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MULTIPLE EXPOSURE FUSION FOR HDR IMAGE ACQUISITION

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ABSTRACT: -Combination of results from supervised and unsupervised classifiers is used to propose "A Decision Fusion Approach". In these the final output takes advantage of the power of a support Vector machine based supervised classification in class separation and also the capability of the unsupervised K-means classifier in reducing spectral variation impact in Homogeneous regions. Decision fusion approach adopts the majority voting rule and can achieve the same objective of object-based classification.
Index Terms — Classification, decision level fusion, hyper spectral imagery

1. INTRODUCTION

As the classification accuracy of individual classifiers cannot be beyond their limitations, many studies have been undertaken to develop and analyze the way to combining results from different classifiers for a better result than using each and every individual classifier [1]. Unlike feature level fusion that extracts features and combines them to improve performance, level of decision fusion adopts a rule to combine the results of individual classifiers to achieve the final decision. Most researchers apply decision level fusion to satellite image classification [2-6]. In a [2], on a support vector machine (SVM) based fusion method was used for multisource satellite image classification. Technique utilizing both feature and decision level fusion capabilities were proposed in [3]. In this [4] method was developed to evaluate the effect of combination schemes. Neural network based classifier fusion was proposed in [5]. And [6] suggested several voting schemes to be employed in decision level fusion. The most decision fusion approaches mainly focus on supervised classifiers as base learner, i.e., all classifiers need training and also the classification results can only be as good as training data. On to avoid the possible negative influence from the limited quality of training data, we are motivated to proposed a method which can combine supervised and
unsupervised classifiers. For in general, a supervised classifier can provide better
classification than an unsupervised classifier. In the addition to training data limitation, a supervised classifier may result in the over-classification for some homogeneous areas. An
unsupervised classifier, although it may be less powerful and it can generally well classify those spectrally homogeneous areas. Thus for fusing supervised and unsupervised classification may yield better performance since the impact for 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 [7-9]; however, the overall impact/performance using supervised and unsupervised classifier fusion is less sensitive to region segmentation result.

2. METHODOLOGY

In this paper, the supervised classifier is SVM and the unsupervised classifier is K-means clustering. Fig. 1 shows the simple diagram of the proposed decision level fusion.

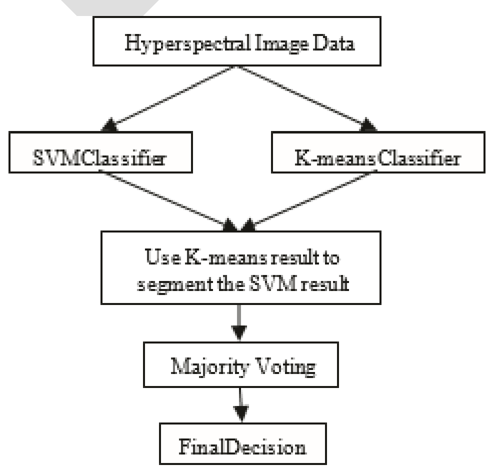

Figure 1. The diagram for the proposed decision fusion for supervised and unsupervised classifiers.

After classifications results are completed from both classifiers, the K-means based classifications has been deployed on the SVM based classification as region segmentation. Spatially adjacent pixels grouped by the K-means classifier are re-classified using the majority voting rule by considering the SVM classification result. In other words, all the pixels in each segmented region are classified into the same class, which is the class that most pixels belong to using the SVM based decision.

K-means clustering can be conducted with different similarity metrics, such as L_2 norm (Euclidean distance), L_1 norm, spectral angle (SA), or spectral correlation coefficient (CC). From the experimental result, it seems that L_2 norm is not a good choice since it may be too sensitive to the absolute spectral difference. The K-means clustering can also be initiated using the prior information, including the number of classes and their sample means.

3. *EXPERIMENTS*

The hyper spectral data used in the experiments was taken by the airborne hyper spectral 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. The water-absorption bands were deleted, resulting in 191 bands. The original data has 1280×307
Pixels.

