Classification of Pavia University Hyperspectral Image using Gabor and SVM Classifier

Kavitha K.[1], Arivazhagan S.[2], Suriya B.[3]

Abstract: Hyperspectral remote sensing technology is used for identification and detection of objects on the earth. Hyperspectral images are composed of several bands, each band comprises of spectral and spatial information's. Recent developments involve both spectral and spatial classification for hyperspectral image analysis. This rich and detailed spectral, spatial information can be used to classifying and identifying a wide range of earth surface materials. In this paper spectral and spatial information's from each band are derived using Gabor filter. Classification is done using Support Vector Machine (SVM) classifier. SVM advocates good results in the linear domain classification but, Hyperspectral domain is a non-linear domain which can be converted into linear domain by using kernel methods. Hyperspectral dataset of Pavia University acquired by ROSIS sensor is chosen as the input image for this experiment and classification accuracy of 63.62% is obtained.

Keywords: Gabor Filter, Support Vector Machines

I.NTRODUCTION

Remote Sensing is a field of study for gathering data and information by measuring signals from objects at long distances. Land cover classification is concerned with identifying different types of coverage on the Earth's surface and has been used for many purposes, such as urban planning and management, forestry, environmental monitoring, agriculture, etc. Remote Sensing methods are used to gain a better understanding of the Earth and its functions. Recent developments in remote sensing technologies have made hyperspectral imagery (HSI) readily available to detect and classify objects on the earth using pattern recognition techniques. Hyperspectral remote sensing, also known as imaging spectroscopy, is an emerging technology that is currently investigated by researchers for the detection of terrestrial vegetation, man-made materials, minerals, and backgrounds. Hyperspectral images are acquired using satellite/airborne sensors, like Hyperion in several hundred narrow and continuous bands. These bands provide wealth of spatial and spectral information. This rich and detailed spectral, spatial information can be used to classifying and identifying a wide range of earth surface materials. Hyperspectral imaging is excellent source of information for the classification of materials. Hyperspectral sensors contain hundreds of spectral channel where each channel covers a small portion of electromagnetic spectrum.

Kavitha K: working as Assistant Professor in Dept of E.C.E, Mepco Schlenk Engineering College, Sivakasi, Email: vihadakavi@yahoo.com.

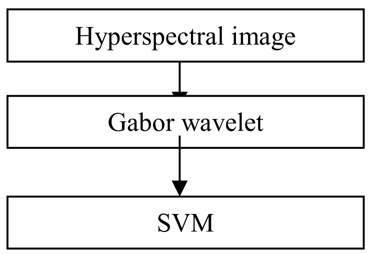
Arivazhagan S: working as principal in Mepco Schlenk Engineering College, Sivakasi, Email: sarivu@yahoo.com.

Suriya B: student at Mepco Schlenk Engineering College, Sivakasi, Email: suryabmepco@gmail.com.

Classifying the pixels in the Hyperspectral Images and identifying their relevant classes depends on the feature extraction, and classifier used. Feature extraction is done using Gabor Transform for getting transformed raw image. Gabor function provides the optimal resolution in both the spatial and frequency domains [1]. Classification is done using Support Vector Machine (SVM) classifier. SVM advocates good results in the linear domain classification [4] but, non-linear domain can be converted into linear domain by using kernel trick. Kernel methods constitute a machine learning paradigm for building nonlinear methods from linear ones. The superiority of SVMs, implementing structural risk minimization SVMs aim to discriminate two classes by fitting an optimal separating hyperplanes to the training data within a multidimensional feature space by using only the closest training samples. Thus, the approach works well with small training set, even when high-dimensional data sets are classified [5]. Tarabalka et al. [6] proposed the use of probability estimates obtained by the support vector machine (SVM) classification, in order to determine the most reliable classified pixels as seeds of spatial regions.

