

HYPERSPECTRAL IMAGE CLASSIFICATION USING M-BAND WAVELET TRANSFORM

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ABSTRACT

This work presents a new technique that classifies various land cover classes present in the hyperspectral images by making use of the features from transformed version of the input image. A hyperspectral image is characterized by a large dimensionality data, recorded at very fine spatial resolution in hundreds of narrow frequency bands. These bands provide a wealth of spatial and spectral information of the scene, imaged by the sensors. Being inspired by the properties of M-band wavelets, a transform called M-Band Wavelet Transform (MBWT) is used. All the bands of the hyperspectral dataset are decomposed into sub-bands by using MBWT. Then, the features such as mean, standard deviation, variance, skewness and kurtosis are extracted from all the sub-bands of M-Band Wavelet transformed image. The extracted features are used for classification. Support Vector Machines with Binary Hierarchical Tree (BHT) is developed to classify the data by One Against All (OAA) methodology. Then, the Performance of MBWT is evaluated. The experiment is conducted on the AVIRIS hyperspectral dataset taken over the North-western Indiana's Indian Pine Site.

KEYWORDS: *M-Band Wavelet Transform (MBWT), Hyperspectral Image Classification, Multi-class Classifier, Support Vector Machine (SVM), OAA, BHT*

I. INTRODUCTION

Over the past decade hyperspectral image analysis has matured into one of the most powerful and fastest growing technologies in the field of remote sensing. The “hyper” in hyperspectral means “over” as in “too many” and refers to the large number of measured wavelength bands. Hyperspectral images are spectrally over determined, which means that they provide ample spectral information to identify and distinguish spectrally unique materials and each pixel in a Hyperspectral image has its own characteristic spectrum. It provides the potential of wealthy information extraction which was not possible with any other type of remotely sensed data. David Landgrebe proposed that high dimensional data can have the substantially increased capability for deriving more detailed and more accurate information [1]. A generalized procedure for hyperspectral data analysis is suggested and it involves identification and labeling of training samples followed by feature extraction and classification [1]. Classification of heterogeneous classes present in the Hyperspectral image is one of the recent research issues in the field of remote sensing. Classifying the pixels in the Hyperspectral Images and identifying their relevant class belongings depends on the feature extraction and classifier selection processes. Feature extraction is an agnate process while classifying images.

In Remote Sensing, the number of training samples available is often limited and in order to avoid the problems caused by the limited training samples, several feature extraction methods based on the wavelet transform have been proposed for hyperspectral images [2]. DWT gives better accuracy when used for texture classification [3]. P.S.Hiremath discussed the concept of extracting the features from wavelet sub-bands [4]. A wavelet transform-based texture classification algorithm has several important characteristics like the ability of decorrelating the data, providing orientation sensitive information and reduced computational complexity [4]. One of the drawbacks of standard wavelets is that they are not suitable for the analysis of high- frequency signals with relatively narrow bandwidth [5]. To overcome this problem, M-band orthonormal wavelet were created as a direct generalization

by Daubechies [6]. It has been reported that M-band orthonormal wavelets are able to zoom onto narrow band high frequency components of a signal as they give a better energy compaction than 2-band wavelets [7].

In general, the M-Band wavelet transforms are more efficient in signal decomposition than traditional wavelet transforms [8]. Chitre and Dhawan [9] have used the M-band wavelet for texture classification. Classification of medical images using M-band wavelet transforms is a promising technique for getting higher accuracy [10]. Always, Hyperspectral datasets are non-linear in nature. The Kernel methods used in machine learning models converts these non-linear datasets into a linear one, thereby making it useful for applications like classification, regression and clustering [11-12]. Kernel methods are suitable for the classification of high dimensional data while the availability of the training samples is limited. Many types of kernels like linear, polynomial, radial Basis Function (RBF), Sigmoid etc., are available. Selection of proper kernel gives proper results. Support Vector Machine (SVM) with Radial Basis Function (RBF) is a preferred combination which balances the complexity and accuracy [13]. The usage of SVM classifier for Hyperspectral images is shown by J.Gualtieri [14]. Multiclass classifier for Hyperspectral images is explained by T.Joachims [11]. The support vector machine (SVM) with kernel trick has been successfully used in hyperspectral image classification [15]. Yuliya uses probabilistic Support Vector Machine (SVM) for pixel wise classification of Hyperspectral images followed by the Markov Random Field (MRF) regularization method for refining the classification results based on spatial contextual information [16].

