

A Novel Multiple-Kernel Learning Based Hyperspectral Imagery Analysis

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Abstract:

This paper presents a novel and efficient spectral-spatial classification method for hyperspectral images. It combines the spectral and texture features to improve the classification accuracy. The moment invariants are computed within a small window centered at the pixel to determine pixel-wise texture features. The texture and spectral features are concatenated to form a joint feature vector that is used for classification with support vector machine (SVM). The experiments are carried out on three hyperspectral datasets and results are compared with some other spectral-spatial techniques. The results indicate that the proposed method statistically significantly improved the classification accuracies over the conventional spectral method. The new method has also outperformed the other recently used spectral-spatial methods in terms of both classification accuracies and computational cost. The results also showed that the proposed method can produce good classification accuracy with smaller training sets.

Index Terms:

Classification, hyper Spectral imaging, moment invariants, spectral-spatial, support vector machine (SVM), texture.

I.INTRODUCTION:

SEMANTIC classification is an important image analysis task having application in agricultural monitoring, hydrological science, environmental studies, military applications, urban planning, etc. Hyperspectral sensors capture an image in tens or hundreds of fine contiguous spectral bands from ultraviolet to infrared region.

The rich spectral information can be helpful for better discrimination of the surface material, and objects of interest. The conventional pixel-wise classifiers that use spectral features only often produce noisy classified maps. In remotely sensed images, the spatial context of a pixel can provide additional information as neighboring pixels are highly correlated and likely to have same label. By integrating spectral and complementary spatial information, more accurate results can be obtained. The spatial feature extraction involves determining information about shape, size, co-occurrence, texture, etc., from a crisp or adaptive neighborhood. The major approaches are based on Markov random field (MRF), Gabor filters, mathematical morphological operators, wavelet decomposition, etc. The high dimensionality poses the major challenge to the spatial feature extraction. The traditional two-dimensional (2-D) approaches need to adapt to three-dimensional (3-D) structure of the hyperspectral imagery.

A number of methods have been proposed to extract spatial features based on contextual information. In Benediktsson et al. used extended morphological profiles (EMPs) to model structural information. EMPs have both spectral and spatial contents. EMP approach is also explored in different ways to significantly improve the accuracy. References investigated attribute profiles (APs), which are an extension of MPs and can model different structural information. In 3-D discrete wavelet transform (DWT) was applied for spectral-spatial feature extraction. The 3-D DWT can capture spectral, geometrical, and texture information and is especially good for noisy images. References [6], demonstrated that 3-D Gabor filters can extract

joint spectral and texture features by exploiting scale and orientation properties of hyperspectral data to improve the results. Among postclassification refinement approaches, MRFs have been extensively used. Tarabalka et al. applied MRF relaxation on probabilistic support vector machine (SVM) results to significantly improve the accuracies. MRFs were also considered to embed spatial information in classification. Zhang and Zia modified the conditional random fields (CRFs), which is a generalization model of MRF to reduce the training load and applied it for spectral–spatial classification. Ghamisi et al. [] used hidden MRF, which is a special case of MRF to extract spatial information and combined it with SVM results by majority vote. Segmentation-based techniques are other important approaches to refine spectral classification results.

In watershed segmentation algorithm was extended for hyperspectral images and SVM results were improved by applying majority vote within watershed regions. A different segmentation technique based on minimum spanning forest (MSF) was used and classification map was refined by majority vote within connected components. Some other works based on multiclassifier systems, graph-based learning, and kernel-based approaches are also reported. In this research, we propose a texture-based spectral–spatial supervised classification framework. The main contribution of the work is texture feature computation for hyperspectral images using moment invariants.

II. EXISTING METHOD:

In this paper, a new method for supervised hyperspectral data classification is proposed. In particular, the notion of stochastic minimum spanning forest (MSF) is introduced. For a given hyperspectral image, a pixel wise classification is first performed. From this classification map, M marker maps are generated by randomly selecting pixels and labeling them as markers for the construction of MSFs. The next step consists in building an MSF from each of the M marker maps.

