WAVELET SHRINKAGE DENOISING OF INTRINSIC MODE FUNCTIONS OF HYPERSPECTRAL IMAGE BANDS FOR CLASSIFICATION WITH HIGH ACCURACY

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1. INTRODUCTION

This paper proposes Empirical Mode Decomposition (EMD) followed by wavelet shrinkage denoising in hyperspectral image classification to improve classification accuracy. EMD is a signal decomposition approach proposed for the analysis of nonlinear and non-stationary data [1]. EMD decomposes signals into several Intrinsic Mode Functions (IMFs) and a final residue. The original signal can exactly be reconstructed by adding all corresponding IMFs and the final residue. EMD is originally presented for one-dimensional signals, and then extended to two-dimensional (2D) signals [2]. In 2D-EMD applied to images, the first IMF includes the highest local spatial frequency detail and the second IMF includes the next highest local spatial frequency detail and so on. Each IMF actually contains both low and high spatial frequency detail at different spatial locations, which is a basic feature of EMD [2]. Lower order IMFs capture fast spatial oscillation modes while higher order IMFs typically represent slow spatial oscillation modes. Thus, if 2D-EMD is interpreted as a spatial-scale analysis method, lower-order IMFs and higher-order IMFs correspond to the fine and coarse scales, respectively. Detailed information about EMD is provided in [1, 2]. In [3], 2D-EMD is performed to each hyperspectral image band separately, new bands are reconstructed as the sum of lower order IMFs and classification is carried out using these new bands. It is shown in [3] that 2D-EMD can increase hyperspectral image classification accuracy. In this paper it is proposed to apply wavelet shrinkage denoising [4] to the first IMF obtained in EMD to further increase classification accuracy. In [4], a spatially adaptive Bayesian shrinkage approach, which uses a generalized Laplacian prior, and estimates the probability of a coefficient to contain a noise free component, has been presented for image denoising. This approach has been utilized in this paper for the denoising of the first IMF of each hyperspectral image band. Only the first IMF of each band is applied to wavelet shrinkage denoising, as this IMF includes all local high spatial frequency components and is therefore most suitable for denoising. (Experiments have shown that denoising higher order IMFs does not provide further gain) After denoising the first IMF, the sums of lower order IMFs are used to reconstruct Hyperspectral image bands and are therefore used as new features for classification. Support Vector Machine (SVM) based classification is used as classification approach in this paper. The proposed algorithm can be summarized as follows:

1- Apply 2D-EMD to each hyperspectral image band and obtain IMFs.
2- Apply wavelet shrinkage denoising to the first IMF of each band.
3- Sum lower-order IMFs to reconstruct the new data of each band.
4- Perform SVM classification.

The difference between the approach proposed in this paper and the method presented in [3] is in the additional wavelet shrinkage denoising introduced in the first IMF.

2. EXPERIMENTAL RESULTS

A sample hyperspectral image which is taken over northwest Indiana's Indian Pine test site in June 1992 [5] is used to demonstrate the performance of the proposed approach. Because of space limitations results are presented for a single data set in this abstract, but similar results are obtained for the DC Mall data set and will be included in the full paper. The total number of samples corresponding to each selected class are as follows: Corn-no till 1434 samples, Corn-min till 834 samples, Grass/Pasture 497 samples, Grass/Trees 747 samples, Hay-windrowed 489 samples, Soybean-no till 968 samples, Soybean-min till 2468 samples, Soybean-clean till 614 samples, and Woods 1294 samples (Total of 9345 samples). The classification performances of the proposed approaches are demonstrated using SVM classification with Radial Basis Function (RBF) kernel. In the experiments, the penalty parameter of SVM is set to 40 and the gamma parameter of the RBF kernel is tested between [0.1-2] using a five fold cross validation. The proposed algorithm is compared to direct SVM [6], the EMD based approach proposed in [3] (denoted as 2D-EMD-SVM), wavelet denoising applied without EMD [7] (denoted as WD-SVM) as well as Morphological Profile based classification [8] (denoted as EMP). Classification results are presented with respect to different training data rates (TDR). For example, a TDR of 10% illustrates the case where 10% of the total data samples are used as training data. For both, 2D-EMD-SVM and the proposed algorithm, Table I provides results for the cases where only the first IMF is used (1 IMF), the sum of the first two IMFs is used (2 IMFs), the sum of the first three IMFs is used (3 IMFs) and the sum of the first four IMFs is used (4 IMFs). Note that for bands that have less IMFs than used in the summation, the absent IMFs are taken as zero. In Table II, it is seen that the proposed approach significantly improves classification accuracy. Fig. 1 shows a sample original band of the Indian Pine data with first IMF and denoised first IMF.

3. REFERENCES

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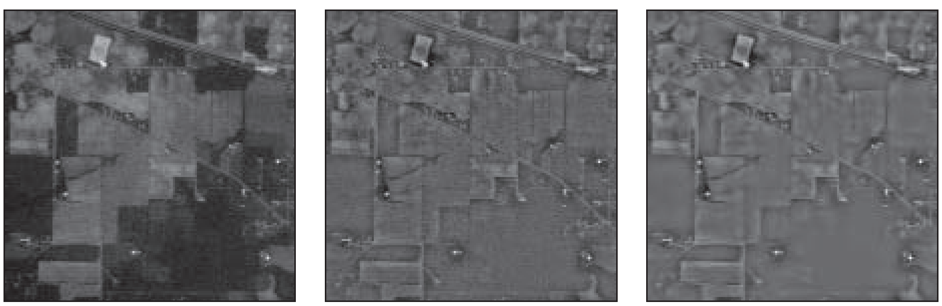

(a) (b) (c)

Fig 1. Indian Pine Image Band # 6: (a) original band (b) First IMF (c) First IMF after wavelet shrinkage denoising.

TABLE I. OVERALL ACCURACY (OA) VALUES OF DIRECT SVM, WD-SVM, EMP, 2D-EMD-SVM AND PROPOSED APPROACH USING 10 % , 20 %, 35 % AND 50 % TDR

Method		10% TDR	20% TDR	35% TDR	50% TDR
		OA	OA	OA	OA
SVM [6]		82.24	88.94	91.47	92.57
WD-SVM [7]		89.04	95.03	96.62	97.90
EMP [8]		94.56	98.90	99.27	99.07
2D-EMD-SVM [3]	1 IMF	73.96	86.95	92.13	94.75
	2 IMFs	94.00	98.39	99.13	99.37
	3 IMFs	92.56	96.64	97.59	97.70
	4 IMFs	92.23	96.52	97.43	97.43
Proposed	1 IMF	93.66	**99.70**	**99.89**	99.95
	2 IMFs	**95.88**	99.33	99.71	**100**
	3 IMFs	92.17	97.21	98.05	98.37
	4 IMFs	91.70	96.88	97.22	97.81