Performance of various Wavelet based Features on AVIRIS Data Classification

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Abstract
Remote Sensing is the technique which is used for obtaining the information about an earth surface and identification of earth surface features to estimate the geographical properties using electromagnetic radiation. Hyperspectral Image consists of hundreds of spectral bands which provide detailed information and this can be used for land cover classification. In this paper Feature Extraction is done by using various Discrete Wavelet Transform (DWT) and Co-occurrence features are extracted by using this transformed co-efficient. DWT consists of many wavelet families such as Daubechies, Symlet etc. Such wavelets are used for extracting co-occurrence features. Image classification is done by using SVM classifier. Results obtained from the different wavelet families are compared. In this paper Hyperspectral dataset obtained by an AVIRIS sensor is used. Accuracy for Haar is 75.32%, DB 4 is 82.39%, DB8 74.45%and for Sym4 and Sym8 is 64.59% and 70.65% respectively.

Keywords—*Hyperspectral Image Classification, Discrete Wavelet Transform (DWT), Daubechies, Symlet, Support Vector Machine.*

1. INTRODUCTION

Hyperspectral Image obtained from the AVIRIS sensor consists of wide range of the electromagnetic spectrum and its coverage area which includes the visible and infrared region. The special characteristics of hyperspectral image it can give detailed information for each pixel and also discriminating the physical materials and objects is possible even at pixel level [1].

For example, the AVIRIS hyperspectral sensor has 220 spectral bands. Due to the availability of a huge number of bands indicates high dimensionality data, presenting several significant challenges to image classification. The dimensionality of input space strongly affects the performance of many supervised classification methods [2]. Due to large availability of bands this may suffer from redundancy, this redundancy is an unwanted phenomenon and it must be minimized. Feature extraction technique is one of the preprocessing steps for classifying the hyperspectral image. This process will eliminate only the redundant information whereas all the main characteristic information of that band is retained [3].

Various Feature Extraction methods are compared in literature [4] such as Principal Component Analysis (PCA) Independent Component Analysis (ICA) and wavelet transform are taken for comparison. Principal Component Analysis gives a better classification performance yet it has the drawback of greater computational complexity [5].

Zheng et al explained Principal Component Analysis has been recognized as an successful preprocessing tool for extracting the feature but the computational cost of PCA preprocessing is high [6]. Principal Component Analysis used for calculating the maximum amount of data variance in a new uncorrelated bands while Independent Component analysis is used for minimizing the dependencies in statistical independent component [7].

Feature Extraction can also be done by using Discrete Wavelet it provide better accuracy results [8]. Wavelet Transform (WT) methods have also been proposed for dimensionality reduction in the spectral domain [9]. For Hyperspectral image, the Support Vector Machine perform better results in classification accuracy even though the training samples is very less [10]

From the literature it is inferred as Feature Extraction done by Discrete Wavelet Transform (DWT) provides a better accuracy compared with other conventional Feature Extraction technique (Principal Component Analysis). DWT can process huge datasets simultaneously. DWT consists of different Wavelets such as Haar, Daubechies wavelets, Coiflet, Symlet, Mexican hat, bior etc and further that families can be again classified as Db4, Db8, Sym4, Sym8 etc. In this work feature is extracted by using various wavelet families and their obtained accuracy is tabulated and their performance is analyzed.

In this Paper Section 2 gives detailed explanation about the proposed methodology and Section 3 deals with the results obtained by various wavelets were compared.

2 PROPOSED METHODOLOGY

2.1 Input image

Hyperspectral image obtained by AVIRIS (Airborne Visible Infrared Imaging Spectrometer) sensor over the North western Indiana's Indian Pine set. This hyperspectral dataset of 220 bands and each band consists of 145x145 pixels. This dataset consist of 16 Classes.

2.2 Discrete Wavelet Transform

In hyperspectral image classification problems, the discriminative efficiency of the classifier depends on the features so while extracting the feature suitable Extracting technique should be used. In this paper Discrete Wavelet Transform (DWT) is applied for feature extraction.

