International Journal of Scientific & Engineering Research, Volume 5, Issue 7, July-2014
ISSN 2229-5518

Classification of hyperspectral images using scattering transform

Ashitha P S, V Sowmya, K P Soman

Abstract- In this paper, we applied scattering transform approach for the classification of hyperspectral images. This method integrates features, such as the translational and rotational invariance features for image classification. The classification of hyperspectral images is more challenging because of the very high dimensionality of the pixels and the small number of labelled examples typically available for learning. The scattering transform technique is validated with two standard hyperspectral datasets i.e, SalinasA_Scene and Salinas_Scene. The experimental result analysis proves that the applied scattering transform method provides high classification accuracy of 99.35% and 89.30% and kappa coefficients of 0.99 and 0.88 for the mentioned hyperspectral image dataset respectively.

Index Terms— Scattering transform, Invariant features, Perona Malik Diffusion, Support vector machine, Hyperspectral images, Overall accuracy, Kappa Coefficient.

1 Introduction

The classification of hyperspectral images become challenging since the dimension of the images is considerable for the classification algorithms. The high dimensionality of the data/pixels and the small number of labeled samples typically available for the learning of the classifier is also a fact which leads the classification a challenging task. To overcome this problem, the method of feature extraction is introduced before training the classifier. These extracted features of the images are given for the learning of the classifier, so that the overall performance of the classifier increases to a great extent. Many supervised and non-supervised methods are proposed earlier for the classification of the hyperspectral images by reducing the dimension of the image [1].

The classification of hyperspectral images is done using Optimized Laplacian SVM with Distance Metric Learning method in [2]. Optimized Laplacian SVM are developed for semisupervised hyperspectral image classification, by introducing with Distance Metric Learning instead of the traditional Eucliden distance which are used in the existing LapSVM. In the given reference [3] the kernel method is applied to extend NWFE to kernel-based NWFE (KNWFE). The experimental results of three hyperspectral images show that KNWFE can have the highest classification accuracy under three training-sample-size conditions.

- *Ashitha P S is currently pursuing masters degree program in Remote sensing and wireless sensor networks,at Amrita Vishwa Vidyaeetham,Tamilnadu. E-mail: 2k7ashi@mail.com*
- *V Sowmya, Assistant professor in the Centre for Excellence in Computational Engineering and Networking, Amrita Vishwa Vidyaetham, Tamilnadu. She is currently pursuing her Phd in Image processing.*
- *Dr.K P Soman, Head of the Centre for Excellence in Computational Engineering and Networking, Amrita Vishwa Vidyaetham, Tamilnadu.*

Experimental results also show that the performance of KNWFE is not consistently better than those of the other methods under small number of features and training sample condition. A new method for hyperspectral image classification is proposed in [4] based on manifold learning algorithm. A new Laplacian eigen map pixels distribution flow (LEPD-Flow) is proposed for hyperspectral image analysis, in which, a new joint spatial-pixel characteristic distance (JSPCD) measure is constructed to improve the accuracy of classification. In this proposed work, a new method for the classification of the hyperspectral images in which the translational and rotational invariance features of each pixel in the image is extracted by applying the scattering transform to the image. These extracted features give a high accuracy of classification for Salinas_Scene and SalinasA_Scene hyperspectral image datasets.

This paper is organized as follows: The diffusion technique used in this work is described in sect 2. Sect.3 provides the description of the proposed feature extraction method. Sect.4 describes the classifier algorithm used. A brief note on the dataset used in this work is given in sect.5. Experimental results are presented in sect.6, followed by the conclusion.

2 Perona- Malik Diffusion

Perona Malik diffusion also called anisotropic diffusion is a technique for reducing the image noise, without removing the significant parts of the image. It preserves the information significant for the interpretation of the image. The resulting image is obtained by the convolution between the image and a two dimensional isotropic Gaussian filters. This is a nonlinear and space variant transformation of the image [5]. Each successive image in the family is computed by an iterative process where a relatively simple set of computations are performed and the process can be repeated until the required degree of smoothing is obtained [6]. The proposed method iterated with a number of values of

International Journal of Scientific & Engineering Research, Volume 5, Issue 7, July-2014
ISSN 2229-5518

iterations to find out the best value for sufficient smoothening. The two datasets are iterated several times and the resulting pre-processed diffused image is taken further for feature extraction step.

