HSI Classification: Analysis

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Abstract: *Spatial features are extracted for the classification of Hyperspectral Image (HSI) image. For features extraction Local Binary Pattern is used (LBP), Gabor filters used to extract global features. Then two level fusions are applied like feature level & decision fusion. To get classification output Extreme learning machine (ELM) is added. With the use of LBP & ELM we get more efficient& cost effective results.*

Key features: Local binary pattern (LBP), Extreme learning Machine (ELM) and Feature level fusion

I. INTRODUCTION

The main objective is to develop a technique using technologies of computational intelligence to classify HSI. To classify HSI here in our method steps are included like feature extraction, filtration, & classification. In this paper an LBP, Gabor filter, and ELM are used. LBP is used to extract local features, to generate encode image. For global feature extraction, Gabor filter a type of linear filter is used and then all features including spectral features are concatenated. A classifier i.e. an ELM is used to classify HSI image. [4]

II. PROBLEM STATEMENT

Hyperspectral image processing has been a very dynamic area in remote sensing and other applications in recent years. Hyperspectral images provide abundant spectral information to identify and distinguish spectrally similar materials for more accurate and detailed information extraction. Wide range of advanced classification techniques are available based on spectral information and spatial information. To improve classification accuracy it is essential to identify and reduce uncertainties in image processing chain

Large number of high spatial resolution images is available through various advances of sensor technology. In conventional HSI classification systems, classifiers only consider spectral signatures and ignore the spatial information at neighboring locations. So we focused on classification of Hyperspectral images using local binary patterns

III. POPOSED SOLUTION

In our project we use an unsupervised band selection method using linear prediction error is used to select distinctive and informative bands. After that local binary pattern to extract local features then Gabor filter to extract global features, concatenate all features like local global including spectral features using feature level fusion and classifier i.e. Extreme Learning Machine is apply to classify image. Decision level fusion is used to individual features along with classifier.

IV. SYSTEM ANALYSIS

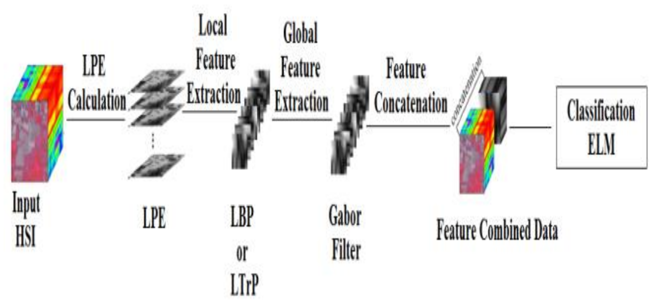

Figure 1 Block Diagram of HSI Classification

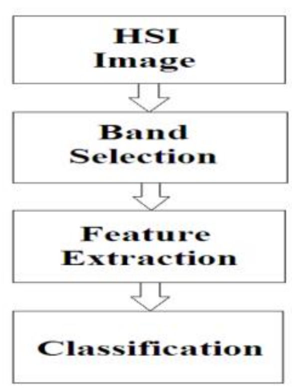

Figure 2 Flowchart

V. BAND SELECTION

For unsupervised band selection Linear Prediction Error (LPE) & Principal Component Analysis (PCA) is used.
LPE is a simple efficient band selection method based on band similarity measurement

Band Selection Algorithm:

1. Assume two initial bands B_1 and B_2
2. Then for every other band B, an approximation can be expressed as

$$B = a0 + a1B1 + a2B2 \qquad (1)$$

Where a_0, a_1, a_2 are the parameters to minimize the LPE error

$$e = \|B - B'\|2. \qquad (2)$$

3. The band which produces the maximum error e is considered as the most dissimilar band to B1 and B2, and it will be selected.
4. Using these three bands, a fourth band can be found by using the same strategy and so on. [1]

