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Hyperspectral image classification using support vector machines

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ABSTRACT

In this paper, a novel approach for hyperspectral image classification technique is presented using principal component analysis (PCA), bi-dimensional empirical mode decomposition (BEMD) and support vector machines (SVM). In this process, using PCA feature extraction technique on Hyperspectral Dataset, the first principal component is extracted. This component is supplied as input to BEMD algorithm, which divides the component into four parts, the first three parts represents intrensic mode functions (IMF) and last part shows the residue. These BIMFs and residue image is further taken as input to the SVM for classification. The results of experiments on two popular datasets of hyperspectral remote sensing scenes represent that the proposed-model offers a competitive analytical-performance in comparison to some established methods.

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1. INTRODUCTION

Hyperspectral imaging (HI) has been gaining importance in many real-life applications of image analysis [1]. Some includes agriculture, cultural heritage, food quality, bio-medicine, remotesensingand many more. In remote sensing, researchers started using the novel concepts of spectroscopy and imaging from late1970s [2].

Present remote sensing based HSI contain abundant spectral and spatial information of a scene. These images are captured in multiple wavelength bands using hyperspectral image sensors. The image exhibits with three dimensional data cube and in the form of H(x, y, I) where 'x', 'y' represent the 'spatial dimension' and 'I' represents wavelength bands. The data cube in general has an array of reflectance values at different wavelengths. Hyperspectral image classification aims to allocate individual pixel to a designated class [3]. The high dimensional spectral features of captured image(s) leads to a state of discrimination capability. Most of the conventional methods of classification on HI were considered either on spectral/spatial information or experimented with both features from simple scenes (images) [4]. Somemajor limitations to those include, practice of manual tuning of parameters and difficulty in extracting high level features from compleximages.

Hughes phenomenon [5] shows that there is a limit to number of bands, beyond which the classification accuracy decreases. In addition, it also increases space and time complexity. Several feature extraction [6] and feature selection [7] techniques have been proposed to reduce the dimensions of the image and to enhance classification accuracy.

PCA is normally applied as a feature extraction techniqueto extract the most informative band called principal component (PC) [8]. The BEMD [9] is used to fragment the principle component into non-destructive hierarchical components known as, bi-dimensional intrinsic mode functions (BIMFs) and Residue. These BIMFs are non-stationary and non- linear functions resulted from sifting process. BEMD is used in image processing, remote sensing applications. The BIMFs offer local features of the image. Support vector machines use BIMFs and residue image as input for classification of HI(s).

Image processing seems to be one of the main purposes of HI analysis and with remote sensing features it further leads to some of the objectives like, 'calibration', 'classification', 'feature extraction', 'radiometric corrections', 'scene understanding' and 'target recognition'. The potential capabilities of deep learningbased data management and feature extraction procedures offer wide solutions for HI classifications. In agriculture analysis, the landcover classification is taken care with two popular approaches like 'pure spectral' and 'joint spectral-spatial'. Some of the other HI techniques in agriculture analysis include on 'monitoring', 'modeling', 'quantification' and 'analysis' processes for pre- harvesting, post-harvesting controls, food quality testing (noninvasive and nondestructive).

Hyperspectral data analysis (due to spatial, spectral or combination of both) and classifications have been evolving from 1-dimensional approaches to 2-dimensional and 3- dimensional (most recent). In higher dimensional classifications, various dimensionality reduction procedures are adopted in pre-processing phase to tackle the spectral information redundancy.

Problem in Hyperspectral Image Analysis: Hyperspectral images popularly used in remote sensing contain abundant spectral and spatial information of a scene. These images are captured in multiple wavelength bands using Hyperspectral image sensors. The image is a three dimensional data cube represented as H (x,y,λ) where x,y represent the spatial dimension and λ represents wavelength bands. This cube is an array of reflectance values at different wavelengths. Hyperspectral image classification is one of major application where the goal is assigning each pixel to a class. The high dimensional spectral features of hyperspectral image gives increases discrimination capability. But Hughes phenomenon [10] shows that there is a limit to number of bands, beyond which the classification accuracy decreases. In addition, it also increases space and time complexity. Several feature extraction and feature selection techniques are proposed to reduce the dimensions of the image and enhancing classification accuracy.