SVM with Radial Basis Function (RBF) is a preferred combination which balances the complexity and accuracy [7]. The SVM with kernel trick has been successfully used in Hyperspectral image classification [8]. Kernel based methods like one-class SVM, identifies samples of one particular class and rejecting the others [9]. Lately , [10] semi supervised kernel-based classifiers for example, the transductive SVM [11] and Laplacian SVM [12] have been introduced to exploit the wealth of unlabeled data in the image.

II. Proposed method



A Hyper spectral image consists of many classes. In the classification of hyperspectral image, getting the input image is the initial step. For evaluating the performance of the proposed method, a sample hyper spectral image of Pavia University dataset is chosen.

Gabor Wavelets

Feature is defined as an associate that characterise the difference from one class to other class. A feature is a significant representative of an image which can be used for classification. When the input data to an algorithm is too large to process, the data can be transformed into a reduced representation set called features. The method of transforming an input data into the set of features is called Feature extraction. Features are extracted from transformed image bands. Gabor function provides the optimal resolution in both the spatial and frequency domains. Spatial resolution is a measure of the coarseness or fineness of a raster grid. The higher the spatial resolution of a digital image, the more detail it contains. Spectral resolution is the ability of a sensor to detect small differences in wavelength. Due to this optimal resolution in both domains, Gabor function has been considered as a very useful tool for feature extraction. In the proposed method, the Gabor feature of orientation 4 and scale of 6 is selected and 24 Gabor features have been extracted for all the pixels in the hyperspectral data cube.

SVM

The classification is done with Support vector machines. A Support vector machine performs classification by constructing an N-dimensional hyper plane that optimally separates the data into two categories. Classification is done using SVM classifier. SVM advocates good results in the linear domain classification [15] but, Hyperspectral domain is a non-linear domain. Kernel tricks are used to convert non-linear domain into linear domain. Kernel methods constitute a machine learning paradigm for building nonlinear methods from linear ones [16-17]. SVM with Radial Basis Function (RBF) is a preferred combination which balances the complexity and accuracy [20].

III. Experimental results

Hyperspectral image acquired using ROSIS (Reflective Optics System Imaging Spectrometer) over the Pavia University is chosen for this experiment.

Pavia University dataset acquired using ROSIS sensor is a 610*340 pixel image. The number of bands in this image is 103 spectral bands with a spectral coverage ranging from 0.43 to 0.86 μ m and a spatial resolution of 1.3 meter per pixel. This dataset has 9 different classes. Out of 103 spectral bands only 50 bands are chosen for this experiment.

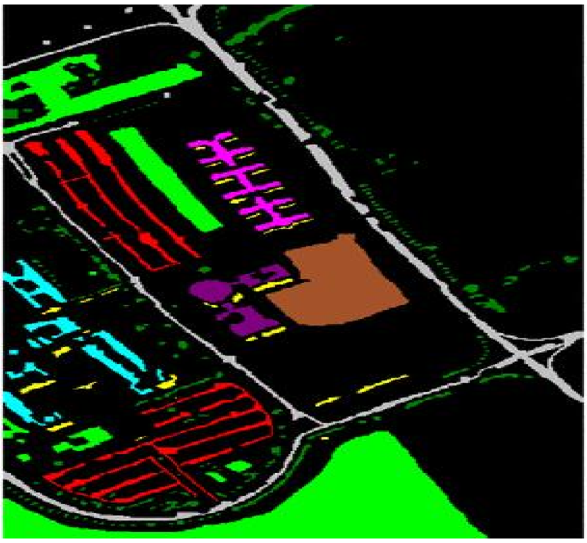


Fig 1: Ground truth for Pavia University

Input image is transformed using Gabor Filter the value of scale and orientation is fixed as six and four respectively. 24 Gabor Features are extracted from the input image. Pixels are randomly chosen from each class and their features are used for training. Here 5-30% of pixels from each class are used for training. All the pixels are tested against the training samples. The classifier produces the output, whether the pixel under test belongs to the interested trained class or not.

