IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 13, Issue 8, August 2024

DOI: 10.17148/IJARCCE.2024.13842

Dimensionality Reduction based on Spatial Features for Efficient Multivariate Image Classification

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Abstract: Multivariate imaging advanced in recent years which prompted many applications for detailed understanding in the fields of satellite imaging, medical imaging, and microscopic imaging. To achieve more insights about it, various feature extraction techniques exist which utilize the ample spectral and spatial details in an image. But apart from feature extraction dimensionality reduction (DR) and efficient classification has become a key aspect in multivariate image analysis (MIA). Adding more and more variables in feature space of multivariate image results into high dimensionality which in turn increases the complexity in classification. Therefore, it becomes important to apply DR techniques before classification process. Most widely used DR method is Principal component analysis (PCA) which is linear DR method. The main disadvantage of PCA is that it does not consider the nonlinearity in data. The proposed new method is invariant to nonlinearity in data. To consider nonlinearity, Gabor filter is used to extract spatial features from multivariate data. Gabor filter based method performs dimensionality reduction of nonlinear multivariate images while improving the classification accuracy.

Keywords - Multivariate image analysis (MIA), dimensionality reduction (DR), Gabor filter, Support Vector Machine (SVM), Convolutional Neural Network (CNN)

I. INTRODUCTION

The use of images in the sciences is expanding and has been around for a while. Only visualization as graphics is capable of displaying large volumes of data describing complicated systems. There are numerous sources of multivariate images. Multivariate image is three dimensional array with width and height as two dimension and variable index as a third as depicted in Fig. 1. Variable index can be any physical quantities like temperature, magnetic field, electrical field, wavelength, ultrasound wavelength, polarization, electron energy, gravitational field, impedance etc [1]. Some of the examples of multivariate image are hyperspectral image, thermal images, MRI scan, CT scan, Ultrasonography. Three fields roughly correspond to the subdivision of multivariate images are satellite imaging, medical imaging and the microscopic imaging. In a digital image, resolution is a crucial factor. Multivariate images have spatial, intensity, spectral and temporal resolution [2].

The most common multivariate image form is hyperspectral image (HSI). HSI is cube of hundreds of narrowly spaced spectral bands. These bands contains vital information. Bands are large in numbers and possesses correlation among them. Because of huge features in various bands, classification accuracy is affected due to the computational complexity. Additionally, it is challenging to increase classification accuracy for multivariate images due to redundancy from the spectral and spatial domains [3].

When number of features from input subspace outstrips permissible sample size required for training, classification accuracy decreases. This is called as Hughes phenomenon which leads into challenges in classification. High dimensionality means that subspace size will exponentially increases with dimension of data [4], [5]. Therefore, it is must to reduce dimensionality of multivariate images before the classification process. Reduction methods must conserve the vital information of objects so as to retain classification accuracy. Dimensionality reduction is not only useful to speed up method execution but also to improve model performance in terms of overall accuracy and reduction rate.

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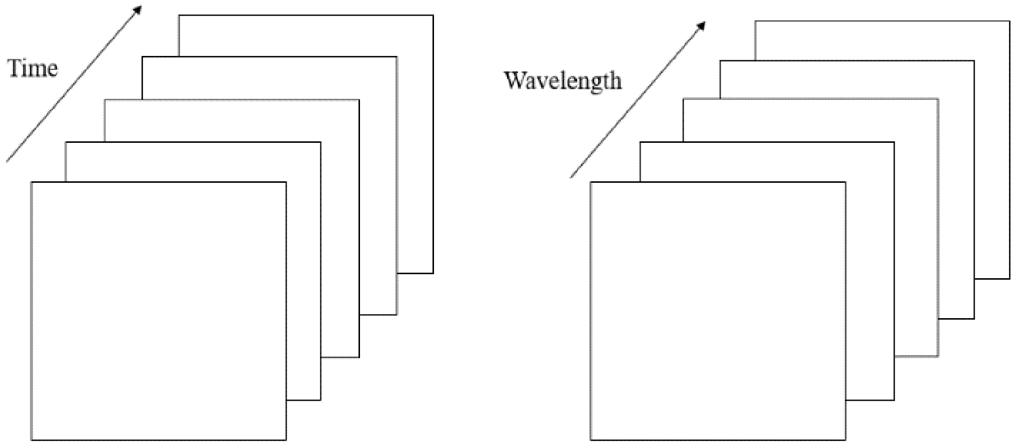

Fig. 1. A multivariate image is an array of images, each captured for a different variable.

