Weighted Decision Fusion for Supervised and Unsupervised Hyperspectral Image Classification

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Many studies have been undertaken to develop and analyze the combination of results from different classifiers for a better result than using each individual classifier [1-2]. Most decision fusion approaches mainly focus on supervised classifiers as base learner, i.e., all classifiers need training, so the classification results can only be as good as training data. To avoid the possible negative influence from the limited quality of training data, it is motivated to propose a method that can combine supervised and unsupervised classifiers.

In general, a supervised classifier can provide better classification than an unsupervised classifier. In addition to training data limitation, a supervised classifier may result in over-classification for some homogeneous areas. An unsupervised classifier, although it may be less powerful, it can generally well classify those spectrally homogeneous areas. Thus, fusing supervised and unsupervised classification may yield better performance since the impact from trivial spectral variations may be alleviated and the subtle difference between spectrally similar pixels may not be exaggerated. Although individual classifiers are pixel-based, the final fused classification has a similar result to an object-based classifier [3]; however, the overall performance using classifier fusion is less sensitive to region segmentation result.

In our previous work, we presented a majority-voting (MV)-based decision fusion for support vector machine (SVM) and Kmeans clustering results, which are typical supervised and unsupervised classifier, respectively [4]. After classification is completed by both classifiers, the Kmeans-based classification is deployed on the SVM-based classification as region segmentation. Spatially adjacent pixels grouped by the Kmeans clustering are re-classified using the majority-voting rule by considering the SVM classification result. In other words, all the pixels in each local segmented region are classified into the same class, which is the class that most pixels belong to using the SVM-based decision. The same idea was independently proposed by other researchers in [5].

In this paper, we will investigate several different unsupervised classification methods and present the performance difference. In particular, we propose a new decision rule, which is Mahalanobis distance-based weighted majority voting (WMV). Its basic idea is that pixels in the same segment should play different roles on the final decision; a pixel with smaller distance to the cluster centriod is more important and should be assigned a high weight, while a pixel more different from the centriod has a low weight. The assigned weight is the inverse of the Mahalanobis distance between the pixel to the centroid. The concept is illustrated in Fig. 1. In Case I, there are two Class I pixels and two Class II pixels in the same cluster; in MV rule, this will come to a draw, and the output can be either Class I or Class II. However, if using the WMV, the total weight for Class I is $\frac{1}{1}+\frac{1}{2}=\frac{3}{2}$, the total weight for Class II is $\frac{1}{3}+\frac{1}{3}=\frac{2}{3}$, and $\frac{3}{2}>\frac{2}{3}$; so the final output of WMV is Class I, which is reasonable. In Case II, there are two Class II pixels and one Class I pixels. The MV rule will give Class II as output, while the WMV rule will get $1>\frac{2}{3}$, resulting in Class I as the final output.

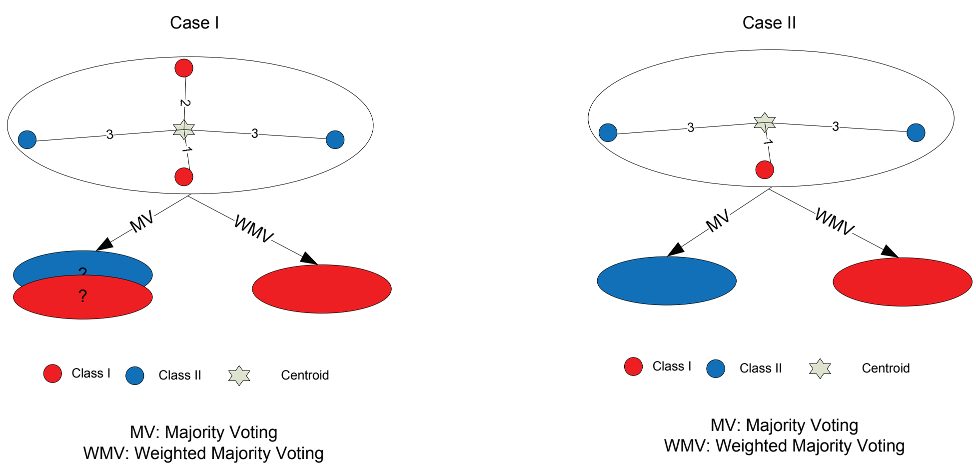


Figure 1: Majority Voting Rule versus Weighted Voting Rule.