Proposed Methodlogy: This paper uses principal component analysis (PCA) as a feature extraction technique to extract the most informative band called principal component (PC). Bi-dimensional empirical mode decomposition (BEMD) [11] signal processing method is used to fragment the principle component into non-destructive hierarchical components called bi-dimensional intrinsic mode functions (BIMFs) and Residue image. These BIMFs are non-stationary and non-linear functions resulted from sifting process. BEMD is used in image processing, remote sensing applications. The BIMFs give the local features of the image. Further IMFs along with the residue image is fed to the support vector machines for classification.

The paper is organized as follows: section 2 focus on Empirical Mode decomposition, section 3 focus on Bi-dimensional empirical Mode decomposition, Section 4 focus on PCA, Section 5 focus on Support Vector Machines, Section 6 focus on proposed model of Hyperspectral image classification using SVM, Section 7 focus on experimental results and section 8 reports conclusions.

2. EMPIRICAL MODE DECOMPOSITION

In [12] Huang *et al*., introduced a seminal approach of EMD, a powerful signal processing concept for adaptive multi scale analysis of non-stationary signals. In using EMD, signals can be divided into a non-empty group of components (known as IMFs) which are non-destructive types. The last IMF is known as the residue. The frequency is high in first IMF and decreases linearly in subsequent IMFs resulting lowest in last component (residue). This process of decomposition is also termed as shifting process. Some researchers started using EMD for one dimensional case solutions with the basis to construct some intrinsic mode functions (IMF) using sifting process (SP) [13].

Definition 1: Intrinsic mode function (IMF) has a 'zero local mean' and Number_of(extrema)= Number_of (zero-crossings). In using the above definition, the EMD principle for a 1-D signal $(imf[i])_{i\in Z}$ can be described as:

Step 1: INITIALIZE: $resd_0$= imf, p=1

Step 2: COMPUTE p^{th}imf, $decomp_p$(SiftingProcess)

a. $h_0= resd_{p-1}$,q=1

b. FIND allLocal_Extrema(h_{q-1})

c. 'Interpolate the Local Minima (resp. maxima) to get' $Envl_{min,q-1}$ ($resp\_Envl_{max,q-1}$)

d. 'COMPUTE the mean of theseEnvelopes:'

$Envl_{mean,q-1}$ (t)= ($Envl_{min,q-1}$(t) + $Envl_{max,q-1}$ (t))/2
e. h_q[n]= h_{q-1}[n] – $Envl_{mean,q-1}$(n)
f. IF (the stopping criterion is fulfilled) THEN $decomp_p$=h_j
ELSE q=q+1
Step 3: $resd_p$[n]= $resd_{p-1}$[n] – $decomp_p$[n]
Step 4: IF ($resd_p$ is not monotonic) GOTOStep2
ELSE (Decomposition is complete)

3. BI-DIMENSIONAL EMD (BEMD)

It is observed so far that, one dimensional sifting process (SP) is a fixed number of iterative process with interpolation function and a stopping criterion. BEMD has the SP which in turn based on the '*Delaunay Triangulation*' [14] and then '*Cubic Interpolation*' [15] on triangles. BEMD offers a low computation time. We present a review of BEMD algorithm as follows [16-17]:

