EMPIRICAL MODE DECOMPOSITION PRE-PROCESS FOR HIGHER ACCURACY HYPERSPECTRAL IMAGE CLASSIFICATION

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ABSTRACT

This paper proposes Empirical Mode Decomposition (EMD) based pre-process to increase classification accuracy of hyperspectral images. EMD is an adaptive and non-linear signal decomposition approach and decomposes the data into intrinsic mode functions (IMFs) and a residue. In this paper, EMD is applied to each hyperspectral image band to obtain IMFs. After EMD is performed to each band, new bands are reconstructed as the sum of higher level IMFs and classification is executed over these new bands. Support vector machine (SVM) is used to show the classification performance of the proposed approach. Experimental results show that, utilization of the first two IMFs significantly increases the classification accuracy compared to applying SVM directly to the original data set.

***Index Terms*—** Hyperspectral images, empirical mode decomposition, support vector machine

1. INTRODUCTION

Hyperspectral imaging systems capture a continuous reflectance spectrum for each pixel [1]. Every pixel in the hyperspectral image has data for hundreds of hyperspectral bands, and so it is generally difficult to make use of this large amount of data. For this reason, classification tools are needed to summarize information.

Support vector machine (SVM) based approaches have recently been proposed to classify hyperspectral images. The efficiency of SVM based hyperspectral image classification is shown in [2]. SVM with composite kernels is used in [3] for enhanced classification of hyperspectral images. Hyperspectral image classification using different kernel-based approaches is studied in [4]. Relevance vector machine (RVM) based hyperspectral image classification is presented in [5] and it has been shown that RVM based classification is more suitable for applications that need low-complexity and probably real-time classification.

Empirical Mode Decomposition (EMD) developed by Huang [6], is used in this paper as a pre-process before classification. The EMD is a technique to process nonlinear and nonstationary signals and it is an alternative to the wavelet analysis, and the short–time Fourier transform. The only application of EMD to hyperspectral data so far is reported in [7], where EMD is used as preliminary dimensionality reduction method. EMD is compared to wavelets in terms of fractal dimension estimation of a discrete sample path in [8]. EMD is utilized for denoising in [9]. EMD is used as a pre-process in a face recognition application to remove illumination artifacts in [10]. In [11], residual components of the iris image which are obtained using EMD are selected as features for iris recognition. EMD is used for image compression in [12] and [13].

In this paper it is proposed to apply two-dimensional EMD (2D-EMD) to hyperspectral image bands to increase SVM classification accuracy. The rest of the paper is organized as follows: information about EMD is given in following section; in the third section SVM is briefly presented and experimental results are given in the fourth section, while conclusions are given in the final section.

2. EMPIRICAL MODE DECOMPOSITION

EMD is an adaptive and non-linear signal decomposition approach. While the data is assumed to be stationary and linear in the Fourier Transform, EMD does not make any assumptions about the data and decomposes the data into intrinsic mode functions (IMFs) and a residue. It is shown in the literature that EMD is therefore more successful for non-linear and non-stationary data than Fourier or Wavelet transforms [6]. In EMD, the original signal can be reconstructed without information loss by adding all the IMFs and the residue. All IMFs are nearly orthogonal to each other and satisfy two conditions [6]. The first condition is that the number of zero crossing and the number of extreme points are equal or differ at most by one. The other property is that the mean values of the envelopes defined by the local maxima and the local minima are zero at any point.

Because 2D-EMD is used for hyperspectral image bands in this paper, information about 2D-EMD [12,13] is provided only. The sifting process to find the two-dimensional IMFs of a hyperspectral band ($X(m,n)$) starts from the original band (i.e., $input_{11}(m,n) = X(m,n)$). Here, the first index ($l = 1,2...,L$) denotes the number of the IMF and the second index ($k = 1,2...K$) shows the iteration number. The sifting process can be summarized as follows:

1- Find all points of local maxima and the points of local minima of $input_{lk}$.
2- Create the upper envelope ($e_{\max}(m,n)$) by spline interpolation of the local maxima; and the lower envelope ($e_{\min}(m,n)$) by spline interpolation of the local minima.
3- Calculate the mean of the upper and lower envelopes ($mean_{lk}(m,n) = \left(e_{\max}(m,n) + e_{\min}(m,n)\right)/2$).
4- Subtract the envelope mean from the input signal ($h_{lk}(m,n) = input_{lk}(m,n) - mean_{lk}(m,n)$).
5- Check if the envelope mean signal fulfills the stop criterion. If not the signal resulting from 4 is taken as the input signal ($input_{l(k+1)}(m,n) = h_{lk}(m,n)$) and the process is repeated from step 1. If the stop criterion is met at step $k = K$, the IMF of the current iteration is defined as the last results of step 4 ($IMF_l(m,n) = h_{lK}(m,n)$).
6- The next IMF is found by starting from step 1 using the residue signal (r) as the input signal ($r_l(m,n) = input_{l1}(m,n) - IMF_l(m,n)$).