3 Scattering Transform

In this section, the mathematical background of the scattering features used for image classification is presented. Scattering transform [7] is used to extract the features of hyperspectral images used in this work. This method is efficient for extracting features based on the translation, rotational and convolutional invariance of the image pixels. The scattering transform is implemented in Scat Net using the scat function [8]. This function can be used to calculate several types of scattering transforms by varying the linear operators supplied to it.

The features extracted for classification need to be invariant with respect to the transformations which do not affect our ability to recognize. Scattering transforms build invariant, stable and informative representations through a non-linear, unitary transform, which delocalizes the information into scattering decomposition paths. They are computed with a cascade of wavelet modulus operators, and correspond to a convolutional network where filter coefficients are given by a wavelet operator [9].

In particular, as the scale of the low pass window grows, and after an appropriate renormalization, the scattering transform converges into a translation invariant integral transform, defined on an uncountable path space [10]. The resulting integral transform shares some properties with the Fourier transform; in particular, signal decay can be related with the regularity on the integral scattering domain.

The translational and rotational invariant features of an image ‘x’ is obtained by averaging the image over all translations ‘j’ and rotations ‘γ’ . i.e., the convolution with the low ass filter ϕ_J .The high frequencies eliminated in $\left|x * \psi_{j_1,\gamma_1}\right| * \phi_J$ by the convolution with ϕ_J are recovered by convolution with wavelets $\left|x * \psi_{j_1,\gamma_1}\right| * \psi_{j_2,\gamma_2}$ at scales $2^{j_2} < 2^J$. To become insensitive to local translation and reduce the variability of these coefficients their complex phase is removed by a modulus and it is averaged by ϕ_J which are the scattering coefficients represented by Eq (1).

$$\left\|x * \psi_{j_1,\gamma_1}\right| * \psi_{j_2,\gamma_2}\right| * \phi_J \qquad (1)$$

A scattering vector computed with a cascade of convolutions and modulus operators over m+1 layers, like in convolution network architecture is given in Eq (2).

$$\begin{aligned} &x(n) \rightarrow x * \phi_J(2^J n) \\ &\left|x * \psi_{j_1,\gamma_1}\right| \rightarrow \left|x * \psi_{j_1,\gamma_1}\right| * \phi_J(2^J n) \\ &\left\|x * \psi_{j_1,\gamma_1}\right| * \psi_{j_2,\gamma_2}\right| \rightarrow \left\|x * \psi_{j_1,\gamma_1}\right| * \psi_{j_2,\gamma_2}\right| * \phi_J(2^J n) \end{aligned} \qquad (2)$$

Scattering propagator U_J applied to ‘x’ computes each $U[\lambda_1]x = \left|x * \psi_{\lambda_1}\right|$ and gives the output features $S_J[\phi]x = x * \phi_{2^J}$. Applying U_J to each $U[\lambda_1]x$ computes all $U[\lambda_1, \lambda_2]x$ and output $S_J[\lambda_1] = U[\lambda_1] * \phi_{2^J}$ is given. Applying U_J iteratively to each $U[p]x$ gives the output features and computes the next path layer. The three layers of coefficients obtained by applying the scattering transform to an image ’x’ is shown in fig 1.

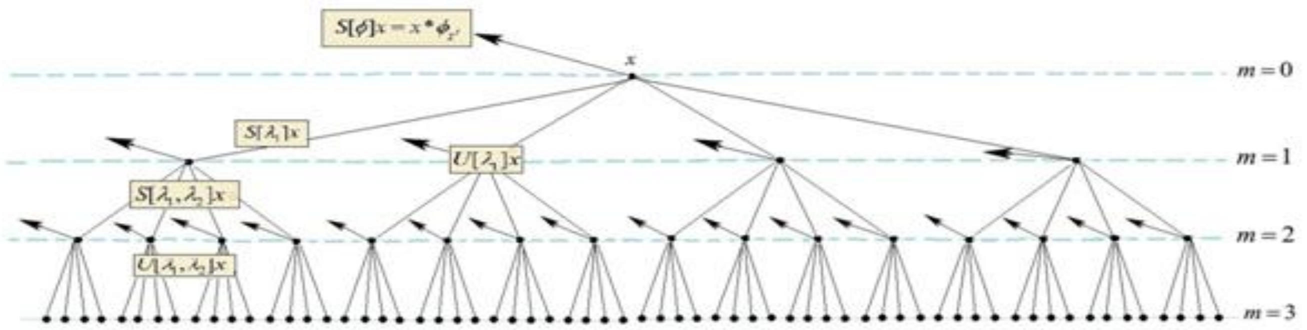


Fig 1, Scattering Convolution Network [9]