Thus the pixels of interested classes are identified among the whole dataset. Similarly other classes are also trained. Randomly selected pixels are tested against the training samples. By this way, classes are separated hierarchically. The training and testing information are shown in Table 1

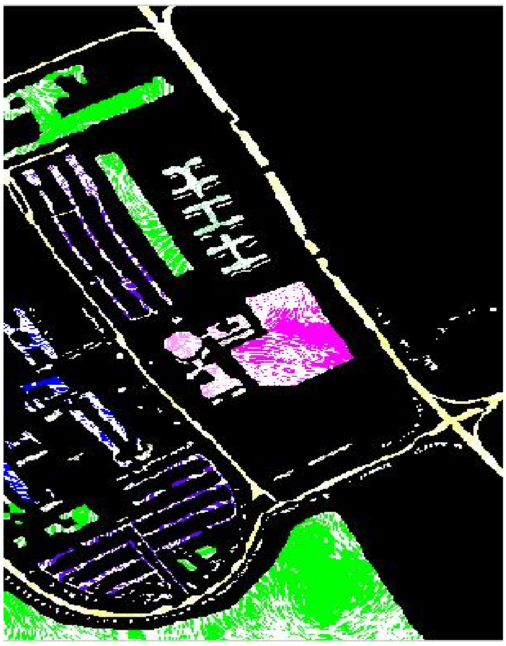
Table 1: Training Samples

Classes	**Number of samples**	**Trained samples (5%)**	**Trained samples (10%)**	**Trained samples (20%)**	**Trained samples (30%)**
Asphalt	6631	331	663	1326	1989
Meadows	18649	932	1865	3730	5595
Gravel	2099	105	210	420	630
Trees	3064	153	306	613	919
Paint metal sheet	1345	67	135	269	403
Bare soil	5029	251	503	1006	1509
Bitumen	1330	67	133	266	399
Self block bricks	3682	184	368	736	1105
Shadows	947	47	95	189	284

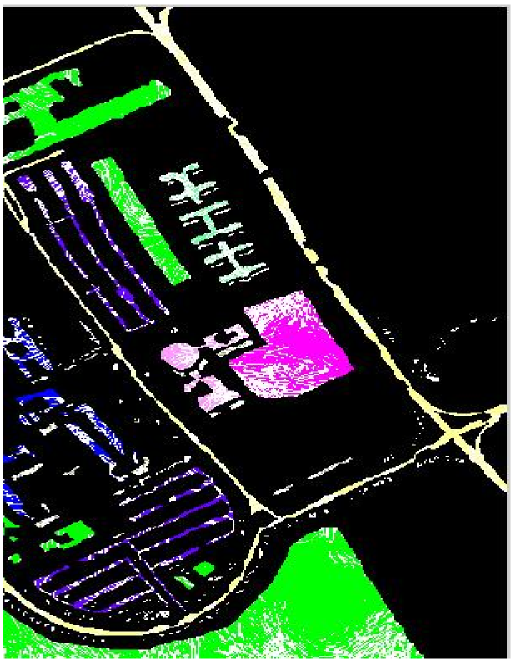
Table 2: Overall Accuracy Table

Classes	**Accuracy for 5% trained samples**	**Accuracy for 10% trained samples**	**Accuracy for 20% trained samples**	**Accuracy for 30% trained samples**
Asphalt	22.18	35.58	55.41	69.37
Meadows	42.93	61.90	78.33	86.84
Gravel	19.63	33.78	52.83	66.75
Trees	15.31	27.87	47.45	60.90
Paint metal sheet	9.07	16.36	30.63	41.71
Bare soil	29.9	45.95	62.44	73.91
Bitumen	18.57	30.23	46.69	60.23
Self block bricks	20.32	37.40	58.56	73.55
Shadows	6.12	13.52	27.56	39.39
Overall Accuracy (%)	**20.44**	**33.62**	**51.1**	**63.62**