The DWT is similar to that of hierarchical sub band method in which sub bands are in logarithmically spaced in frequency and also it indicates decomposition of octave bands. Multilevel Decomposition can be done by using 2D-DWT in this technique filters are used for processing the image. Generally filter will divide the input image into four sub bands (LL, LH, HL, and HH) Low frequency component (LL) provides approximation coefficient information whereas other sub bands give the detailed coefficient information about an input image. Inverse DWT is applied for reconstructing the input hyperspectral image. In this paper DWT families such as Haar wavelet, Daubechies Wavelet with Four taps (DB4) and eight taps (DB8) and Symlet with four taps (Sym4) and eight taps (Sym 8) were used for extracting the feature.

2.2.1 Haar Wavelet

Most commonly used wavelet is Haar due to its, memory efficient and exactly reversible without the edge effects characteristic of other wavelets and computationally cheap. Haar function is orthonormal, rectangular pairs and this function changes in both the position and scale. Haar transform does not have any overlapping windows, but reflects only changes between adjacent pixel pairs this uses just two scaling and wavelet function coefficients, thus calculates pair wise averages and differences

2.2.2Daubechies wavelet

Feature extraction is similar to that of dimensionality reduction. Feature extraction involves reducing quantity of resources required to describe huge set of features. Features are extracted from transformed image bands. This paper makes use of Discrete Wavelet Transform (DWT) for getting transformed image. DWT with single level decomposition is used to divide the images into approximation and detailed coefficients. Statistical and Co-occurrence features are extracted from the approximation coefficients. The resultant features are having the property to distinguish one class from other. By using wavelet filters (Daubechies DB4 and DB8) features can be extracted without losing any important information and Dimensionality reduction is also achieved. Feature Extraction is one of the preprocessing steps in hyperspectral classification.

2.2.3Symlet

Symlet wavelet is one of the families of Wavelet. In Daubechies there is a lack of symmetry in order to obtain symmetry this wavelet retains greater simplicity. Properties of Daubechies and Symlets are almost similar. Symlets is also known as symmetrical wavelets so they have least asymmetry and also they exhibit maximum number of vanishing moment so that it can give a compact support. Symlet wavelets can be denoted as SymN where N gives the number of taps.

2.3 Feature Extraction

Features are attributes of the data elements based on which the elements are assigned to various class Transforming the input data into set of features is called feature extraction. Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately. Characteristics of every pixel can be obtained by using Feature Extraction technique. Both statistical as well as co-occurrence features are extracted by using various Discrete Wavelets. Statistical features provide the gray level information of pixels. The statistical moments such as Mean, Variance, are calculated. Mean is used to average out the image thus eliminating the noise. The Variance feature for a dataset is calculated by taking the arithmetic mean of the squared difference between each value and the mean value, Co- occurrence features such as Energy, Contrast, Entropy, Homogeneity, Kurtosis, Skewness were extracted by DWT. Feature contrast is a measure of intensity or gray-level variations between the reference pixel and its neighbor. Skewness feature will measure the symmetry

2.4 SVM Classifier

Hyperspectral image classification can be done by using various methods but SVM classifier provides a better classification still for a less number of training samples. The standard two- class SVM classifier consists in finding the optimal hyper plane which separates two training classes, maximizing the distance between the closest points of each class. The training samples that give the maximum margin between the two classes are known as support vectors (SVs). The number of SVs gives an idea of how easy it was to separate the two classes. Therefore, a smaller number of SVs lead to smaller classification times

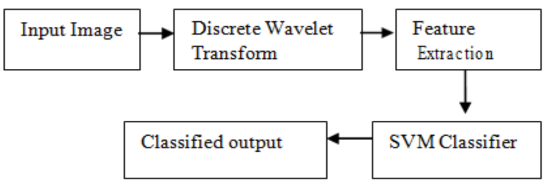

Fig: 1 *Work Flow*

3. RESULTS AND DISCUSSION

Extracted statistical and co-occurrence feature by using various wavelets are classified by using Support Vector Machine(SVM) from each class pixels are selected randomly and their combined features are trained afterwards pixels which is other than the trained pixels will act as a testing pixels.