From the literature, it is obvious that, for classification, the textural information is important and it can be extracted with the help of wavelets. So, in this proposed methodology, transform domain is used for classification. The transform domain enhances the classification rate by decorrelating the pixels in an image into different sub-band images. First the hyperspectral image is transformed using M-Band Wavelet Transform. Then the features are extracted from the transformed images. The extracted features are used for efficient classification of hyperspectral image. Rest of the paper is organized in the following manner. Section-II deals with the Proposed Work followed by the background of SVM as Section-III. Section-IV describes the Experiment Design and Section-V is dedicated to the Results and Discussions. Section-VI gives the conclusion about the work.

II. PROPOSED WORK

2.1. M-Band Wavelet Transform

Standard M-band wavelet is a new part of wavelet analysis theories and it can offer wider range of wavelet base selection and wavelet function with better properties than two band wavelet. Present applications of M-band wavelet include image compression, edge detection, image fusion, image classification, etc. One of the drawbacks of standard wavelets is that they are not suitable for the analysis of high- frequency signals with relatively narrow bandwidth. Unlike the standard wavelet decomposition, which gives a logarithmic frequency resolution, the M-band decomposition gives a mixture of a logarithmic and linear frequency resolution. Further as an additional advantage, M-band wavelet decomposition yields a large number of sub-bands, which is required for improving the classification accuracy.

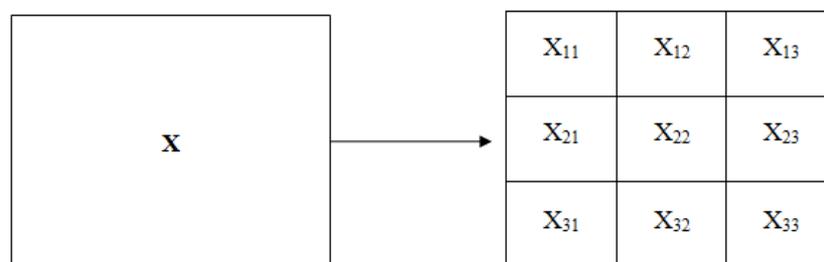


Figure 1. M-Band Wavelet decomposition of an image (M=3)

M-band wavelet transform is used to decompose the image into $M \times M$ sub-bands [18] i.e., an M-level decomposition yields M^2 sub-bands as shown in figure 1. Because M^2 channel will be generated through M-band decomposition at the first level, further decomposition of M-band is not suggested.

Compared with traditional two-band wavelet, the M-Band wavelets have three advantages, when applying to feature extraction.

- M-band wavelet overcomes the limitation of two-band wavelet in wavelet base selection.
- Besides logarithmic frequency resolution, M-band wavelet can offer linear frequency resolution.
- More sub-bands are generated and more detailed information is included at each level, making it suitable for enhancing the accuracy of classification.

M-channel filters used for decomposing the time-scale space into $M \times M$ sub-bands play a vital role in increasing the classification accuracy and are essentially selected as frequency and direction oriented band pass filters. The different combinations of M-Band Wavelet filters decompose an image at different scales and orientations in frequency space. Figure 2 shows the M-channel filter bank for $M=3$. In general, the wavelet transform of an image is defined as the 2D signal decomposition onto a set of basis functions called wavelets. A full wavelet expansion of a 2D signal can be represented by a set of basis functions called scaling and wavelet functions (φ and ψ), respectively and are associated with the analyzing (or synthesizing) filters h and g .