Algorithm BEMD
```
Step 1: Input:Hyperspectral Image Dataset
Step 2: Img(cx,cy)= First Principal Component of HI image
Step 3: Find local_maxima points in Img(cx,cy)
Find local_minima points inImg(cx,cy)
Step 4: 'UpperEnvelope'
        Up(cx, cy)= Interpolation_of ('maxima points') 'LowerEnvelope'
        Lw(cx, cy)= Interpolation_of ('minima points')
Step 5: Mean(cx,cy)= [Up(cx, cy)+Lw(cx, cy)]
Step 6: sub(cx, cy)= Img(cx, cy)-Mean(cx, cy)
Step 7: IMFi=Sub(cx,cy)ifSub(cx,cy) satisfies Properties(IMF)
Step 8: Img(cx, cy)= Img(cx, cy)-IMFi
Step 9: IF Img(cx, cy) has maxima and minima points to create envelopes THEN GOTO Step-3
Step 10: Stop
```

4. PRINCIPAL COMPONENT ANALYSIS (PCA)

Principal component analysis (PCA) is a statistical procedure for dimensionality reduction using feature extraction technique [18]. It is orthogonal transformation that takes a set of observations of possibly correlated variables (Numerical entities) and transform them into a set of values of linearly uncorrelated variables called principal components [19]. This process results in computation of principal components in which the first principal component has the largest possible variance accounting maximum variability in the data. This is followed by second principal components that contains second largest variability and so on [20]. We can consider each pixel in hyperspectral image at a given location as:

$$Xi=[x1,x2.......................,xN]i^T$$

N=Number of bands in a given hyperspectral image. i=1, 2, 3.....M represents number of pixel vectors of hyperspectral image. M=m*n (for m rows and n columns of the hyperspectral image data) PCA technique is based on the Eigen decomposition of the covariance matrix of x. Finally, it results in k where (k<N) principal component images which contain majority of information [21]. The amount of variance or information decreases as we move to kth principle component image. After the transformation there is no correlation between two principle component images. In the proposed model, PCA is applied on the Indian Pines and Pavia university datasets which are widely used hyperspectral image datasets. First principle component from both the datasets are computed and chosen for the input to the BEMD decomposition.

5. SUPPORT VECTOR MACHINES (SVM)

Support vector machine is a discriminator and modeled by a discriminative hyperplane. It is a representation of data as points in space that are mapped, so that the points of different categories are separated by a gap as wide as possible. These hyperplanes are boundaries for classifying the data samples. Data points can be assigned to different classes irrespective of its position to the hyperplane. Number of features plays a crucial role in deciding dimension of the hyperplane. The hyperplane is just a line if the number of independent features is two. Figure 1 shows the process of Support Vector Machine. The hyperplane becomes a two-dimensional plane if the number of independent features is three.

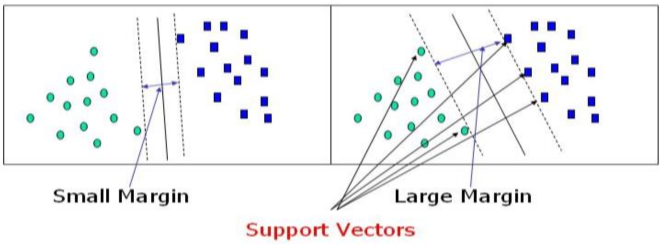

Figure 1. Support vector machine

The data samples which are closer to the hyperplane are called as support vectors. These support vectors influence the orientation and position of the hyperplane. We maximize the margin of the classifier, by using these support vectors. After training SVM, if we get greater than 1 as output of SVM function, we label it as one class, otherwise we label it as another class in binary-class classification. Different SVM algorithms use different types of kernel functions. These functions can be different types. For example polynomial, radial basis function (RBF), sigmoid and Gaussian kernel etc [22]. Using the features of BEMD, the SVM algorithm creates a maximal-margin hyperplane which divides the image pixels into classes.

6. HYPERSPECTRAL IMAGE CLASSIFICATION USING SVM

PROPOSED ALGORITHM: The objective of this proposed model, shown in Figure 2 is to predict the class of individual pixel of a hyperspectralimage using supervised learning technique. The proposed method is summarized as below:

1. First principal component (PC) is extracted by applying PCA on the Hyperspectral image dataset.
2. PC is input to BEMD signal processing method that decomposes it into three BIMFs and residue image
3. These BIMFs along with residue image serves as the features of our hyperspectral image dataset and is fed to pre-trained SVM model.