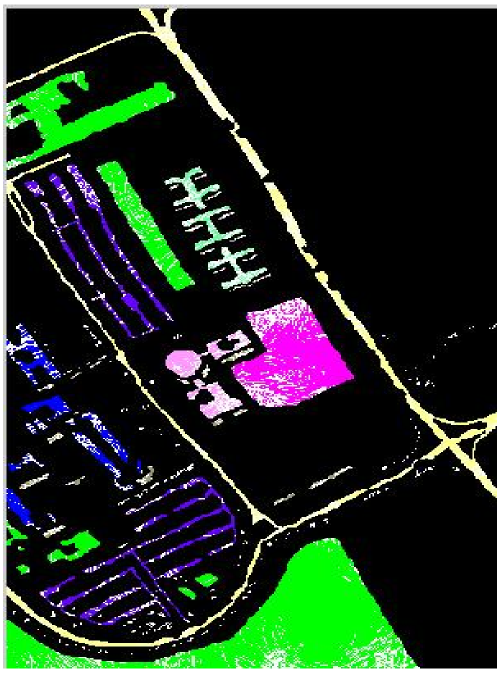
(a)



(b)



(c)



(d)

Fig 2: Pseudo colour SVM output (a) 5% trained (b) 10% trained (c) 20% trained (d) 30% trained samples

IV. Conclusion

The classification of hyper spectral 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 extraction procedure is carried out using Gabor. Gabor function provides the optimal resolution in both the spatial and frequency domains and then the 5-30% trained feature samples are used for classification using SVM classifier. This proposed method provides classification accuracy of 20.44 for 5% trained, 33.62 for 10% trained, 51.1 for 20% trained and 63.62 for 30% trained samples for the Pavia University Dataset.

ACKNOWLEDGMENT

The authors are grateful to the Management and Principal of our college for their constant support and encouragement.

REFERENCES

[1] D. Gabor, Theory of Communication, Journal of the Institute of Electrical Engineers, v.93, pp. 429-457, 1946.

[2] P.Sonali , S.Milmile, S. Godbol "Land Classification and Crop Identification Using Gabor Wavelet Transform on Satellite Images" International Journal of Advances in Electrical Engineering, Vol:1 Issue:1 ISSN 2278-215, 2006.

[3] B.S Manjunathi and W.Y.Ma,"Texture Features for Browsing and Retrieval of Image Data", IEEE Trans on pattern analysis and machine intelligence, vol. 18, no.8, August, 1996.

[4] T. V. Bandos, L. Bruzzone, and G. Camps-Valls, "Classification of hyperspectral images with regularized linear discriminant analysis," IEEE Trans. Geosci. Remote Sens., vol. 47, no. 3, pp. 862–873, Mar. 2009.

[5] Y. Tarabalka, J. Benediktsson, J. Chanussot, and J. Tilton, "Multiplespectral- spatial classification approach for hyperspectral data," IEEE Trans. Geosci. Remote Sens., vol. 48, no. 11, pp. 4122–4132, Nov. 2010.

[6] B. Waske and J. A. Benediktsson, "Fusion of support vector machines for classification of multisensor data," IEEE Trans. Geosci. Remote Sens., vol. 45, no. 12, pp. 3858–3866, Dec. 2007.

[7] G. Camps-Valls, L. Gomez-Chova, J. Munoz-Mari, J. L. Rojo-Alvarez, and M. Martinez-Ramo, "Kernel-based framework for multitemporal and multisource remote sensing data classification and change detection," IEEE Trans. Geosci. Remote Sens., vol. 46, no. 6, pp. 1822–1835, Jun. 2008.

[8] N. Ghoggali, F. Melgani, and Y. Bazi, "A multiobjective genetic SVM approach for classification problems with limited training samples," IEEE Trans. Geosci. Remote Sens., vol. 47, no. 6, pp. 1707–1718, Jun. 2009.