Multivariate images have rich information, but it possesses great challenges due to abundant data [1]. Techniques like Gabor Wavelet analysis can be used as feature extraction method which is useful to extract not only spatial but also rich spectral information from images [6]. Features are extracted by convolving multivariate images with Gabor filter bank. The components which have uniform frequency indicates that pixels are from same class. Pixels located on boundary of class exhibits high frequency components [7],[8]. Along with feature extraction, dimensionality reduction and classification are also important aspects of multivariate image analysis. DR techniques are categorized as projection-based methods and band selection methods.

Principal component analysis (PCA) is popular DR techniques. In multivariate images like hyperspectral data in which neighboring bands are correlated and highly redundant, PCA is very useful [9], [10]. PCA as DR techniques reduce number of features by projecting high dimensional feature space into low dimensional feature space, called as latent variables. Resulting feature space are orthogonal and has no correlation. The multivariate image's variability can be largely explained by a latent variable. The remaining features can be discarded as it shows minimal variability [11],[12].

The inability of linear approaches, such as PCA, to identify the curved and nonlinear structure of the data is one of its drawbacks [13]. Because of nonlinear fluctuations in reflectance, multipath scatter, and changing levels of attenuating medium in the scene, hyperspectral photography exhibits nonlinearity. Additionally, the increased spectral resolution brought on by image sensors puts more nonlinearity into physical processes, making it more challenging for linear approaches like PCA to extract this nonlinearity [14]. So, to improve classification accuracy, spatial features must be considered. To overcome the issue of non-linearity, spatial features extraction approach is used in which textural features of multivariate images are extracted using Gabor filter.

II. PROPOSED METHOD

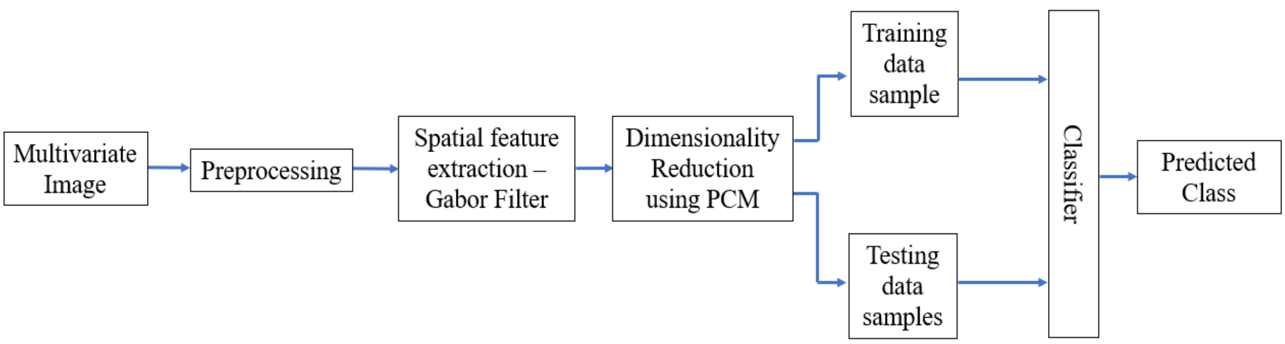

Fig. 2. Gabor filter based spatial dimensionality reduction method

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The proposed method for dimensionality reduction is illustrated in Fig. 2. Multivariate images are first pre-processed. In preprocessing Gaussian filter is applied to reduce the high frequency noise from bands. The water absorption bands which don't contain any information are removed. Gabor filter is applied on multivariate image data. Gabor filter extracts textural features of multivariate image which constitutes a spatial feature space. The dimensionality of spatial feature space is then reduced by applying PCA. PCA transforms the feature space into reduced feature space. The classifier is used for classification of multivariate feature space. The classifiers used are Support Vector Machine and Convolutional Neural Network whose results are discussed in subsequent section.