A. *Test 1 Experiment*

The original image was cropped into a sub image of size 304 × 301 pixels. The image in pseudo color is shown in Fig. 2, which includes six classes: {road, grass, shadow, trail, tree, roof}. Fig. 3 illustrates the location of training and test samples, and the number of samples for every class is listed in Table I.
Fig. 4(a) shows the classification result from SVM. Compared with Fig. 2, also there were some misclassifications in roof, trail, and road pixels. Fig. 4(b) is the K means classification map using L1 norm as the similarity metric, where the misclassifications between roof and trail were obvious. Fig. 4(c) is the combined decision, where the roof areas became smoother and many roof pixels misclassified to trail or road before were corrected.

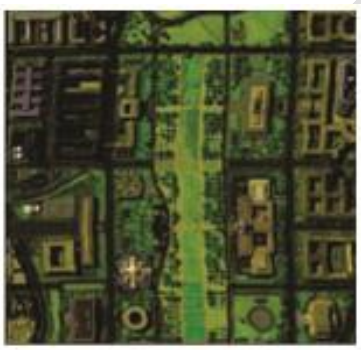

Figure 2. Test 1 image.

TABLE I

NUMBER OF TRAINING AND TEST SAMPLE FOR TEST 1 EXPERIMENT

	Training	Test
Road	55	892
Grass	57	906
Shadow	50	539
Trail	46	578
Tree	49	630
Roof	69	1500

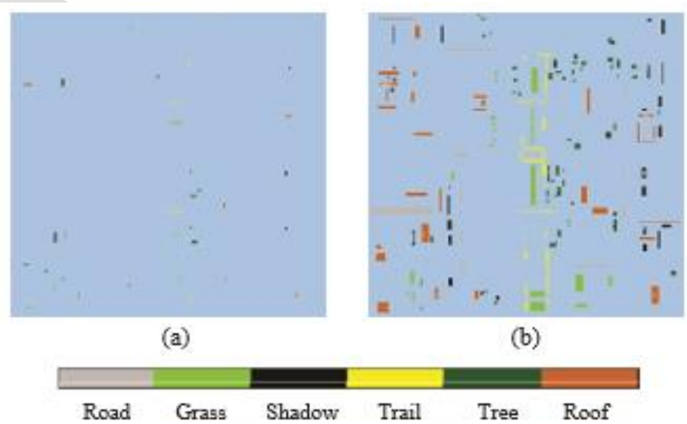

Figure 3. (a) Training and (b) test samples used in Test 1 experiment.

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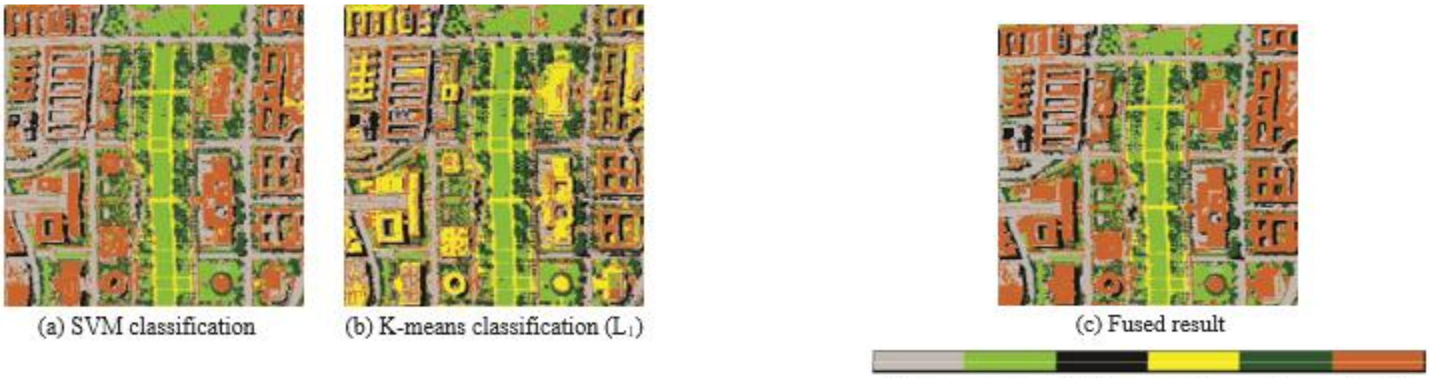

(a) SVM classification (b) K-means classification (L_1) (c) Fused result

Figure 4. Classification results for Test 1 data.