Finally, all the M realizations are aggregated with a maximum vote decision rule in order to build the final classification map. The proposed method is tested on three different data sets of hyperspectral airborne images with different resolutions and contexts. The influences of the number of markers and of the number of realizations M on the results are investigated in experiments. The performance of the proposed method is compared to several classification techniques (both pixelwise and spectral-spatial) using standard quantitative criteria and visual qualitative evaluation. The disadvantages of the existing method are

1. Not Applicable on all satellite based images
2. Less computational cost on high quality images

III. PROPOSED METHOD:

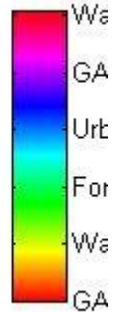
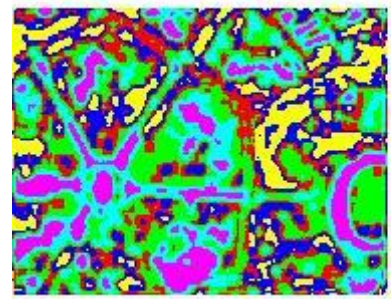
This paper presents a novel and efficient spectral spatial classification method for hyper-spectral images. It combines the spectral and texture features to improve the classification accuracy. The moment invariants are computed within a small window centered at the pixel to determine pixel-wise texture features. The texture and spectral features are concatenated to form a joint feature vector that is used for classification with support vector machine (SVM). The experiments are carried out on three hyperspectral datasets and results are compared with some other spectral–spatial techniques. The results indicate that the proposed method statistically significantly improved the classification accuracies over the conventional spectral method. The new method also outperformed the other recently used spectral–spatial methods in terms of both classification accuracies and computation cost. The results also showed that the proposed method can produce good classification accuracy with smaller training sets. The drawbacks of existing system are overcome in this proposed system.

IV.SIMULATION RESULTS:

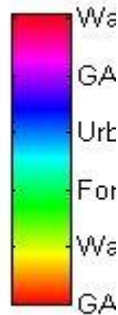
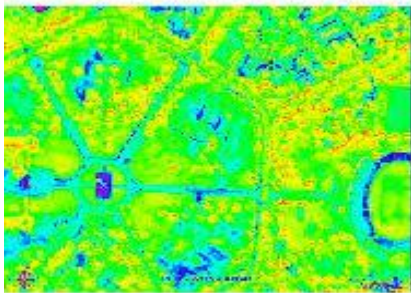
Input Image



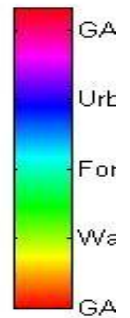
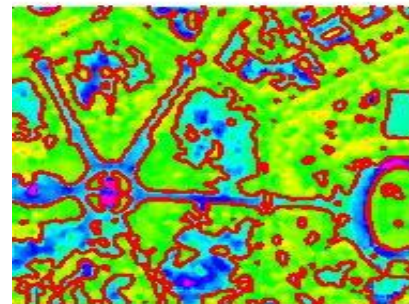
EMP



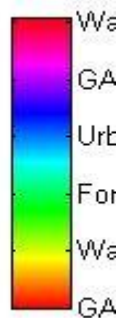
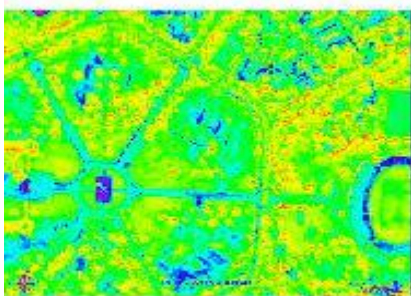
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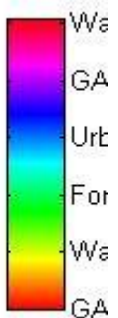
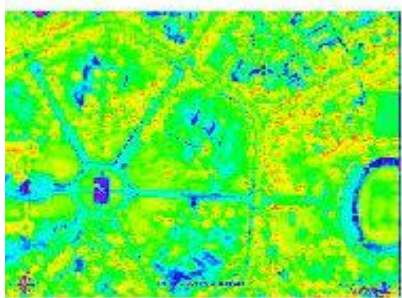
MKL