[9] M. Chi and L. Bruzzone, "Semisupervised classification of hyperspectral images by SVMs optimized in the primal," IEEE Trans. Geosci. Remote Sens., vol. 45, no. 6, pp. 1870–1880, Jun. 2007.

[10] R. Polikar, "Ensemble based systems in decision making," IEEE Circuits Syst. Mag., vol. 6, no. 3, pp. 21–45, 2006.

[11] T. K. Ho, "The random subspace method for constructing decision forests," IEEE Trans. Pattern Anal. Mach. Intell., vol. 20, no. 8, pp. 832–844, Aug. 1998.

[12] S. van der Linden, A. Janz, B. Waske, M. Eiden, and P. Hostert, "Classifying segmented hyperspectral data from a heterogeneous urban environment using support vector machines," J. Appl. Remote Sens., vol. 1, p. 013 543, 2007.

[13] M. Fauvel, J. A. Benediktsson, J. Chanussot, and J. R. Sveinsson, "Spectral and spatial classification of hyperspectral data using SVMs and morphological profiles," IEEE Trans. Geosci. Remote Sens., vol. 46, no. 11, pp. 3804–3814, Nov. 2008.

[14] X. Huang and L. Zhang, "An adaptive mean-shift analysis approach for object extraction and classification from urban hyperspectral imagery," IEEE Trans. Geosci. Remote Sens., vol. 46, no. 12, pp. 4173–4185, Dec. 2008.

[15] M. Zortea, M. De Martino, and S. Serpico, "A SVM ensemble approach for spectral-contextual classification of optical high spatial resolution imagery," in Proc. IGARSS, Boston, MA, pp. 1489–1492, 2008.

[16] Munoz-Mari, J. L. Rojo-Alvarez, and M. Martinez-Ramo, "Kernel-based framework for multitemporal and multisource remote sensing data classification and change detection," IEEE Trans. Geosci. Remote Sens., vol. 46, no. 6, pp. 1822–1835, Jun. 2008

[17] P. O. Gislason, J. A. Benediktsson, & J. R. Sveinsson, "Random forests for Land cover classification," Pattern Recognit. Lett., vol. 27, no. 4, pp. 294–300, Mar. 2006.

[18] H. C. Kim, S. Pang, H. M. Je, D. Kim, and S. Yang Bang, "Constructing support vector machine ensemble," Pattern Recognit., vol. 36, no. 12, pp. 2757–2767, Dec. 2003.

ived the B.E degree in Electronics and Engineering from Mepco Schlenk Engineering in 1998 and M.E. degree in Microwave and :ring from Alagappa Chettiar College of Technology, karaikudi in 2000. She is an sor in Department of ECE, Mepco Schlenk ege, Sivakasi. She is currently Working toward with the Anna University, Tirunelveli. Her s include Image Classification and Change

S.Arivazhagan received his B.E degree in Electronics and Communication Engineering from Alagappa Chettiar College of Engineering and Technology, Karaikudi in 1986 and M.E. degree in Applied Electronics from College of Engineering, Guindy, Anna University, Chennai in 1992. He has been awarded with Ph.D. degree by Manonmaniam Sundaranar University, Tirunelveli in the year 2005. He is currently working as principal, Mepco Schlenk Engineering College, Sivakasi. He has twenty six years of teaching and research experience. He has been awarded with Young Scientist Fellowship by TNSCST, Chennai in the year 1999. He has published around 130 Technical papers in International / National Journals and Conferences. He has completed 9 Research and Development Projects, funded by ISRO, Trivandrum, DRDL, Hyderabad, ADE, Bangalore, DRDO, New Delhi, DST, New Delhi and AICTE, New Delhi.

B.Suriya received her B.E degree in Electronics and Communication Engineering from R.V.S College of Engineering and Technology, Coimbatore in 2012. She is currently a Post Graduate Student in Communication Systems from Mepco Schlenk Engineering College, Sivakasi. Her area of research is Hyperspectral Image Classification.