Table II lists the overall accuracy (OA) and Kappa coefficient for different cases. The original SVM produced 92.86% OA and 0.9177 Kappa values. If fused with K means clustering with L_2 norm as similarity metric, these values were slightly improved. If the similarity metric was changed to L_1 norm, SA, or CC, then the improvement was more significant. Using L_1 norm the result was the best.

TABLE II
CLASSIFICATION ACCURACY USING DIFFERENT SIMILARITYS METRICS FOR K-MEANS CLUSTERING IN TEST1 EXPERIMENT

	OA	Kappa
SVM	92.86%	0.9177
SVM + K means (L_2)	93.44%	0.9185
SVM + K means (L_1)	96.71%	0.9593
SVM + K means (SA)	95.88%	0.9491
SVM + K means (CC)	96.47%	0.9564

B. Test 2 Experiment

The original image was cropped into Test 2 data with 266 × 304 pixels as shown in the Fig. 5 in pseudo color. It also includes seven classes: {road, grass, water, shadow, trail, tree, roof}. Fig. 6 illustrates location of training and test samples. The number of sample in each class is listed in Table III.

Figure 5. Test 2 image.

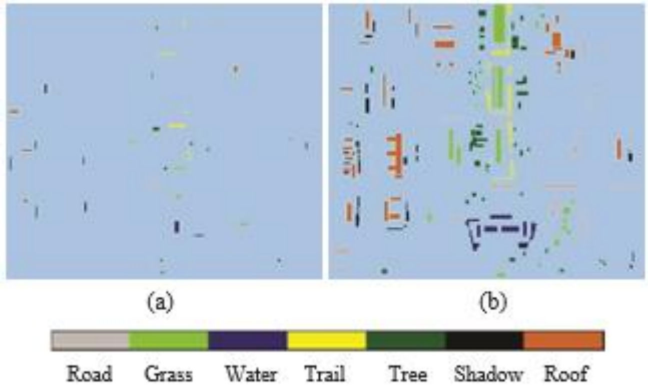

Figure 6. () a Trae in ng and (b) test samples used in Test 2 experiment.

Fig. 7(a) shows the classification result using SVM. Compared with Fig. 5, we can see that there are some misclassifications among roof, trail, and road pixels as well as among shadow, road, and water pixels. Fig. 7(b) is the K means classification map using L_1 norm as the similarity metric, where the misclassifications between roof and trail were obvious; there were also lots of misclassified shadow and water pixels. Fig. 7(c) is the fused decision, where the improvement as in roof regions was significant.

TABLE III

NUMBER OF TRAINING AND TEST SAMPLES FOR TEST 2 EXPERIMENT

	Training	Test
Road	63	1074
Grass	62	1071
Water	53	449
Trail	59	354
Tree	60	693
Shadow	61	413
Roof	60	1280