A small neighboring pixel in an image usually exhibits high coherence among each other. To avoid loss of spatial information in this experimental patches of size 33x33x4 are extracted from the stacked BIMFs along with the residue image.

To handle the imbalance hyperspectral datasets, the extracted sample patches are oversampled for weak classes. Further these samples are split into 80% training and 20% testing patches. The training patches are augmented to increase the training samples. Finally the SVM model is trained and tested which gives a remark of promising results for two benchmarks.

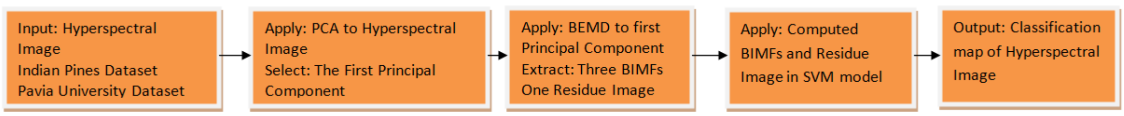

Figure 2. Proposed model

7. EXPERIMENTAL RESULTS AND ANALYSIS

This section demonstrates the effectiveness of the proposed PCA-BEMD-RESNET model. Experiments were carried out in cloud environment with downloaded hyperspectral image datasets (Source: www.ehu.eus/ccwintco/index.php?title=HyperspectralRemoteSensingScenes). Brief descriptions of both the HI datasets (India pines and Pavia University) are outlined below.

a. India PinesDataset

This is a scene in ‘Indian Pines’ test site (North-western Indiana) captured by the ‘AVIRIS’ hyperspectral image sensor during June. The dataset contains the reflectance values. The image has 145 rows and 145 columns and with 224 spectral bands having wavelength (from 0.4 to 2.5 10^{-6} meters). Agriculture coverage contains two third of the scene and forest coverage has rest one third of the scene. There are highways, railway lines, low density houses, manmade- structures and small roads. Agriculture constitutes the corps like corn and soybeans. The ground truth contains 16 classes. The image has undergone through corrections by removing some unwanted bands and the final corrected images has dimension 145x145x200.

b. Pavia UniversityDataset

This scene is captured by the ‘ROSIS’ on Pavia University at Pavia (Northern Italy). PVU dataset consistsof103 ‘*spectral bands*’. The image has 610 rows and 610 columns. The ground truth contains 9 classes each. Some samples of the image were discarded before analysis as they do not contain any information. This is represented by black stripes. The dimension of the image is 610x610x103.

c. Classification Results

Figure 3 shows the principal components of Indian Pines and Pavia University Dataset respectively. Figure 4 shows the BEMD IMFs of first PCA of each dataset.