International Journal of Scientific & Engineering Research, Volume 5, Issue 7, July-2014
ISSN 2229-5518

4 CLASSIFIER

The scattering transform selects the discriminating features and a classification scheme must be identified to exploit them. This section discusses the support vector machine (SVM) classification algorithm used in this work. A classification task usually involves separating data into training and testing sets [11]. Each instance in the training set contains one target value and several attributes. The goal of SVM is to produce a model (based on the training data) which predicts the target values of the test data. The reason for opting SVM classifier is mainly to overcome the local minima problem which is generally faced in neural network classifier. Furthermore, most of the problems are modeled using Gaussian distribution function which may not be the case in most of the real-life applications.

Given a training set of instance-label pairs (x_i, y_i), i=1,...,l where $x_i \in R^n$ and $y \in \{1,-1\}^l$. The objective function and kernel functions are given in Eq (3) and Eq (4) [12]. The support vector machine require the solution of the following optimization problem:

$$\min_{w,b,\xi} \frac{1}{2} w^T w + C \sum_{i=1}^{l} \xi_i$$

$$\text{Subject to} \quad y_i (w^T \phi(x_i) + b) \geq 1 - \xi_i, \qquad (3)$$

$$\xi_i \geq 0$$

$K(x_i, x_j) \equiv \phi(x_i)^T \phi(x_j)$ is called the kernel function.

$$K(x_i, x_j) = (\gamma x_i^T x_j + r)^d, \gamma > 0 \qquad (4)$$

If the number of features is large, one may not need to map to a higher dimensional space. That is, the nonlinear mapping does not improve the performance [13]. Using the linear or polynomial kernel is good enough, and the one only searches for the control parameter 'C'. Here in this work, LIBSVM [14] which is an integrated software for support vector classification, (C-SVC, nu-SVC), regression (epsilon-SVR, nu-SVR) and distribution estimation (one-class SVM) is used for the classification.

5 DATASET DESCRIPTION

Two standard datasets namely Salinas_Scene and SalinasA_Scene are used to analyse the performance of the scattering transform technique for image classification. The first dataset, Salinas_Scene is collected by the 224-band Airborne Visible Infrared Imaging Spectrometer(AVIRIS) sensor over Salinas Vally, California, and is characterized by high spatial resolution (3.7-meter pix). The area covered comprises 512 lines by 217 samples and the bands : [108-112], [154-167], 224 are rejected as water absorption bands. This image is available only as at-sensor radiance data. It includes vegetables, bare soils, and vineyard fields and its ground truth contains 16 classes. The next dataset used in this work is SalinasA_Scene. A small sub scene of Salinas image, denoted SalinasA , is usually used. It comprises 86×83 pixels located within the same scene at [samples, lines] = [591-676, 158-240] and includes six classes [15].

6 EXPERIMENTAL RESULTS AND DISCUSSIONS

Accuracy assessment is an essential metric for image classification to determine the performance of the classification technique used. The accuracy assessment reflects the difference between the classified data and the ground truth data [16]. Classification accuracy in case of hyperspectral image can be statistically measured using various parameters. These statistical measures can be easily obtained from the Confusion Matrix or the Classification Error Matrix (also known as contingency table)[2]. The overall accuracy is calculated as the total number of correctly classified pixels divided by the total number of test pixels. The kappa statistics is the most popular technique for comparing different classifiers. To quantify the agreement of classification, the kappa coefficient can be used. The mathematical equation for calculating the overall accuracy and kappa coefficient is given by Eq (5) and Eq (6) [16].

$$Overall\ Accuracy = \frac{Total\ number\ of\ correctly\ classified\ pixels}{Total\ number\ of\ pixels} \qquad (5)$$

$$kappa\ coefficient(k) = (N * A - B) / (N^2 - B) \qquad (6)$$

Where 'N' is the total number of pixels, 'A' is the number of correctly classified pixels (Sum of diagonal elements in the confusion matrix), 'B' is the sum of product of row and column total in confusion matrix.

