

RANDOM ENSEMBLE FEATURE SELECTION FOR LAND COVER MAPPING

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ABSTRACT

Random ensemble feature selection is a means through which diversity in ensemble systems is imposed by randomly selecting the features (bands) that constitute the base classifiers. This paper provides insight and discusses the interplay between the size of the resulting ensembles and the consequent classification accuracy. From the results, it was observed that classification accuracy increased more as the number of features per base classifier increases than as the number of base classifiers increases. That said however, classification accuracy was seen to increase with additional features up to a given limit beyond which increasing the number of features per base classifier did not significantly increase classification accuracy, a peaking effect probably due to Hughes phenomenon.

Index Terms – Random Ensemble Feature Selection

1. INTRODUCTION

The advent of ever improving spectral resolution in satellite data has led to the interest in ensemble classification systems for land cover mapping. Whereas previously research focused on the development and adoption of modern classification techniques e.g. fuzzy classifiers, Support Vector Machines and Artificial Neural Networks, there has of recent been an interest in ensemble approaches whereby the final output is based on a ‘consensus’ of a group of classifiers, otherwise called base classifiers. Ensemble classification systems are premised on the need for diversity between the constituent base classifiers as well as determining the ‘consensus’ rules by which the base classifier outputs are to be combined [1], [2]. Ensemble feature selection is a unique approach to ensemble classification whereby diversity is imposed by using base classifiers with different band combinations [1]. Traditionally, diversity in ensemble systems is ensured using different classifiers or constituting base classifiers by training a classifier with different training data e.g. in boosting and bagging [1]. Varying the feature subsets used to generate the ensemble classifier similarly ensures diversity since the base classifiers tend to err in different

subspaces of the feature space [3]. Of the available ‘consensus’ rules, majority voting was used in this research in all classification outputs, principally due to its simplicity [4]. Other consensus rules include: weighted majority voting [3] or more sophisticated methods like consensus theory [5] and stacking [6].

In random ensemble feature selection, the base classifiers are constituted by randomly selecting the bands [7]. Random ensemble feature selection has been seen to yield comparable results with standard feature selection techniques such as genetic algorithms [1] and exhaustive search methods [7]. This research seeks to further the understanding of random ensemble feature selection by investigating if and/or how the size of ensemble influences the consequent classification accuracies, with particular reference to land cover mapping.

2. METHODOLOGY

The online hyperspectral Indiana Pines dataset sourced from the AVIRIS sensor was used in this research. It is a freely accessible online dataset which comes with accompanying ground truth data. 180 of the 224 bands were used, 4 were discarded because they contained zeros and the remaining 20 bands were left out due to atmospheric distortion [8]. The classes in this dataset included: alfalfa, corn-notill, corn-minimum till, corn, grass/pasture, grass/trees, grass/pasture-mowed, hay-windrowed, oats, soybeans-notill, soybeans-minimum till, soybean-clean, wheat, woods, building-grass-tree-drives, stone-steel towers. Training data for the mentioned classes were selected in reference to the provided ground truth data.

Image classification was effected through the use of Support Vector Machines (SVMs). SVMs are a supervised classification technique that has its roots in Statistical Learning Theory. They basically operate by placing a linear discriminant between two given classes of interest. Remote sensing data is rarely linearly separable and SVMs counter this by nonlinearly projecting the data to a very high dimension space where the previously nonlinearly separable data becomes separable. Placing a linear discriminant in this

very high dimension has the same effect of placing a nonlinear discriminant in the previous space. Polynomial, Gaussian and Sigmoid functions may be used to project the data to the high dimension space. In this research, Gaussian SVMs were used. SVMs are primarily binary classifiers, however there exist techniques to adopt them to the multiple classes encountered in remote sensing. In this research, the one against one approach was adopted. A more detailed treatise of SVMs can be found in [9].

Two approaches were used to investigate the effect of ensemble size on classification accuracy. In the first case classification accuracy was related to increasing numbers of features per base classifier and in the second case accuracy was related to increasing the number of base classifiers per ensemble. A total of seven ensembles was constituted with increasing numbers of features per base classifier. For each collection of base classifiers, the first ensemble had two features per base classifier while the last one had 14 features per base classifier. Table 1 shows the variation in the overall classification accuracy as the number of features per base classifier was increased from 2, in multiples of 2 to 14. Similarly, for each ensemble, base classifiers were cumulatively added and increased from the initial 3 base classifiers per ensemble to 10 base classifiers per ensemble. In all cases the features were randomly selected.