The process can be completed when the residue does not contain any more extreme points.

3. SUPPORT VECTOR MACHINES

SVMs use a linear separating hyperplane to create a classifier. The training principle of SVM is to find a linear optimal separating hyperplane in the sense of being a maximum margin classifier with respect to training data. In the SVM classification approach, support vectors which are critical for classification are obtained in a learning phase that uses training samples. In the classification (test) phase, class labels are found for new (i.e. unknown) hyperspectral vectors based on support vectors. Detailed information about SVM can be found in [2-4].

Kernel methods are used in SVM when the training data is not linearly separable. Kernel methods are based on mapping data from the original input space to a kernel feature space of higher dimensionality. Better classification results are obtained choosing suitable parameters. Kernel functions which are used in SVM, must satisfy Mercer's condition which requires the kernel to be a continuous symmetric kernel of a positive integral operator. The Radial Basis Function (RBF) kernel is one of the most popular kernels implementing this condition. The RBF kernel is used for results presented in this paper.

4. EXPERIMENTAL RESULTS

A sample hyperspectral image which is taken over northwest Indiana's Indian Pine test site in June 1992 [14] whose ground truth is available, is selected to demonstrate the performance of the proposed approach. The data consists of 145×145 pixels with 220 bands. The number of bands is initially reduced to 200 by removing bands covering water absorption and noisy bands. The original ground truth has actually 16 classes, but some classes have a very small number of elements; and therefore, nine classes that have a higher number of samples have been selected and used to generate 4757 training samples and 4588 test samples which are shown with respect to the corresponding classes in Table I.

TABLE I
NUMBER OF TRAINING AND TEST SAMPLES FOR EACH CLASS OF THE EXPERIMENTAL DATA

Class	Training	Test
C1-Corn-no till	742	692
C2-Corn-min till	442	392
C3-Grass/Pasture	260	237
C4-Grass/Trees	389	358
C5-Hay-windrowed	236	253
C6-Soybean-no till	487	481
C7-Soybean-min till	1245	1223
C8-Soybean-clean till	305	309
C9-Woods	651	643
Total	4757	4588

SVM classification is utilized to show the performance of the proposed algorithms and for this purpose an RBF kernel is used with gamma parameter is selected as 2 and SVM penalty parameter is chosen as 40.

The maximum and minimum extreme points are selected by comparing the candidate data points with their nearest 8 neighbours. Thin plate smoothing spline interpolation, as suggested in [15], is used for the two dimensional interpolation. This method gives a surface with continuous second derivative everywhere and turns out to successfully decompose a hyperspectral band into its IMFs and a smooth residue with no or only a few extrema points [13]. After EMD is performed for each band, new bands are reconstructed as the sum of high level IMFs and the new band data is forwarded to SVM classification.

Table II shows the SVM classification accuracy of direct SVM applied to the original data set, and also SVM classification results with EMD preprocess. For EMD, the table shows results for the cases where only the first IMF (1 IMF) is used, the sum of the first two IMFs (2 IMF) is used, the sum of the first three IMFs (3 IMF) is used and the sum of the first four IMFs (4 IMF) is used. These results are compared to SVM classification with original data. Results show that the highest classification accuracy is obtained for two IMFs, in which case the classification accuracy is increased by more than 6% compared to direct SVM. If one IMFs or three IMFs are used, the classification accuracy is below the value obtained for two IMFs but still higher than direct SVM. It is seen that the utilization of four IMFs gives similar classification accuracy compared to direct SVM.

TABLE II
CLASSIFICATION ACCURACY OF DIRECT SVM AND EMD PREPROCESS SVM

METHOD		AC
SVM		92.67
EMD-SVM	1 IMF	94.63
	2 İMF	**99.49**
	3 İMF	96.94
	4 İMF	92.78

5. CONCLUSION

EMD which decomposes the data into IMFs and a residue is used as a pre-process approach to increase hyperspectral image classification accuracy in this paper. Firstly, EMD is performed to each image band and IMFs are obtained. Then, the sum of higher level IMFs are taken to construct new bands, and SVM classification is carried out using these new bands. It has been shown that, using the first three or four IMFs considerably increases the classification accuracy compared to applying SVM directly to the original data set.

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