In this paper 5% of pixels from every class are taken for training. SVM classifier determine if the test pixel belongs to the trained pixels or not, depending upon the classification obtained by the classifier class wise accuracy were calculated by using the formula (1)

$$\text{Accuracy} = \frac{\text{Correctly Classified Pixels}}{\text{Total Number of Pixels}} \quad (1)$$

Table 1: *Comparison table of various wavelets for AVIRIS dataset*

Class	Class Name	No of Pixels	Average Accuracy (%)				
			Haar	**DB4**	**DB8**	**SYM 4**	**SYM 8**
C1	Alfalfa	54	57.41	96.30	77.78	14.81	38.89
C2	Corn Notil	1434	99.93	98.95	97.98	26.22	95.26
C3	Corn Mintil	834	10.43	89.69	97.00	89.21	92.33
C4	Corn	234	44.44	2.99	2.99	5.13	2.99
C5	Grass Pasture	497	98.19	98.79	97.59	93.36	93.36
C6	Grass Trees	747	97.99	99.20	98.80	90.36	86.88
C7	Grass Pasture Mowed	26	92.31	30.77	84.62	92.31	34.62
C8	Hay	489	99.80	99.80	98.57	96.52	95.50
C9	Oats	20	95.00	5.00	95.00	20.00	10.00
C10	Soybean Notil	968	99.48	93.08	45.35	95.35	96.38
C11	Soybean Mintil	2468	96.47	98.26	98.82	96.47	95.50
C12	Soybean Clean	614	91.21	96.91	96.58	91.21	87.62
C13	Wheat	212	64.62	82.08	95.28	64.62	92.92
C14	Woods	1294	95.52	99.46	94.05	95.52	94.74
C15	BLDG	380	56.05	85.53	5.53	56.05	89.21
C16	Steel	95	6.32	11.58	5.26	6.32	24.21
	Overall Accuracy (%)		**75.32**	**82.39**	**74.45**	**64.59**	**70.65**