The best value for control parameter 'C' and gamma is fixed by randomly selecting 80% of the pixels for training and the remaining 20% for testing. The same procedure is iterated five times for all different possible combinations of 'C' and gamma (C=10,100,500 and gamma=0.1, 1, 10) for each dataset. Once the 'C' and gamma value is fixed, the experiment is performed on each dataset with 40% of the pixels for training and the remaining 60% for testing. The experimental results are evaluated with the metric called classification accuracy and kappa coefficient. This procedure is repeated for three different kernels i.e, linear, polynomial and RBF kernels. The classification accuracy and kappa coefficient obtained for different kernels for Salinas_Scene and SalinasA_Scene is given in table 1. The classification map of original ground truth data and the output of the applied scattering transform for three different kernels for Salinas_Scene and SalinasA_Scene hyperspectral image dataset is shown in the fig 2 and fig 3 below.

International Journal of Scientific & Engineering Research, Volume 5, Issue 7, July-2014
ISSN 2229-5518

TABLE 1 CLASSIFICATION ACCURACY AND KAPPA COEFFICIENT FOR THREE DIFFERENT KERNELS FOR HYPERSPECTRAL IMAGE DATASET

	C	Gamma	Linear Kernel		Polynomial Kernel		RBF Kernel	
			Accuracy (%)	*Kappa*	*Accuracy (%)*	*Kappa*	*Accuracy (%)*	*Kappa*
SalinasA_Scene	500	0.1	98.50	0.98	99.35	0.99	98.49	0.98
Salinas_Scene	500	1	86.35	0.84	89.30	0.88	88.87	0.87

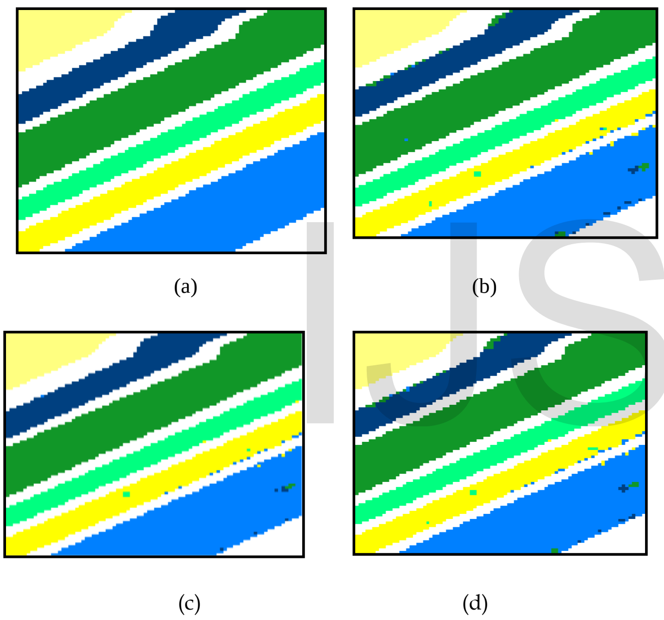


Fig 2, Classification map of SalinasA_Scene
(a) Original Ground truth (b) Linear kernel classifier
(c) Polynomial kernel classifier (d) RBF kernel classifier

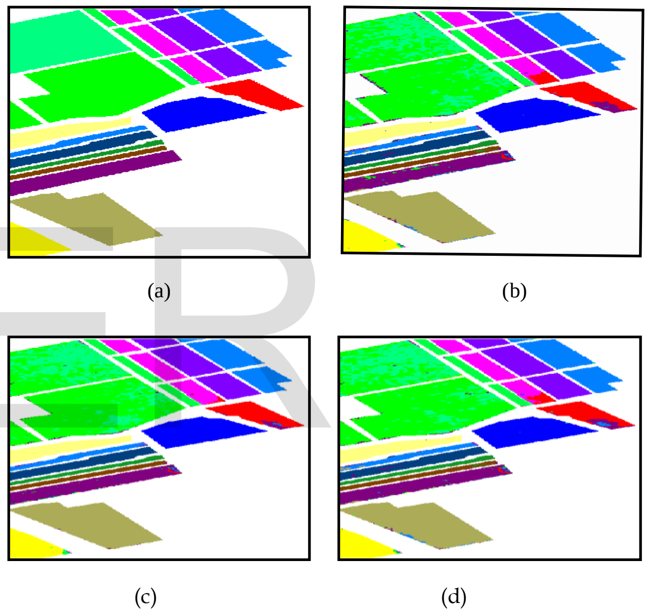
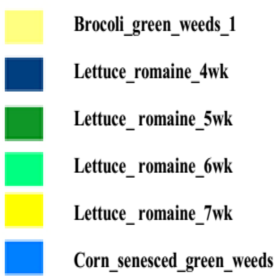


Fig 3, Classification map of Salinas_Scene
(a) Original Ground truth (b) Linear kernel classifier
(c) Polynomial kernel classifier (d) RBF kernel classifier.