M-band wavelets are a set of $M-1$ basis functions. Scaled and translated versions of basis functions forms a tight frame for the set of square integrable functions defined over the set of real numbers $L^2(\mathbb{R})$ [17]. For the $M-1$ wavelets, $\psi_l(x)$, $l=1,2,\dots,M-1$, given any function $f(x) \in L^2(\mathbb{R})$, it has been shown that,

$$f(x) = \sum_{l=1}^{M-1} \sum_{m \in \mathbb{Z}} \sum_{n \in \mathbb{Z}} \langle f(x), \psi_{l,m,n}(x) \rangle \psi_{l,m,n}(x) \quad (1)$$

where $\psi_l(x)$ and $\psi_{l,m,n}(x)$ are scaled and translated wavelet functions and \mathbb{Z} represents the set of integers. Multiresolution analysis is also defined with the scaling function and the $M-1$ wavelet functions [17]. A multiresolution analysis is a sequence of approximation spaces for $L^2(\mathbb{R})$. If the spaces spanned by the scaling function and wavelet function at different resolution for fixed m and $n \in \mathbb{Z}$ is denoted by V_m and W_m , then for $M=3$, it can be shown that [17],

$$V_1 = V_0 \oplus W_{10} \oplus W_{20} \quad (2)$$

$$V_2 = V_1 \oplus W_{11} \oplus W_{21} \quad (3)$$

A typical M-channel filter bank structure for $M=3$ is shown in figure 2.

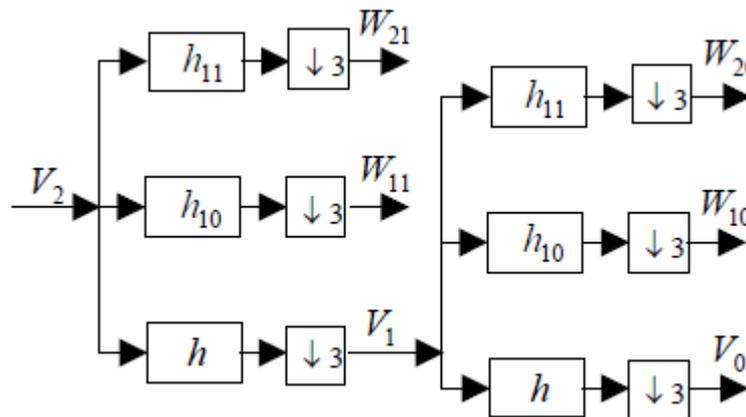


Figure 2. M-channel filter bank (M=3)

2.2. Feature Extraction

Transforming the input data into the set of features is called feature extraction. The extracted feature vectors are given as input to a classifier. By applying transforms, the pixels present in the image can be decorrelated and this in turn increases the classification rate. All the bands of the hyperspectral dataset are decomposed into sub-bands by using MBWT. Then, the features such as mean, standard deviation, variance, skewness and kurtosis are extracted from all the sub-bands of M-Band Wavelet transformed image.

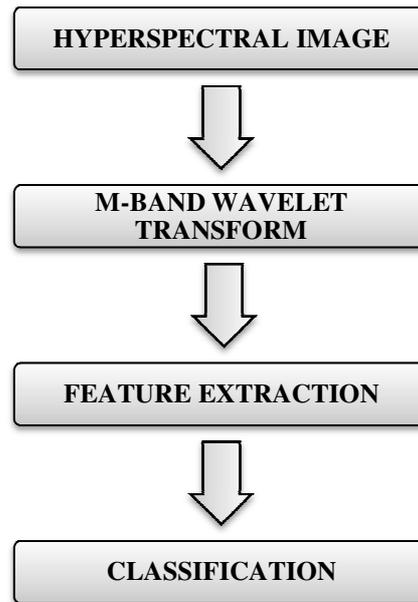


Figure 3. Proposed Methodology

The feature named ‘Mean’ is used to average out the image thus eliminating the noise. The ‘Standard deviation’ feature is used to find how far the pixels are deviated or dispersed from the mean. The ‘Variance’ feature of a data set is calculated by taking the arithmetic mean of the squared differences between each value and the mean value. The feature that is used to find whether the pixel distribution is skewed to the left or right of the mean is termed as ‘Skewness’. The ‘Kurtosis’ feature is the measure of whether the distribution is tall and skinny or short and squat, compared to the normal distribution of the same variance. The features are calculated using the formulas given in Table 1.

