Geographical Science,* vol. 16, pp. 282-288, 2006.

[3] A. Watt and F. Polocarpo, "Image segmentation," in *The Computer Image*: Addison Wesley Longman Limited, 1998, pp. 290-311.

[4] Z. Li, R. Hayward, J. Zhang, Y. Liu, and R. Walker, "Towards Automatic Tree Crown Detection and Delineation in Spectral Feature Space Using PCNN and Morphological Reconstruction," in *IEEE International Conference on Image Processing* Cairo, Egypt, 2009.

[5] M. Kubo, F. Kanda, and k. Muramoto, "Texture Feature Extraction of Tree Using Co-occurrence Matrix from Aerial Images," in *SCIE Annual Conference* Fukui, Japan: The Society of Instrument and Control Engineers, 2003.

[6] D. A. Clausi and H. Deng, "Design-based texture feature fusion using Gabor filters and co-occurrence probabilities," *IEEE Transactions on Image Processing,* vol. 14, pp. 925-936, 2005.

[7] T. Ojala, M. Pietikainen, and T. Maenpaa, "Multiresolution grey-scale and rotation invariant texture classification with local binary patterns," *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 24, pp. 971-987, 2002.

[8] P. H. Sherrod, " DTREG predictive modeling software. Users Manual. ," www.dtreg.com\dtreg.pdf, 2009.