GLCM



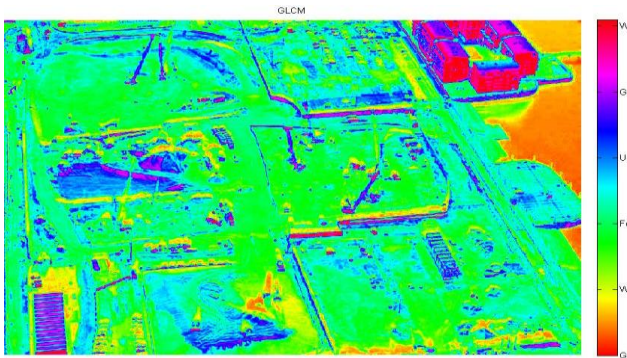
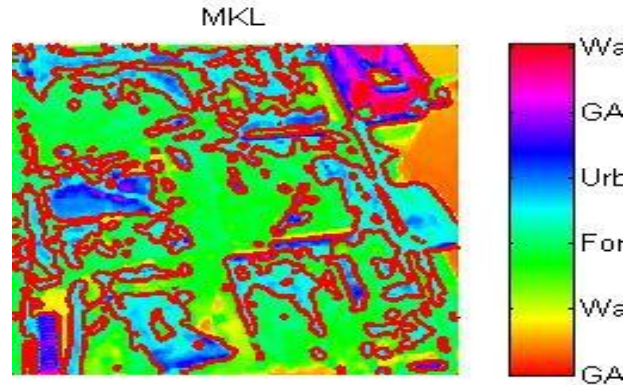
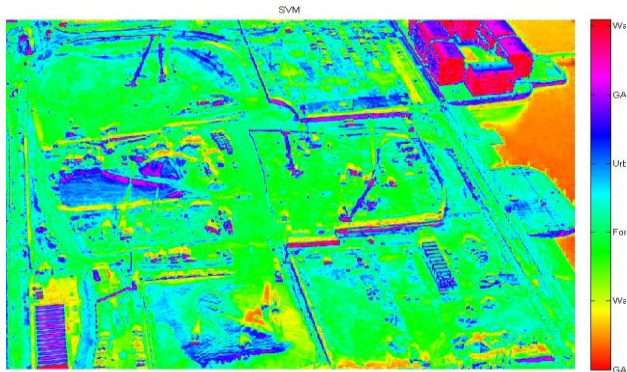
MRF



Method	TPR	FPR	Accuracy	ARI	NMI
EMP+SVM	1.4444	0.1572	90.1995	0.6274	0.0143
MKL	1.4437	0.1569	90.1862	0.6557	0.0757