VI. LBP

By using LBP, texture or feature extraction can be performed. It includes various applications like surface inspection, remote sensing and in biomedical area
For m number of neighbors$\{\, t_i \,\}_{i=0}^{m-1}$, the LBP code for t_c is given by

$$LBP_{m,r}(t_c) = \sum_{i=0}^{m-1} U(ti - tc)\, 2^i \qquad (3)$$

Where, $U(ti - tc) = 1 \;\; if \; ti > tc$ =1
$U(ti - tc) = 0 \; if \; ti \le tc$

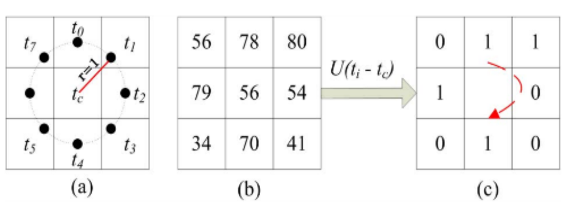

Figure 3 Example of LBP binary thresholding(a) Center pixel t_c and its eight circular neighbors {ti} 7i=0 with radius r=1. (b) 3×3 sample block (c) Binary labels of eight neighbors

Fig.3 shows an example of binary thresholding process of (m, r) = (8, 1). LBP divide examine window into the cells(for e.g., 16x16) For each pixel in the cell, compare the pixels to each of its eight neighbors ;follow the pixel along the circle clockwise or counter clockwise If center pixel value greater than neighbor's value write "0", otherwise write "1" gives 8 digit binary number. LBP code is calculated in clockwise direction i.e. 11001010= 83

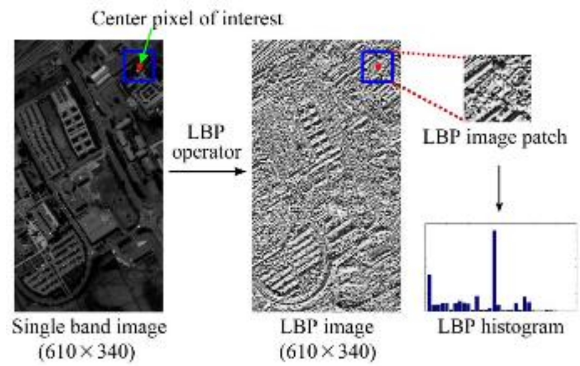

Figure 4 Implementation of LBP feature extraction

After band selection, the LBP feature extraction process or Gabor filtering is applied to each selected band image. Fig. 4 illustrates the implementation of LBP feature extraction. The input image is from the 63th band of the University of Pavia data. In Fig. 4, the LBP code is first calculated for the entire image to form an LBP image, and the LBP features are then generated for the pixel of interest in its corresponding local LBP image patch. Note that patch size is a user-defined parameter.[2]

VII. GABOR FILTER

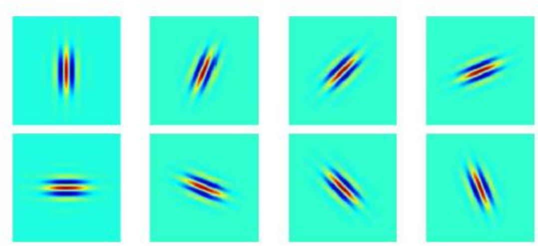

Figure 5 2-D Gabor kernel with different orientations, from top to bottom, left to right:[0,π/8,π/4,3π/8,π/2,5π/8,3π/4,7π/8]

Gabor filter is used to extract global features. A linear band pass filter, with circular symmetric orientation to consider all directions called as Gabor filter. This is given by, [3]

$$G_{\delta,\theta,\sigma,\psi,\gamma}(\mathrm{a,b}) = exp\left(-\frac{a'^2 + \gamma^2 b'^2}{2\sigma^2}\right) exp\left(j\left(2\pi\frac{a'}{\delta} + \psi\right)\right)$$