Table 1. Feature Set

Feature	Formula
Mean	$\mu_{ij} = (\sum_{i=1}^M \sum_{j=1}^N x_{ij}) / MN$
Standard Deviation	$\sigma_{ij} = (\sum_{i=1}^M \sum_{j=1}^N (x_{ij} - \mu_{ij})^2)^{0.5} / MN$
Variance	$\sigma_{ij}^2 = (\sum_{i=1}^M \sum_{j=1}^N (x_{ij} - \mu_{ij})^2) / MN$
Skewness	$Skew(x_{ij}) = \sum_{i=1}^M \sum_{j=1}^N (x_{ij} - \mu_{ij})^3 / \sigma_{ij}^3$
Kurtosis	$Kurt(x_{ij}) = (\sum_{i=1}^M \sum_{j=1}^N (x_{ij} - \mu_{ij})^4 / \sigma_{ij}^4) - 3$

III. SUPPORT VECTOR MACHINE

SVM is a good candidate for remote sensing data classification for a number of reasons. SVM outperforms other classifiers as they work well with a small training data. They can support more number of features during the classification task. SVM performs nonlinear classification using kernel trick. Kernel-based methods are based on mapping data from the original input feature space to a kernel feature space of higher dimensionality and solving a linear problem in that space. The aim is to find a linear separating hyper plane that separates classes of interest. The hyper plane is a plane in a multidimensional space and is also called a decision surface or an optimal separating hyper plane.

Radial Basis Function Kernel is used here. This kernel nonlinearly maps samples into a higher dimensional space, unlike the linear kernel, and so it can handle the case when the relation between class labels and attributes is nonlinear as shown in figure 4.

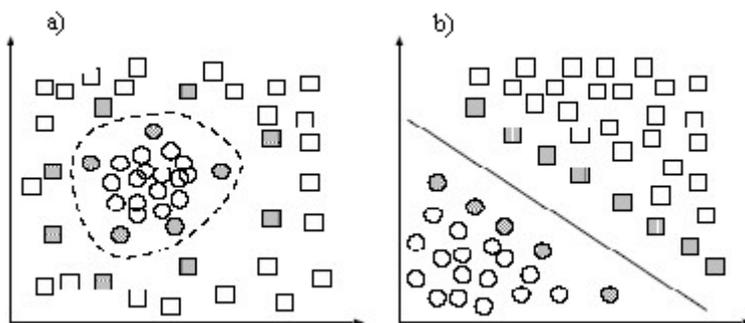


Figure 4. Separable classification using RBF kernel in a) Original Space b) Feature Space

Here, One-against-all (OAA) Binary Hierarchical Tree strategy is used by SVMs while classifying images. It separates the classes hierarchically by considering how one class is separated from others.

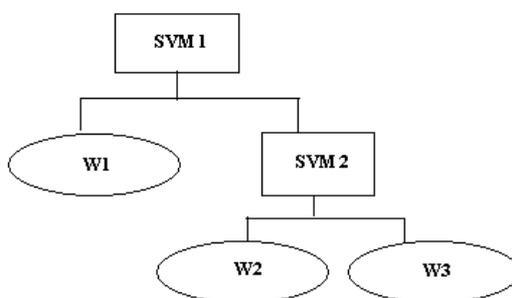


Figure 5. OAA Binary Hierarchical Tree (W_i represents Class $_i$)

Likewise so many SVMs can be run to find out the interested classes. While training, care is shown towards the over fitting of the samples.

IV. EXPERIMENTAL DESIGN

The experiment is conducted on the AVIRIS hyperspectral dataset taken over the Northwestern Indiana's Indian Pine Set. The dataset consists of 220 bands and each band consists of 145x145 pixels. The original dataset contains 16 classes and ground truth is available for that.