III. METHODOLOGIES

1. Gabor Filtering:

The Gabor filter is modulated by a Gaussian function and a sinusoidal plane wave. Discriminant features can be extracted from Gabor filtered images, specially texture and orientation information. The generating function can be defined as follows:

$$\Phi_{u,v}(x,y) = \frac{f^2}{\pi\gamma\eta} \exp\left(-(\alpha^2 x'^2 + \beta^2 y'^2)\right) \exp\left(j2\pi f x'\right) \tag{1}$$

$$x' = \left(x - \frac{m+1}{2}\right) cos\theta + \left(y - \frac{n+1}{2}\right) sin\theta$$

$$y' = -\left(x - \frac{m+1}{2}\right) sin\theta + \left(y - \frac{n+1}{2}\right) cos\theta$$

Where f is is the distribution coefficient of the Gabor function in the frequency domain, and θ represents the rotation angle of the Gaussian function. α defines the sharpness of the Gaussian function along the major axis parallel to the wave. β is the sharpness of the Gaussian function along the minor axis perpendicular to the wave. $\gamma = \frac{f}{\alpha}$ and $\eta = \frac{f}{\beta}$ are defined as the constraint conditions that keep the ratio between frequency and sharpness. α and β are assumed to be equal and $\gamma = \eta = \sqrt{2}$. Generally, m and n are equal to an odd number d, which represents the size of the Gabor filter, i.e., $d = m = n$. [15]

2. Principal Component Analysis (PCA)

PCA is orthogonal transformation that maps feature space that has correlated variables into a comparatively smaller feature space having uncorrelated variables known as Principal Components (PCs). By rotating an existing axis to a new point in space that is determined by the new PC-basis vectors, PCA is able to achieve DR by projecting a high-dimensional data to its lower dimensions while maintaining all of the crucial and cardinal information in the data. PCA selects the projection direction so that the variance of the projected data is increased, and the mean squared error between the original data and the transformed or projected data is reduced [16],[17].

As shown in Fig 2, data cube of multivariate image has resolution $M \times N \times L$ where $M \times N$ is spatial resolution of spectral band and $L$is total number of bands in cube. Let $Z_n = [Z_{1L}, Z_{2L}, Z_{3L}, \ldots, Z_{nL}]^T$ is data matrix vector obtained by unfolding the data cube. The value of n varies from 1 to (M x N). Then obtain the average vector $\bar{J}$ as follows,

$$J_n = Z_n - \bar{J} \tag{2}$$

$$\bar{J} = {}^{1}/_{MN} \sum Z_n \tag{3}$$

Covariance matrix cov is obtained using eq,

$$cov = E\{J_n J_n{}^T\} \tag{4}$$

Then by decompose the covariance matrix to obtain the Eigen values and vectors as,

$$cov = VDV^T \tag{5}$$

where D is a diagonal matrix obtained by arranging the Eigen values of cov and it given as

$D = [\lambda_1, \lambda_2 \ldots, \lambda_L]$, and Eigen vectors constitutes orthonormal matrix V.

DOI: 10.17148/IJARCCE.2024.13842

Uncorrelated vector v_n is obtained using the data vector J_n as,

$$v_n = V^T J_n \tag{6}$$

Then arrange the Eigen values is decreasing order and remove the smallest values. So the projected data will be reduced as,

$$PC = [C_{n1}, C_{n2}, C_{n3}, \dots, C_{nP}]^T \tag{7}$$

where P is number of principal components.

3. Support Vector Machine (SVM)

The support vector machine (SVM) technique is often regarded as the classifier that produces the best outcomes in terms of classification accuracy when used to classify multivariate images. SVM is distinguished by its ability to effectively handle large input areas while only employing a small number of training examples. SVMs are basically binary classifiers [18]. So for multiclass model, SVM requires concurrent discrimination which can be achieved by combining number of binary classifiers [2], [3]. SVM's primary objectives are to increase the margin between the two classes and reduce the possibility of generalization errors. SVM categorizes a set of training images into distinct classes, $(s_1, t_1), (s_2, t_2), (s_3, t_3) \dots (s_n, t_n)$ where s_i is feature space and t_i is class label, {-1,+1}, with $i = 1, 2, 3, \dots, n$. [19],[20]. Hyperplane is decision boundary which is build using Kernel function. One side of hyper plane lies a feature space of group of images whose class label is {+1}, and on other side belongs to class label {-1}. Support vector is margin line passing through a point which is nearest to the hyperplane in opponent class and it will be parallel to the hyperplane. Margine is distance between support vectors and this margin should be maximum for more accuracy and less error rate [21]. Unlike the other available classifiers, SVMs are efficient in high-dimensional data like HSI, making them perfect for analysing HSI feature space. Also, SVM is robust to noise present in high dimensional data.