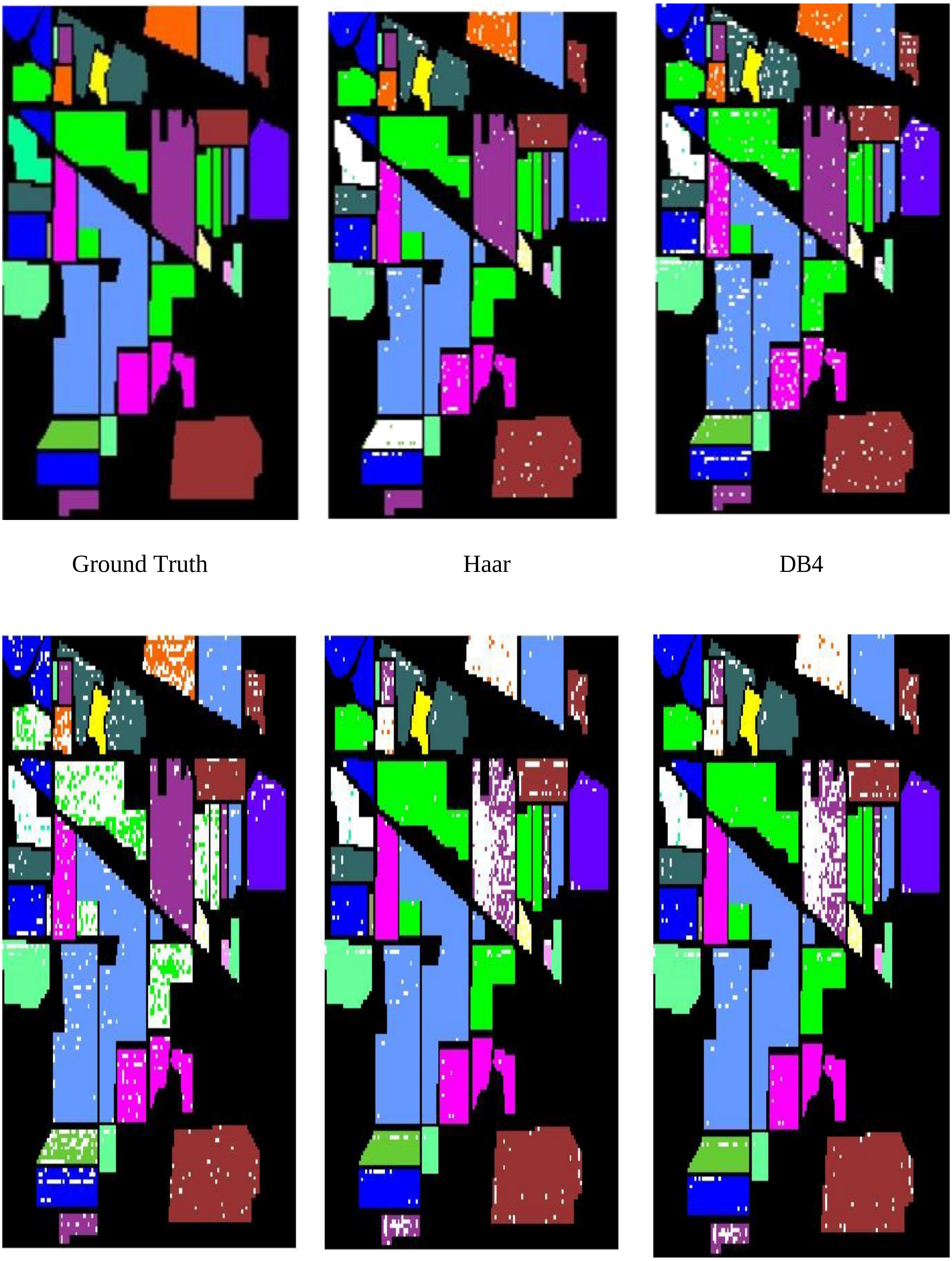

Fig 2 *Pseudo color output for different wavelets*

Figure 2 represents the pseudo color output for Haar, DB4, DB8, Sym4, Sym8 wavelets. Indian pines dataset consists of 16 classes such as Alfalfa, corn ,corn notil, corn mintil, hay, grass trees, grass pasture, oats, grass pasture mowed, Hay, soybean notil, soybean mintil, soybean clean, BLDG, woods, and steel.

For Haar wavelet Class Corn Mintil and Steel shows very low accuracy whereas class corn notil, class grass pasture, soybean notil, and soybean mintil shows very high accuracy. By using Daubechies wavelet with four taps (DB4) provides less accuracy for three classes such as corn notil, grass pasture, grass trees, while other classes hay, soybean mintil and woods provides a accuracy above 98% and their overall accuracy for the DB4 wavelet is 82.39%. For Daubechies wavelet with eight taps (DB 8) gives low accuracy for classes corn, BLDG and steel but for classes corn mintil, corn notil, grass pasture, grass trees and soybean mintil, this wavelet achieves very high accuracy above 97% Soybean notil shows very low accuracy for DB 8 when compared to other wavelets, While using Sym4 wavelet four classes shows very less accuracy which includes Class alfalfa, corn, oats, steel, whereas other classes such as class grass pasture, grass trees, grass pasture mowed, hay, soybean mintil, soybean notil, soybean clean and woods gives accuracy above 90%. Class oats shows less accuracy because total number of samples in the dataset itself very low.

Wavelet Sym 8 shows little improvement for class steel while comparing with other wavelets, whereas for other classes corn and oats always shows very poor accuracy and the classes BLDG, soybean clean, grass trees shows above 80% accuracy and the classes corn notil, hay, soybean notil, soybean mintil, shows above 95% accuracy. For some class such as steel, BLDG, wheat, soybean clean, soybean notil, oats shows almost similar accuracy value for haar and sym4 wavelet but their overall accuracy for two wavelets are 75.32% and 64.59% respectively. From this it is inferred that Class oats and corn always shows very poor accuracy for all wavelets.

4 CONCLUSION

The classification of hyperspectral remote sensing data using support vector machines was experimented. Even in the case of a very limited number of training samples and high dimensional data SVM provides accurate classification. Feature is extracted using Discrete Wavelet Transform (DWT). Wavelet families such as Haar provides 75.32% accuracy and for DB4 82.39 % and for Db8 74.45% for Symlet four taps (Sym 4) gives 64.59% and sym 8 gives 70.65% for Indian Pines dataset. From this we infer that DB4 shows high accuracy compared to all other DWT.

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