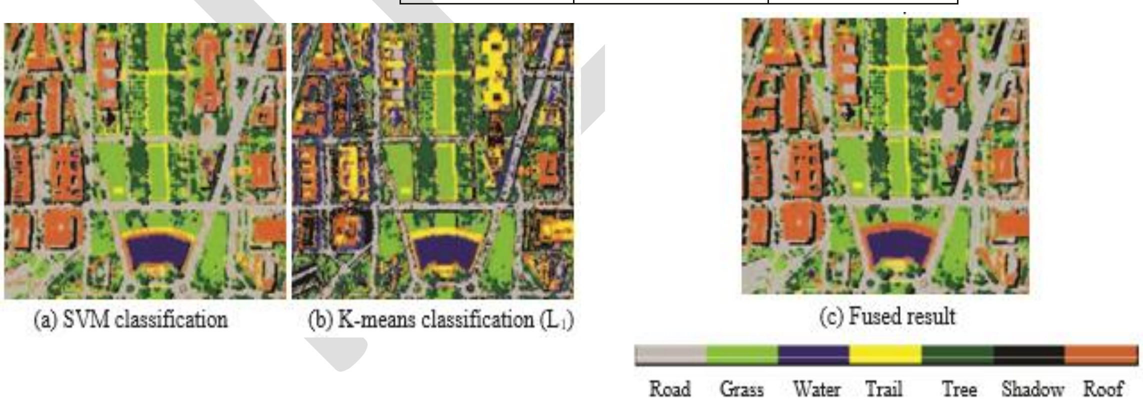

Figure 7. Classification results for Test 2 data.

TABLE IV

CLASSIFICATION ACCURACY USING DIFFERENT SIMILARITY METRICS FOR K-MEANS CLUSTERING IN TEST2 EXPERIMENT

	OA	Kappa
SVM	95.58%	0.9465
SVM + K means (L_2)	92.69%	0.9108
SVM + K means (L_1)	98.33%	0.9798
SVM + K means (SA)	95.97%	0.9512
SVM + K means (CC)	96.03%	0.9519

Table IV list the OA and Kappa coefficient in different cases. If fused with K-means clustering using L1 norm as similarity metric and the OA was improved from 95.88% to 98.33% and Kappa value was from 0.9465 to 0.9798. If the similarity metric was SA or CC, there was some improvements. However, if it is using L2 norm, the result was degraded. To carefully investigate the reason of performance degradation using L2 norm, Tables V and VI list the confusion matrices before and after the fusion using the L2 norm based K-means clustering. Actually, all the class-pair separation was improved except the road and shadow class separation was worsened, resulting in the degradation on average. In this image scene, these are two classes are very difficult to be separated, in a particular when using L2 norm. Table VII list the confusion matrix with L1 norm, where the separation of the shadow-road pair was slightly improved, thereby overall improvement was significant.

TABLE V

CONFUSION MATRIX USING SVM IN TEST2 EXPERIMENT

	Road	Gras	Wate	Trail	Tree	Shado	Roof
Road	1036	0	9	0	0	50	16
Grass	0	1069	0	1	2	0	60
Water	0	0	400	0	0	0	13
Trail	1	0	0	353	0	0	5
Tree	0	2	0	0	691	0	0
Shado	0	0	40	0	0	363	0
Roof	37	0	0	0	0	0	1186

TABLE VI

CONFUSION MATRIX USING SVM AND K-MEANS CLUSTERING WITH

L_2 NORM IN TEST2 EXPERIMENT

	Road	Gras	Wate	Trail	Tree	Shado	Roof
Road	1066	0	0	0	0	342	14
Grass	0	1070	0	0	2	0	16
Water	0	0	449	0	0	0	2
Trail	0	0	0	354	0	0	5
Tree	0	1	0	0	691	0	0
Shado	0	0	0	0	0	71	0
Roof	8	0	0	0	0	0	1243

TABLE VII

CONFUSION MATRIX USING SVM AND K-MEANS CLUSTERING WITH

L_1 NORM IN TEST2 EXPERIMENT

	Road	Gras	Wate	Trail	Tree	Shado	Roof
Road	106	0	10	0	0	48	6
Grass	0	107	0	0	3	0	0
Water	0	0	437	0	0	0	4
Trail	2	0	0	354	0	0	4
Tree	0	1	0	0	690	0	0
Shado	4	0	2	0	0	365	0
Roof	5	0	0	0	0	0	126

4. ***CONCLUSION***

In this paper, we propose a final 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 the K means classifier in minimizing the impact from spectral variations in homogeneous regions. This approach simply adopts the majority voting rule, but can achieve the similar objective of object-based classification. From the preliminary results, it seems that L1 norm is the best metric to be employed for K-means clustering. Currently, no spatial information is considered for classification. For images with high spatial resolution, incorporating spatial features during classification and fusion may further improve classification accuracy. This is the future work to be conducted.

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