input image

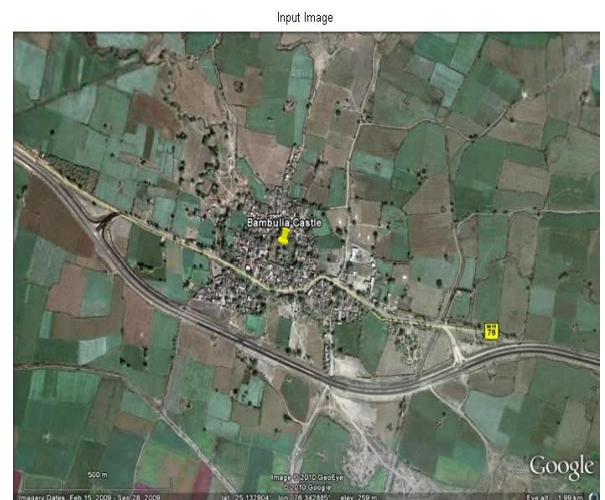
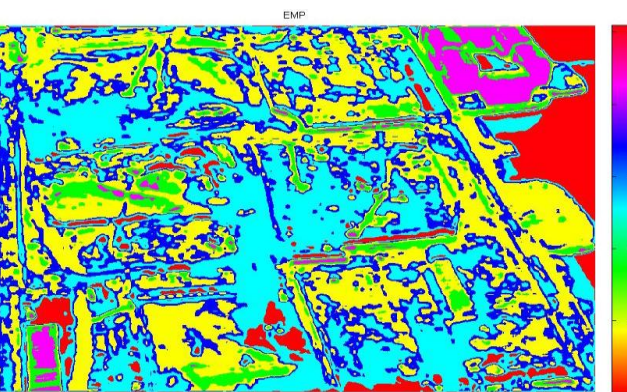
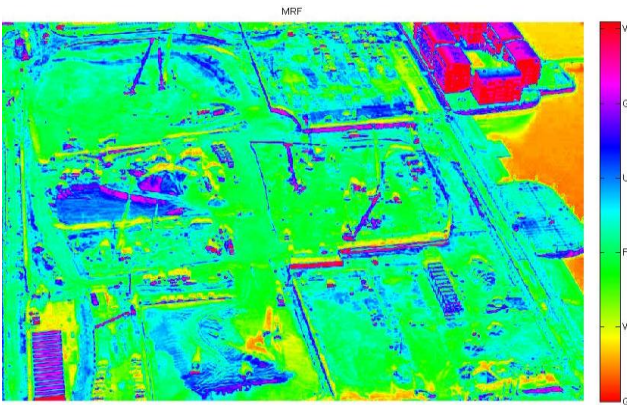