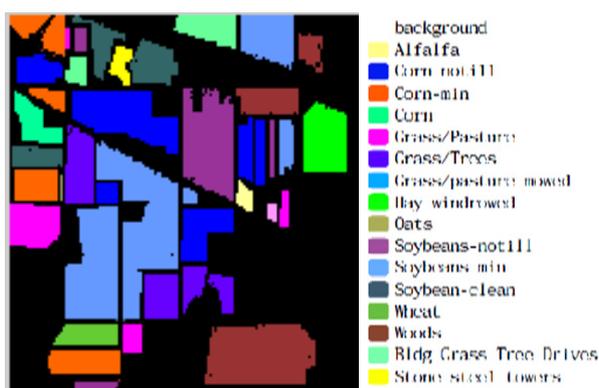


Figure 6. Ground Truth Classes

V. RESULTS AND DISCUSSION

The Feature set derived from the Feature Extraction method is used for classification. Randomly chosen pixels from each class and their corresponding feature vectors are used for training. The classifier produces output based on, whether the particular pixel under test belongs to the interested trained class or not. Thus, the pixels under the same class are separated from whole dataset.

Similarly other classes also trained and by this method, the classes are separated hierarchically. After that the pixels of interested class are assigned white gray level while others are assigned black. By comparing each class of pixels with the ground truth, the number of misclassified pixels can be found and from that the average accuracy can be calculated.

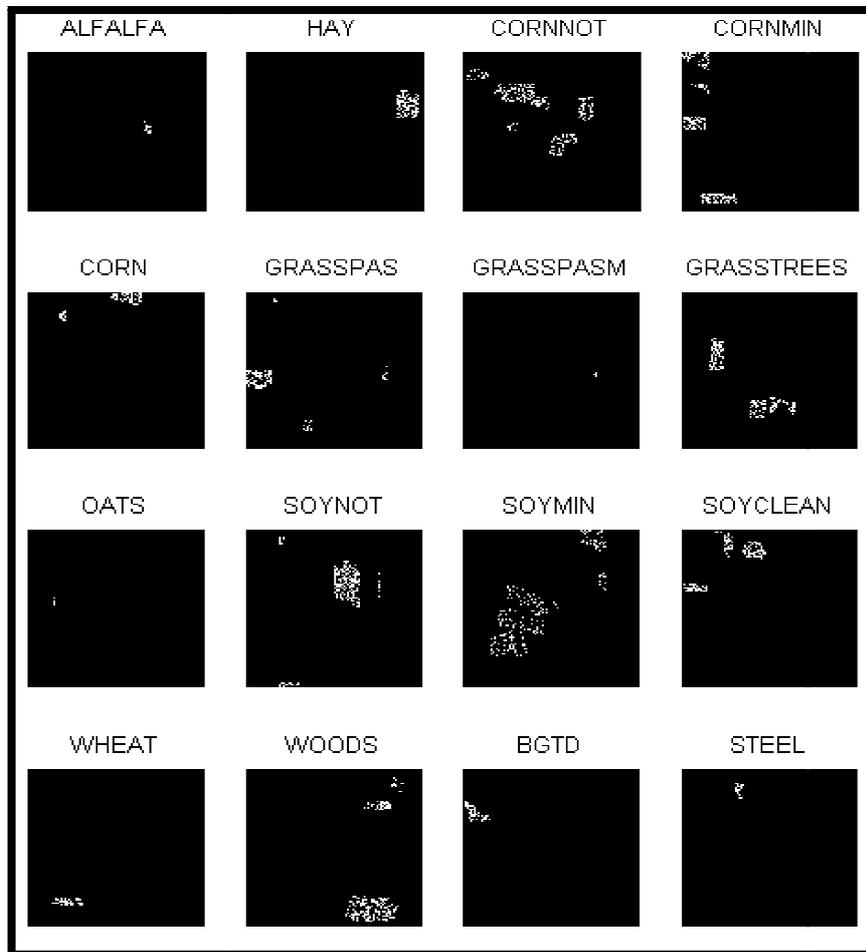


Figure 7. Classified output

From figure 8, it is inferred that, for nearly two-fourth of the classes, the average accuracy obtained by the proposed feature set reaches more than 50%. In specific, classes like Alfalfa, Grass Pasture Mowed, Oats, Soy clean, Wheat and Steel, gives an overall accuracy of more than 50% whereas the classes like Hay-Widrowed, Corn-min, Corn, Grass Trees and Building-Grass Tree Drives attains average accuracy of more than 45%. By comparing the classification result with the ground truth available, the overall accuracy of classification is obtained and is found to be 68.4%.