The hyperspectral data used in the experiments was taken by the airborne Hyperspectral Digital Imagery Collection Experiment (HYDICE) sensor. It was collected for the Mall in Washington, DC with 210 bands covering 0.4-2.4 μm spectral region with approximately 2.8m spatial resolution. The water-absorption bands were deleted, resulting in 191 bands. The original image was cropped into a subimage with 266 × 304 pixels as shown in Fig. 2 in pseducolor. It includes seven classes: {road, grass, water, shadow, trail, tree, roof}. The test set has 418 samples and the training set 5516 samples. Fig. 3(a) shows the classification result using SVM. Compared with Fig. 2, we can see that there are some misclassifications among roof, trail, and road pixels as well as among shadow, road, and water pixels. Fig. 3(b) is the Kmeans classification map, containing obvious misclassifications between roof and trail and between shadow and water pixels. However, the Kmeans output consists of larger homogeneous areas. Fig. 3(c) is the MV-based fused decision, where the improvement in roof regions was significant. However, the trail area around the water pond was misclassified. This area was corrected in Fig. 3(d) using WMV. In addition, the pixels in blue, which were shade pixels being misclassified into water in Fig. 3(c), were also corrected in Fig. 3(d). Table I lists the classification results from eight unsupervised methods in fusion with SVM, where Kmeans (L1), fuzzy Kmeans, and ISODATA are among the best three methods. Using WMV, the classification performance was improved in most cases compared to MV.

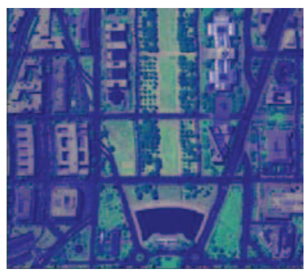
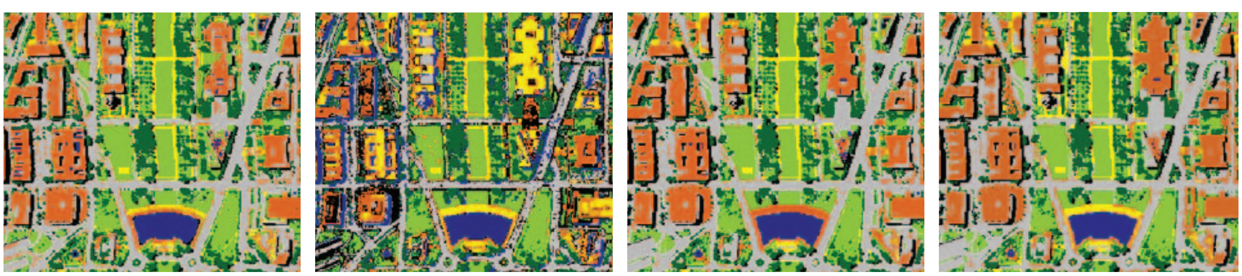


Figure 2: A subimage used in the experiment.



(a) SVM (b) Kmeans (L1) (c)SVM+Kmeans (MV) (d) SVM+Kmeans (WMV)

Figure 3: Classification results using SVM+Kmeans (with similarity metric L1).

In conclusion, we propose a weighted decision fusion approach for supervised and unsupervised classifiers. The final output can take advantage of the power of the SVM-based classification in class separation and the capability of a unsupervised classifier in reducing the impact from intraclass variations in spectrally homogeneous regions. This approach improves the performance of the MV decision rule. The final output is also dependent on the unsupervised classifier selected. Kmeans (L1), fuzzy Kmeans, and ISODATA are robust, while Kmeans (L2) may not be a good choice since it may be too sensitive to the change of the norm of a pixel vector.

TABLE I

CLASSIFICATION PERFORMANCE BEFORE AND AFTER DECISION FUSION

	AA		OA		Kappa	
SVM	93.36%		94.00%		92.74%	
	MV	WMV	MV	WMV	MV	WMV
SVM+Kmeans (L1)	**94.42**	**<u>97.17</u>**	**95.59**	**<u>97.92</u>**	**94.66**	**<u>97.47</u>**
SVM+Kmeans (L2)	86.93	85.08	91.93	89.87	90.17	87.67
SVM+Kmeans (CC)	92.03	**92.42**	93.02	**93.84**	91.54	**92.53**
SVM+Kmeans (SA)	91.65	**91.85**	92.53	**93.17**	90.95	**91.72**
SVM+Fuzzy Kmeans	**94.45**	**<u>96.95</u>**	**95.70**	**<u>97.48</u>**	**94.79**	**<u>96.95</u>**
SVM+ISODATA	**96.30**	**<u>96.60</u>**	**97.26**	**<u>97.66</u>**	**96.69**	**<u>97.16</u>**
SVM+GMM	**93.89**	**94.87**	**94.38**	**96.05**	**93.21**	**95.22**
SVM+Mean-Shift	**94.45**	**94.53**	**96.08**	95.98	**95.26**	95.12

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