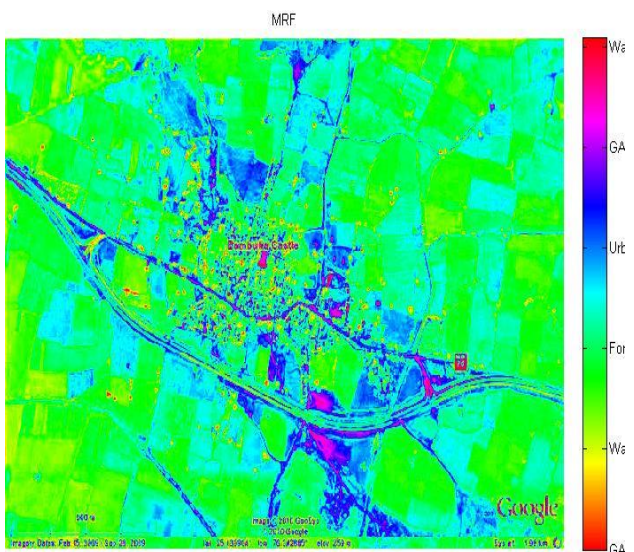
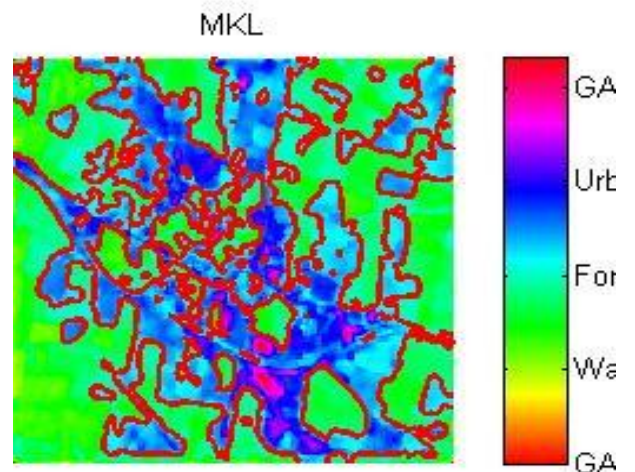
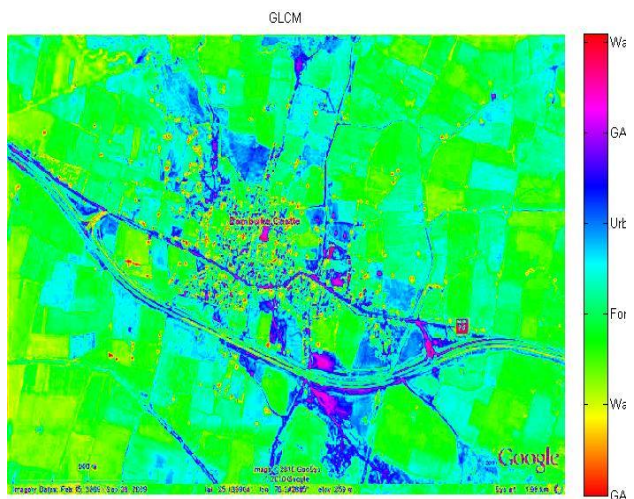
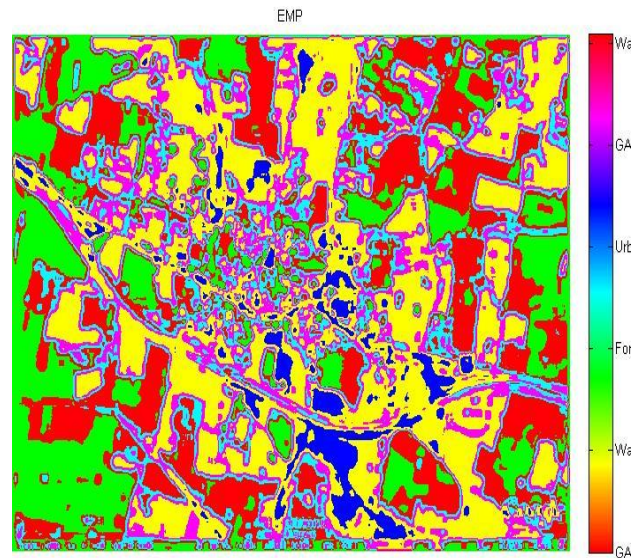
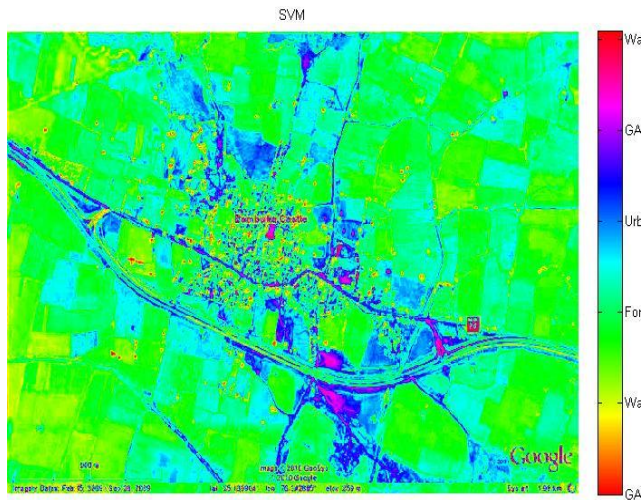


Method	TPR	FPR	Accuracy	ARI	NMI
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EMP+SVM	1.4412	0.1585	90.1812	0.6130	0.1108
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MKL	1.4409	0.1569	90.0915	0.6073	0.0102
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Method	TPR	FPR	Accuracy	ARI	NMI
EMP+SVM	1.4397	0.1584	90.1076	0.6825	0.0254
MKL	1.4402	0.1581	90.0870	0.6934	0.0545

IV. CONCLUSION:

The spatial information is derived from the moment invariants of the image in the form of texture features. The texture features are concatenated with spectral features and classified with SVM. The new method significantly improved the conventional SVM method and outperformed other studied spectral-spatial methods. We have presented a principle way of formulating Multitask Learning as a Multiple Kernel Learning approach. Following the basic idea of task-set-wise decomposition of the kernel matrix, we present a hierarchical decomposition and a power set based approach. These two methods allow us to elegantly identify or refine structure relating the tasks at hand in one global optimization problem. We expect our methods to work particularly well in cases, where edge weights differ within the hierarchical structure or where the task structure is unknown. The global accuracy of more than 99% was achieved for all three images.

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