Where,
$a' = \mathrm{a}\cos\theta + b\sin\theta$

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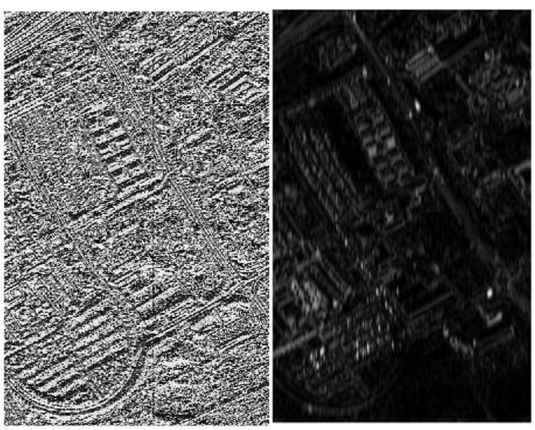
$b' = -a\sin\theta + b\cos\theta$ (4)

δ: wavelength of sinusoidal factor
θ: orientation separation angles (π/8, π/4, π/2 etc)
ψ: phase offset
σ: Standard derivation of Gaussian envelope
γ: Spatial aspect ratio.
With ψ=0 & ψ= π/2 return the real & imaginary parts of the Gabor filter respectively.

$\sigma = \frac{\delta}{\pi}\sqrt{\frac{\ln 2}{2}}\,\frac{2^{bw+1}}{2^{bw-1}}$ (5)

Gabor output image of university of Pavia for single band selection (e.g. Band number 65)
For each selected bands dimensionality (i.e. no of bins) of LBP feature is m (m-1) +3



LBP Image **Gabor Output**

Figure 6 LBP and Gabor Output

VIII. ELM

A feed forward neural network with single layer hidden nodes is actually an ELM which is a type of classifier. It determines the output weights by randomly assigning weights to input node. ELM is extremely fast and efficient classifier compared to SVM. The training samples and labels are represented as $\{xi, yi\}_{i=1}^{n}$, where xi ∈ R^d and yi∈R_C, the output function of an ELM with L hidden nodes. This can be expressed as [6]

$f_{l(x_i)} = \sum_{i=1}^{L} \beta j h(wj.xi + bj) = y_{i,}$ (6)

i=1, 2, 3 …n Where
h(): nonlinear function
βj∈ R^C:weight vector connecting hidden node to output
wj∈ R^d:weight vector connecting hidden nodes to input
For n equations, (6) can be written as

$H\beta = Y$ (7)

Where
Y= [y_1; y_2……. y_n] ∈ $R^{n\times C,}$ β = [β1; β2... βn] ∈ $R^{L\times C}$

$$H = \begin{bmatrix} hx_I \\ \vdots \\ hx_n \end{bmatrix} = \begin{bmatrix} h(w_1.x_I + b_1) & \cdots & h(w_L.x_I + b_L) \\ \vdots & \ddots & \vdots \\ h(w_1.x_I + b_1) & \cdots & h(w_L.x_n + b_L) \end{bmatrix} \quad (8)$$

Where H: hidden layer output matrix [6]

IX. FEATURE LEVEL FUSION

Classification is performed by combining all features in feature level fusion. All LBP, Gabor & spatial features are arranged compositely. But this may cause to less efficient classification. [5]

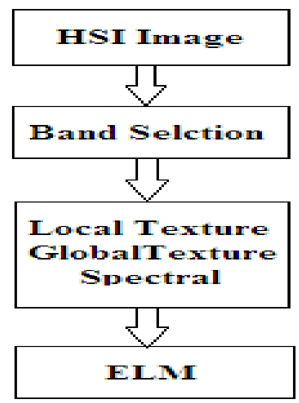


Figure 7 Feature level fusions

X. CLASSIFICATION RESULTS

Here, three aforementioned features, i.e., LBP features (local texture), Gabor features (global texture), and selected bands (spectral features), and their combinations, such as LBP features + Gabor features + spectral features, LBP features + spectral features, Gabor features + spectral features, etc., will be discussed.