3. RESULTS AND DISCUSSIONS

Figure 1 is an extract from Table 1 and graphically illustrates the variation in overall classification accuracy as the ensemble size is increased. It presents the plotting of classification accuracy against increasing number of features (bands) per base classifiers, as the number of base classifiers per ensemble is increased i.e. B3 – B10. From Table 1 and Figure 1 the results show that in general, across all base classifiers, there is a significant improvement in classification accuracy as the number of features (bands) per base classifier increases. This could be due to the fact that given the high number of classes, 16 classes in this case, more features were needed to appropriately separate the classes. Furthermore, from Figure 1 it can be observed that the ensemble classification accuracy increases as the number features per ensemble increases, until a point beyond which the classification accuracy seems to peak. This could be attributed to Hughes phenomenon [10], which postulates that in the presence of a limited training sample size, contrary to intuition, the mean accuracy does not always increase with additional measurements. Rather it exhibits a peaking effect, i.e. the accuracy will increase until a certain point beyond which increase in additional measurement will yield no significant improvement in classification accuracy [11]. From these results, for this dataset, the optimum number of features (bands) per base classifier is 8, since beyond this number of base classifiers there is a peaking effect.

On the other hand, whereas there were few instances where incrementally adding base classifiers to the ensemble significantly improved the classification accuracy, the general trend was that there was no significant improvement in overall accuracy as the number of base classifiers increased. This is especially apparent in Figure 1 whereby as the number of base classifiers per ensemble increases the variation in overall accuracy between the ensembles with increasing base classifiers diminishes. In effect, the smaller the number of features per base classifier, the bigger the variation in classification accuracy as the number of base classifiers in increased. This variation evidently reduces as the number of features per base classifier is increased.

These results principally inform us that in the design of ensemble feature selection classification systems, increasing the number of base classifiers may not necessarily translate into improved ensemble classification accuracies. In which case, the minimum possible number of base classifiers will suffice.

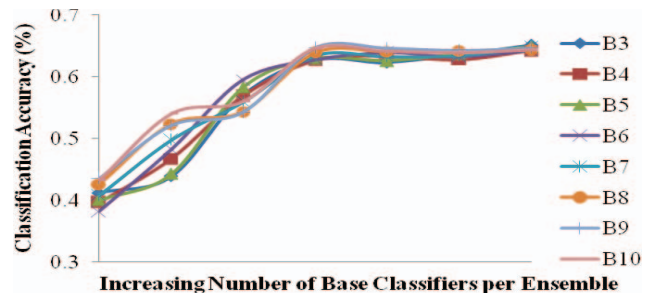


Figure 1: Graphical illustration of classification accuracy as number of base classifiers per ensemble is increased

In summary, random ensemble feature selection provides an adequate means of developing ensemble systems for land cover classification of hyperspectral data. In the design of ensemble feature selection systems, however, ensemble size is important. Classification accuracy evidently increases more as the number of features per base classifier increases than as the number of base classifiers increases. That said however, classification accuracy will only increase with additional features up to a given limit beyond which increasing the number of features per base classifier does not translate into significantly increasing classification accuracy.

Table 1: Summary of Classification Accuracy

Number of Base Classifiers	Number of Features Per Base Classifier						
	2	4	6	8	10	12	14
3	0.412	0.438	0.570	0.627	0.623	0.636	0.651
4	0.396	0.467	0.569	0.626	0.633	0.627	0.642
5	0.400	0.442	0.582	0.629	0.625	0.637	0.649
6	0.382	0.483	0.595	0.627	0.639	0.632	0.642
7	0.407	0.497	0.559	0.634	0.632	0.634	0.648
8	0.426	0.523	0.543	0.639	0.641	0.642	0.643
9	0.435	0.521	0.542	0.646	0.645	0.642	0.646
10	0.433	0.540	0.560	0.645	0.641	0.639	0.643

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