4. Convolutional Neural Network (CNN)

After obtaining the spectral-spatial pixel clusters, the training clusters, and training labels are feed into the designed CNN with the purpose of feature extraction. It transforms a pixel cluster with *P* pixels into *C*+1 channels, each of which predicts the reliability with which *P* pixels belong to the same class. The framework includes eight convolutional layers, three max-pooling layers, and two fully connected layers. All of the convolutional layers are followed by a rectified linear unit (ReLU) layer to increase the nonlinear relationship between different layers [17]. In the convolution layer, multiple shared convolution kernels are used to perform convolution operations on the input pixel-clusters to obtain multiple feature maps. Besides, the dimension of each feature map will be reduced according to the size of the convolution kernel if there is no padding used. Suppose the dimension of input map is $d1$, and the size of convolution kernel is $k1$, then the dimension of output layer is $d1 - k1 + 1$. Pooling layers are often used in CNN to reduce feature dimensions, model parameters and slow down the "overfitting" problem after convolutional layers. The pooling layer can ensure the invariance of the feature to the rotation and reduce the feature dimension. If the dimension of input map is $d2$, and the size of kernel is $k2$, then the dimension of output layer is $d2/k2$ after pooling down sampling. In this article, the max-pool function is used to calculate the maximum value of a rectangular area, which will be used to represent the area. After the input pixel-clusters of the network going through multiple convolutional layers and pooling layers, two fully connected layers are used to reassemble the local features extracted by the convolutional layer into a complete feature map, which is more conducive to classification. After two fully connected layers, the feature map is transformed into the feature vector of the corresponding label [22], [23].

IV. EXPERIMENTAL SETUP AND RESULTS

HSI data Indian pines contains 220 spectral bands having wavelength range of $0.4\ \mu m$ to $2.5\ \mu m$ and each data band has resolution of 145 x 145 pixels. There are 16 groundtruth classes for Indian Pines HSI data. The hyperspectral images contains water absorption bands which were discarded. Then data cube is filtered using Gaussian filter to remove the noise due to high frequency components. The proposed method is applied on filtered data cube, which yields the spatial features of image data. In proposed method, after preprocessing the multivariate data, spatial features are extracted using the Gabor filter. Then spatial feature space is reduced by applying PCA. The spatial features are extracted by considering the local neighbourhood of pixels due to which issue of nonlinearity in multivariate image is resolved to some extent. Finally SVM classifier is applied for classification of data. Apart from SVM classifier, Convolutional Neural Network (CNN) is applied for classification. The final results after classification is displayed in Table I. Overall accuracy (OA) of classification using both the methods is calculated. OA values using SVM and CNN on spatially reduced dimensionality of Indian Pines HSI database for several number of components is mentioned in Table II. OA has increased as local structures are preserved.

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TABLE I. Overall accuracy (OA) in %

Number of components	PCA	Gabor-PCA-SVM	Gabor- PCA-CNN
10	76.6	77.4	78.2
20	78.3	79.2	79.8
30	80.7	81.2	81.6
40	81.2	82.4	82.8
50	81.8	82.9	82.1
60	79.4	80.3	79.6
70	78.6	79.1	78.2

V. CONCLUSION

Multivariate images contain rich information, but because of their structure and volume of data, they pose challenges during classification. To understand the relationships between the components of the image and their overall structure, techniques based on PCA can be applied. But projection-based methods fails to address the nonlinearity in multivariate images. The large dimensionality and complexity of the multivariate image data structures not only make computing more difficult, but they might also make classification difficult. Gabor filter based spatial feature extraction is able to overcome the problem of nonlinearity in data to some extent. Though the OA is slightly increased, but the time required for classification does not improve. The proposed method reduces the dimensionality of multivariate images along with improvement in the classification accuracy.

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