Table 1. Optimal Band Selection for classification using ELM

	No. of Selected Bands	**Patch Size**	**BW**
	University of Pavia		
LBP	7	21x21	-
Gabor	10	-	5
	Indian Pines		
LBP	7	17x17	-
Gabor	7	-	1
	Salinas		

LBP	8	25x25	-
Gabor	8	-	5

The data employed were acquired using National Aeronautics and Space Administration's Airborne Visible/ Infrared Imaging Spectrometer (AVIRIS) sensor and was collected over northwest Indiana's Indian Pine test site in June 1992. The image represents a classification scenario with 145 × 145 pixels and 220 bands in 0.4- to 2.45-μm region of visible and infrared spectrum with a spatial resolution of 20 m. The scenario contains two-thirds agriculture and one-third forest. In this paper, a total of 202 bands are used after removal of water absorption bands. There are 16 different land-covers classes, but not all are mutually exclusive in the designated ground truth map. The number of training and testing samples is shown in Table 2

Take the Indian Pines data for example, (m, r) is fixed to be (8, 1). Cross validation strategy is employed for tuning these parameters. It can be seen that the accuracy tends to be maximum with 7 or more selected bands and with 17 × 17 patch size. Note that, for each selected band, the dimensionality (i.e., number of bins) of the LBP features are $m (m - 1) + 3$. Therefore, more selected bands will increase the dimensionality of the LBP features and computational complexity. [7]

Table 2. Indian Pines Datasets

	Class	Train	Test
1	Alfalfa	6	48
2	Corn-notill	144	1290
3	Corn-mintill	84	750
4	Corn	24	210
5	Grass-Pasture	50	447
6	Grass trees	75	672
7	Grass pasture mowed	3	23
8	Hay windrowed	49	440
9	Oats	2	18
10	Soybean Notill	97	871
11	Soybean-mintill	247	2221
12	Soybean-Clean	62	552
13	Wheat	22	190
14	Woods	130	1164
15	Build-Grass-Trees-Drives	38	342
16	Stone-Steel-Towers	10	85
Total		1043	9323

Indian Pines output with no of bands=7 ,No of samples=m=1:4 (2,4,6,8),Radius r= 1:3 (1,2,3),shown in table 3.

Table 3. Accuracy of classifier with different m and r values

	r		
m	1	2	3
2	0.8981	0.8912	9186
4	0.9827	0.9832	0.9832
6	0.9772	0.9823	0.9826
8	0.9777	0.9795	0.9792

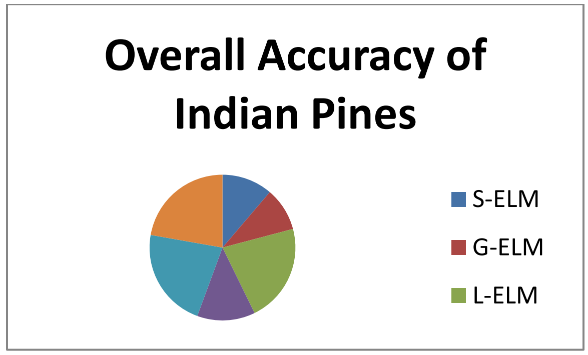


Figure 8 Classifier Accuracy

XI. ADVANTAGES & APLLICATIONS

Advantages:

- An entire spectrum is acquired at each point
- The operator needs no prior knowledge of the sample
- Post-processing allows all available information from the dataset to be mined
- Utilizes the spatial relationships among the various spectra in a neighborhood, thus allowing more elaborate spectral-spatial models for a more accurate segmentation and classification of the image

Applications:

- **Agriculture:** In agriculture for monitoring the development and health of crops.
- **Geology:** In geology for rapidly mapping nearly all minerals of commercial interest
- **Military:** In the military to provide a unique standoff detection, identification and imaging capability for chemical warfare agents

- **Food processing:** In the food processing industry, Hyperspectral imaging, combined with intelligent software, enables digital sorters (also called optical sorters) to identify and remove defects and foreign material (FM) that are invisible to traditional camera and laser sorters.

XII. CONCLUSION AND FUTURE SCOPE

Here in our method we include results with variable number of bands, number of samples for band selection method using LPE and feature extraction using LBP to classify Hyperspectral images using classifier ELM. In our modification we will concentrate on feature selection method using LTrP. The overall accuracy of Indian pines datasets is 0.9795. In our future work we will concentrate on more sophisticated band selection method or classification method.

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