International Journal of Scientific & Engineering Research, Volume 5, Issue 7, July-2014
ISSN 2229-5518

7 CONCLUSION

Features are extracted using scattering transform and the classification is done using support vector machine. The translation and rotation invariant features of an image are extracted using the scattering transform which improves the hyperspectral image classification accuracy to a great extent. The accuracy obtained by this method for SalinasA_Scene dataset is 99.35% for polynomial kernel with a kappa coefficient of 0.99. The accuracy and kappa coefficient for Salinas_Scene dataset is 89.30% and 0.88 for polynomial kernel. The same procedure can be repeated for different wavelet filters used in the scattering transform for feature extraction. This may lead to the high classification accuracy for various other image datasets.

REFERENCES

[1] Ping Zhong, Member, IEEE, And Runsheng Wang, "Learning Conditional Random Fields For Classification Of Hyperspectral Images" IEEE Transactions On Image Processing, Vol. 19, No. 7, July 2010.

[2] Yanf eng gu, member, IEEE, and kai feng, "Optimized laplacian svm with distance metric Learning for hyperspectral image classification" IEEE Journal Of Selected Topics In Applied Earth Observations And Remote Sensing, Vol. 6, No. 3, June2013.

[3] Bor-Chen Kuo,Cheng-Hsuan Li and Jinn-Min Yang, "Kernel Nonparametric Weighted Feature Extraction for Hyperspectral Image Classification" IEEE Transactions On Geoscience And Remote Sensing, Vol. 47, No. 4, April 2009.

[4] Biao Hou, Member, IEEE, Xiangrong Zhang, Member, IEEE, Qiang Ye, and Yaoguo Zheng, "A Novel Method for Hyperspectral Image Classification Based on Laplacian Eigenmap Pixels Distribution-Flow" IEEE Journal Of Selected Topics In Applied Earth Observations And Remote Sensing, Vol. 6, No. 3,June 2013.

[5] Guo W. Wei, Member, IEEE, "Generalized Perona–Malik Equation for Image Restoration" IEEE Signal Processing Letters, Vol. 6, No. 7, July 1999.

[6] Kavitha Balakrishnan, Sowmya V., Dr. K.P. Soman, "Spatial Preprocessing for Improved Sparsity Based Hyperspectral Image Classification", International Journal of Engineering Research & Technology (IJERT) Vol. 1 Issue 5, July – 2012 ISSN: 2278-0181.

[7] Joan Bruna Estrach, CMAP, Ecole Polytechnique, "Scattering Representations for Recognition" PhD thesis Submitted November 2012.

[8] http://www.di.ens.fr/data/software/scatnet/

[9] Joan Bruna and Stephane Mallat, "Invariant Scattering Convolution Networks" CMAP, Ecole Polytechnique, Palaiseau, France.

[10] Huajuan Wu, Mingjun Li ,Mingxin Zhang, Jinlong Zheng and Jian Shen, "Texture Segmentation via Scattering Transform" International Journal of Signal Processing, Image Processing and Pattern Recognition Vol. 6, No. 2, April, 2013.

[11] Gustavo Camps-Valls, Member, IEEE, and Lorenzo Bruzzone, Senior Member, IEEE, "Kernel-Based Methods for Hyperspectral Image Classification" IEEE Transactions On Geoscience And Remote Sensing, Vol. 43, No. 6, June 2005.

[12] K P Soman, R Loganathan, V Ajay, " Machine learning with SVM and other kernel methods", published on 2009 by PHI Learning Private Limited, New Delhi.

[13] Chih-Wei Hsu, Chih-Chung Chang, and Chih-Jen Lin, "A Practical Guide to Support Vector Classication" Department of Computer Science National Taiwan University, Taipei 106, Taiwan.

[14] http://www.csie.ntu.edu.tw/~cjlin/libsvm/

[15]http://www.ehu.es/ccwintco/index.php/Hyperspectral_Remote_Sensing_Scene.

[16] Ryuei Nishii,Member, IEEE,and Shojiro Tanaka,Member, IEEE, "Accuracy and Inaccuracy Assessments in Land-Cover Classification" IEEE Transactions On Geoscience And Remote Sensing, Vol. 37, No. 1, January 1999.