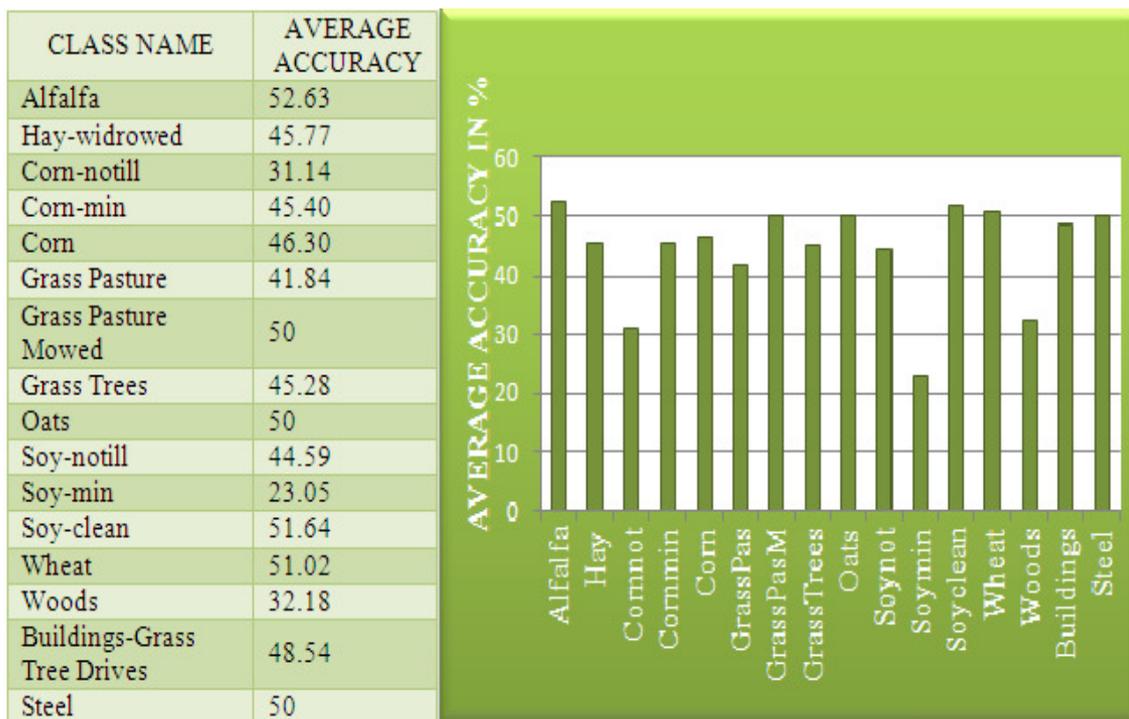


Figure 8. Average Accuracy

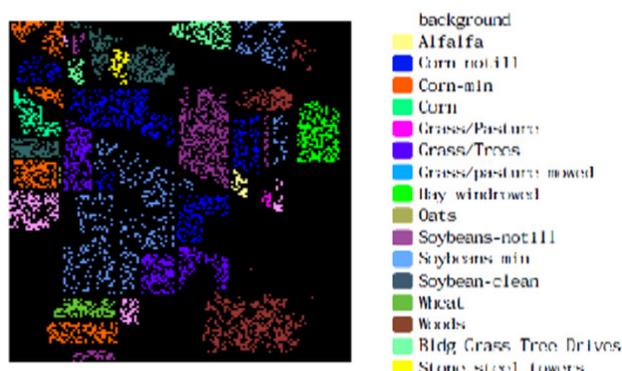


Figure 9. Classified output with OA= 68.4%

VI. CONCLUSIONS

The proposed work developed a classification scheme that uses statistical features alone while classifying an image. It is predicted that those features alone gave an overall classification accuracy of 68.4%. When this application is extended to sub-pixel levels, it is possible to reduce the misclassifications and hence there comes the chance of improvement in overall classification accuracy. For this case of analysis, the knowledge of how much a pixel belongs to a particular class is important. Therefore, proper soft classification algorithms can be identified and can be used to classify the land cover classes, as they are expected to yield good accuracies.

