EMPIRICAL MODE DECOMPOSITION BASED DECISION FUSION FOR HIGHER HYPERSPECTRAL IMAGE CLASSIFICATION ACCURACY

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1. Introduction

This paper proposes an Empirical Mode Decomposition (EMD) based decision fusion approach to improve hyperspectral image classification accuracy. EMD is a recently proposed adaptive signal decomposition method that iteratively decomposes the data into so called Intrinsic Mode Functions (IMFs), which comprise a finite set of adaptive basis functions [1]. EMD initially extracts the highest local frequencies from a signal (i.e., the first IMF includes the highest local frequencies) and repeats the process using the residue signal to obtain the next highest frequencies at each stage (i.e., second IMF includes the next highest local frequencies). It has been shown in [2] that EMD can be used to improve hyperspectral image classification accuracy. This paper presents a novel decision fusion approach using EMD for hyperspectral image classification and provided experimental results demonstrate that the classification accuracy can even further be increased using the proposed approach.

2. 2D Empirical Mode Decomposition of Hyperspectral Bands

In this paper, two dimensional EMD (2D-EMD) is applied to each hyperspectral image band, individually. 2D-EMD [3] uses an iterative process called sifting to decompose data into IMFs. The algorithm of 2D-EMD, which decomposes the *l*-th hyperspectral image band B_l to its IMFs, is presented in detail as follows. In the algorithm, B_l denotes the *l*-th original hyperspectral image band, $IMF_{l,m}$ shows the values of the *m*-th IMF (or *m*-th order IMF) ($m = 1,2,...,M$) of the *l*-th hyperspectral image band and $I_{l,m}^{(n)}$ shows the present values used in the *n*-th iteration to find the *m*-th IMF of the *l*-th band.

<u>Algorithm: 2D-EMD of Hyperspectral Image Bands</u>

Step1: Initialize the present values used in the first iteration to find the *1*-th IMF as $I_{l,1}^{(1)} = B_l$.

Step2: Find all points of both 2D local maxima and local minima of $I_{l,m}^{(n)}$.

Step3: Create the upper envelope $E_{\max}$ and lower envelope $E_{\min}$ by 2D spline interpolation of local maxima and local minima, respectively.

Step4: Calculate the mean of the upper and lower envelopes with the following equation: $A_m^{(n)} = (E_{\max} + E_{\min})/2$

Step5: Subtract the envelope mean from the input signal: $S_m^{(n)} = I_{l,m}^{(n)} - A_m^{(n)}$

Step6: Check if the envelope mean signal is close to the zero: $\frac{\sum_{i=1}^{P}\sum_{j=1}^{R}\left|A_m^{(n)}(i,j)\right|}{P\times R}<\tau$

where *P* and *R* are the dimensions of $A_m^{(n)}$ and τ is a small threshold. If the envelope mean signal is close to zero, the stop criterion is fulfilled (assume at step $n = N$) and the current IMF is obtained as $IMF_{l,m} = S_m^{(N)}$. Otherwise, the next iteration is started from *Step2* with $I_{l,m}^{(n+1)} = S_m^{(n)}$.

Step7: Compute the residue signal R_m as $R_m = I_{l,m}^{(n)} - IMF_{l,m}$.

If the residue does not contain any more extreme points the EMD process is stopped. Otherwise, the next IMF is obtained starting from *Step2* using the current residue as the next input, i.e. $I_{l,m+1}^{(1)} = R_m$.

The original hyperspectral image band B_l is actually equal to the sum of all corresponding IMFs and the final residue (i.e., $B_l = \sum_{m=1}^{M} IMF_{l,m} + R_M$). The properties of IMFs can be summarized as: i) the lowest order IMF (i.e., the first IMF) includes the highest local spatial frequency detail, ii) both lower order and higher order IMFs can have low and high spatial frequency detail at different spatial locations depending on data. and iii) lower order IMFs capture fast spatial oscillation modes while higher order IMFs typically represent slow spatial oscillation modes [1] (therefore, if 2D-EMD is interpreted as a spatial-scale analysis method, lower-order IMFs and higher-order IMFs are related to the fine and coarse scales, respectively).