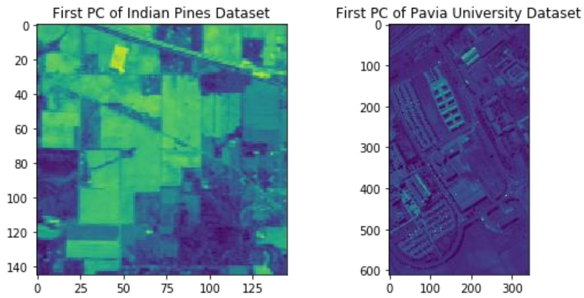

Figure 3. Principal component image of data sets

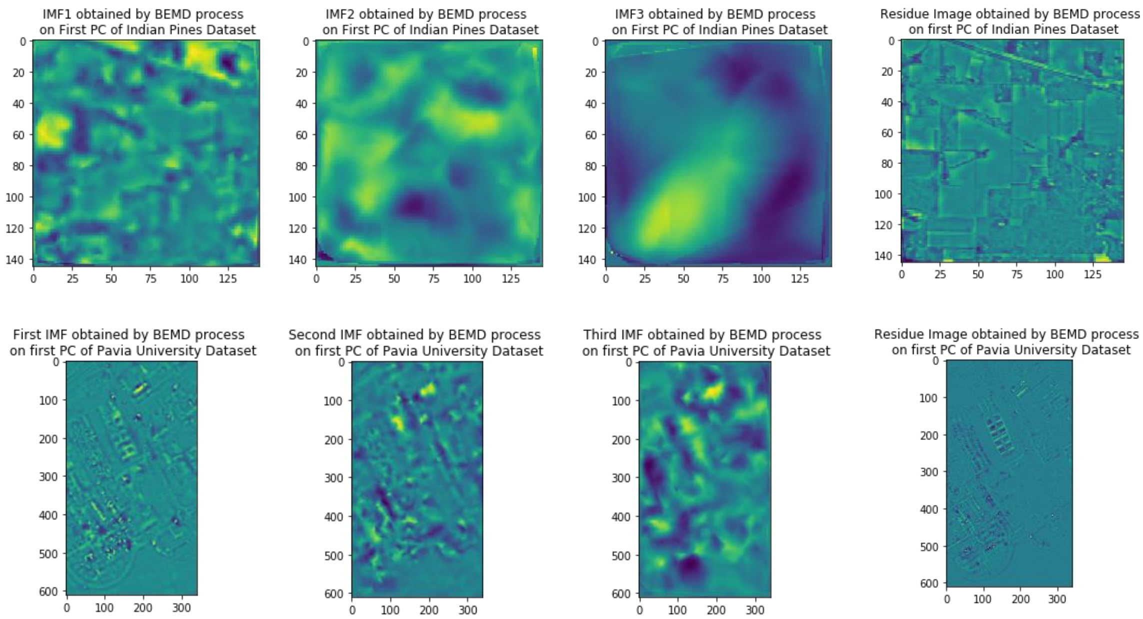

Figure 4. BEMD components of first principle component for each dataset

Table 1 and Table 2 represent the number of samples (Training and Testing) of Indian Pines and Pavia University Dataset respectively. Table 3 shows the accuracy results of proposed model compared with other existing methods. The proposed model achieves 96.7% and 97.6% accuracy in Indian pines and pavia university datasets respectively. The accuracy table in both data sets has compared with the models of MNF+FABEMD + SVM [23], 2-D EMD + SVM [24] and Conventional PCA-KNN [25]

Table 1. Number of training and testing samples in the Indian pines dataset

Class number	Training	Testing	Accuracy (%)
1	1961	9	95
2	2284	286	95.2
3	1992	166	95.6
4	1900	47	96
5	1930	97	95.9
6	1752	146	96
7	1955	5	96
8	1910	96	96
9	1968	4	96
10	2334	194	96
11	1964	491	96.59
12	1896	119	96
13	1968	41	96
14	2024	253	96
15	1854	77	96.9
16	1998	19	96.8
AA			96.7
OA			96.4
KA			96.3

Table 2. Number of training and testing samples in the Indian Pavia university dataset

Class number	Training	Testing	Accuracy (%)
1	15915	1326	97
2	14919	3730	97.89
3	15111	420	96
4	14706	613	97.83
5	15064	269	97
6	16092	1006	97
7	14896	266	97
8	14725	737	97
9	14160	189	97
AA			97.6
OA			97.64
KA			97.92

Table 3. Classification accuracy (%) comparision of our model with different methods

Method	Indian Pines	Pavia University
Conventional PCA-KNN	87.70	88.10
2-D EMD+ SVM	94.7	95
MNF+FABEMD+SVM	94.8	96.2
Proposed PCA-BEMD-SVM	96.7	97.6

8. CONCLUSION

This paper presents a hyperspectral image classification model that uses PCA, BEMD techniques for feature extraction. These features are fed to support vector machines for classification. Experimental results on standard datasets have proved that the proposed model has very good performance compared to other state-of-art-methods.

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