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REFERENCES

- [1]. David Landgrebe, G.E. Cohn, J.C. Owicki, (1999) "Some Fundamentals and Methods for Hyperspectral Image Data Analysis", *SPIE Photonics West*, San Jose CA.

- [2]. Hsu, P.H. , (2003) "Spectral Feature Extraction of Hyperspectral Images Using Wavelet Transform", *Ph.D. Thesis*, Department of Surveying Engineering, National Cheng Kung University, Tainan, Taiwan, R.O.C.
- [3]. Kamarul Hawari Ghazali, Mohd. Marzuki Mustafa, Aini Hussain, (2009) "Image Classification using Two Dimensional Discrete Wavelet Transform", *International Conference on Instrumentation, Control & Automation*, pp71-74.
- [4]. P. S. Hiremath, S. Shivashankar, (2006) "Wavelet Based Features for Texture Classification", *GVIP journal*, Vol.6, Issue-3.
- [5]. P. Steffen et. al., (1993) "Theory of regular M-band wavelets bases", *IEEE Trans. on Signal Processing*, Vol. 41, No. 12, pp3497-3510.
- [6]. I. Daubechies, (1988) "Orthonormal bases of compactly supported wavelets", *Communication Pure Appl. Math. XLI*, pp909-996.
- [7]. H. Zou, A.H. Tewfik, (1992) "Discrete orthogonal M-band wavelet decompositions", *Proc. Int. Conf. on Acoustic Speech and Signal Processing*, Vol.4, ppIV-605-IV-608.
- [8]. Ganesh D. Bhokare, Raghuram J. Karthik, Vikram M. Gadre, (2005) "Modified EZW Coding for the M band Wavelet Transform and its application to Image Compression", *IEEE Workshop on Statistical Signal Processing Proceedings*, pp883-888.
- [9]. Y. Chitre and A.P. Dhawan, (1999) "M-band wavelet discrimination of natural textures", *Pattern Recognition*, Vol. 32, pp773-789.
- [10]. Wen-Li Lee, Yung-Chang Chen, Kai-Sheng Hsieh, (2003) "Ultrasonic liver tissues classification by fractal feature vector based on M-band wavelet transform", *IEEE Transactions on Medical Imaging*, Vol. 22, Issue-3.
- [11]. B. Scholkopf, A. Smola, (2002) "Learning with Kernels—Support Vector Machines, Regularization, Optimization and Beyond", *MIT Press Series*.
- [12]. G. Camps-Valls, J. L. Rojo-Alvarez, and M. Martinez-Ramon, (2007) "Kernel Methods in Bioengineering, Signal and Image Processing", *Idea Group Publishing*, Hershey, PA.
- [13]. G. Camps-Valls, L. Bruzzone, (2005) "Kernel-based methods for hyperspectral image classification", *IEEE Trans. Geosci. Remote Sens.* Vol. 43, No. 6, pp1351-1362.
- [14]. J.Gualtieri and R. Crompt, (1998) "Support vector machines for hyperspectral remote sensing classification", *Proc. 27th AIPR Workshop Advances in Computer Assisted Recognition*, Washington DC, pp121-132.
- [15]. G. Camps-Valls, L. Gomez-Chova, J. Munoz-Marí, J. Vila-Frances, J. Calpe-Maravilla, (2006) "Composite kernels for hyperspectral image classification", *IEEE Geosci. Remote Sens. Lett.* , Vol. 3, No. 1, pp93-97.
- [16]. Y. Tarabalka, M. Fauvel, J. Chanussot, J. A. Benediktsson, (2010) "SVM and MRF-based method for accurate classification of hyperspectral images", *IEEE Geoscience and Remote Sensing Letters*, Vol. 7, Issue-4, pp736-740.
- [17]. Mausumi Acharya, Malay. K. Kundu, (2000) "Two Texture Segmentation using M-Band Wavelet Transform", *15th International Conference on Pattern Recognition (ICPR'00)*, Vol. 3, pp.3405
- [18]. Turgut Aydm, Yucel Yemez, Emin Ananm, Bulent Sankur, (1996) "Multidirectional and Multiscale Edge Detection via M-Band Wavelet Transform", *IEEE Transactions on Image Processing*, Vol. 5, No. 9, pp1370-1377.

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