3. Decision Fusion using EMD

The aim of this paper is to fuse the decisions of different data representations: i) the first IMF (IMF_1), ii) the second IMF (IMF_2), iii) the sum of the first and second IMFs ($IMF_1 + IMF_2$) and iv) the original data (without EMD) in order to increase the overall SVM classification accuracy obtained using only the original data. Firstly, 2D-EMD is applied to each hyperspectral image band to obtain IMFs and the abovementioned data representations are evaluated. Then the utilized data representation is used in classification with SVM [4] adopting the one against all (OAA) strategy for multiclass problems. The OAA strategy splits the problem into *n* SVMs for *n* class problems and each SVM solves a two-class problem defined by one class against all the others [3]. In OAA, each test sample is assigned to the class which gets the highest distance to the hyperplane. In this paper, the maximum distance values for each data representation are evaluated for each test sample, and decision fusion is achieved by assigning the sample to the class which provides the largest distance value. As an example, in order to fuse the classification results of IMF_1 and IMF_2, the maximum distance $f(\mathbf{x})_{IMF1}$ obtained using IMF_1 and the maximum distance $f(\mathbf{x})_{IMF2}$ obtained using IMF_2 are evaluated and the final decision is given by assigning the sample $\mathbf{x}$ to the class which provides the highest distance (i.e., max $\boldsymbol{f}(\mathbf{x})_{IMF1}, f(\mathbf{x})_{IMF2})$). Results show that proposed approach provides superior classification performance compared to standard SVM and the best result is obtained in case of fusing the classification results of IMF_2 and $IMF_1 + IMF_2$.

4. Experimental Results

The Indian Pine hyperspectral image [5], which consists of 145×145 pixels with 220 bands, is used in the experimental results presented in this paper. The number of bands is initially reduced to 200 by removing bands covering water absorption and noise. The classes and the related number of samples used in the experiments are shown in Table I. In this case 10% of the total data samples are used as training data and the rest is used for testing data. In the experiments, an SVM classifier with RBF kernel was used. Table II reports the overall accuracies of SVM obtained using different data representations: i) original data set, ii) IMF_1, iii) IMF_2, and iv) $IMF_1 + IMF_2$. Fig. 1 shows the IMF_1, IMF_2 and $IMF_1 + IMF_2$ images for a sample band of the Indian Pine data together with the original band. In Table II, one can observe that IMF_2 and $IMF_1 + IMF_2$ provide the best two classification performances individually. The focus of this paper is to improve these already good accuracies with the proposed decision fusion approach. Table III reports the fused classification results of the abovementioned data representations. In this table, the data representations whose classification results are included in the fusing step are explicitly shown. From the table, one can observe that standard SVM classification performance is significantly improved by the proposed fusing approach and the best result is obtained by fusing the classification results of IMF_2 and $IMF_1 + IMF_2$.

5. Acknowledgements

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6. References

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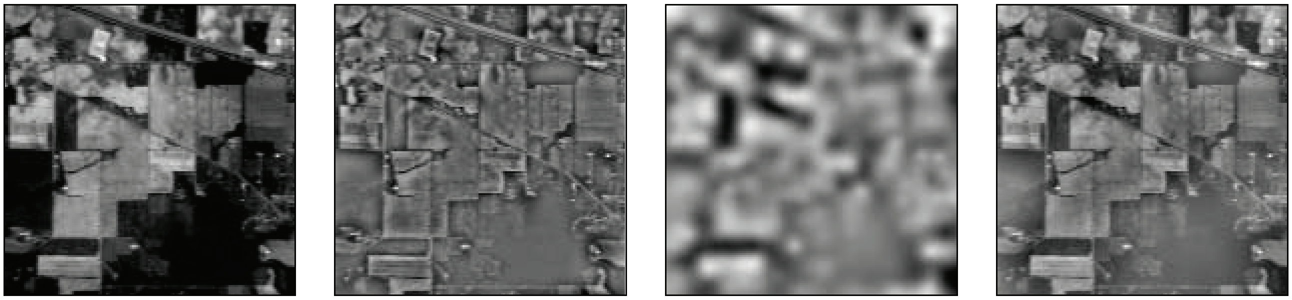

(a) (b) (c) (d)

Fig 1. Indian Pine Image Band #28: (a) original band (b) first IMF (c) second IMF (d) sum of first and second IMFs

TABLE I
NUMBER OF SAMPLES (NOS) FOR EACH CLASS OF THE INDIAN PINE DATA

Class	NoS
Corn-no till	1434
Corn-min till	834
Grass/Pasture	497
Grass/Trees	747
Hay-windrowed	489
Soybean-no till	968
Soybean-min till	2468
Soybean-clean till	614
Woods	1294
Total	9345

TABLE II
SVM OVERALL ACCURACY (OA) VALUES OBTAINED USING DIFFERENT DATA REPRESENTATIONS

Feature Representations	OA
Original Data	82.80
IMF_1	77.68
IMF_2	95.75
$IMF_1 + IMF_2$	94.27

TABLE III
OVERALL ACCURACY (OA) VALUES OBTAINED USING DECISION FUSION OF DIFFERENT DATA REPRESENTATIONS

Fused Data Representations				OA
Original Data	IMF_1	IMF_2	$IMF_1 + IMF_2$	
√	√			87.17
√		√		94.56
√			√	93.63
	√	√		93.77
	√		√	92.63
		√	√	**96.22**
	√	√	√	94.92
√	√	√	√	94.37