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GGPS Method 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 methods are invariant to nonlinearity in data. To consider nonlinearity, Geodesic distance measure is used to extract features from multivariate data. Method GGPS performs dimensionality reduction while improving the classification accuracy.

Keywords: Multivariate Image Analysis (MIA), Principal Component Analysis (PCA), Support Vector Machine.

I. INTRODUCTION

Use of modern sensors, multivariate imaging becomes encouraging techniques for applications like medical science, microscopic science, forensic science, ecological science, geological science, precision agriculture, land mapping, urban planning, mineral exploration, food safety, pollution monitoring, and military applications [1]. The most common multivariate image form is hyperspectral image (HSI). HSI is cube of hundreds of narrowly spaced spectral bands as shown in Fig. 1. These bands contains vital information. Bands are large in numbers and possesses correlation among them [2].

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. 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 [3], [4]. 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[5].

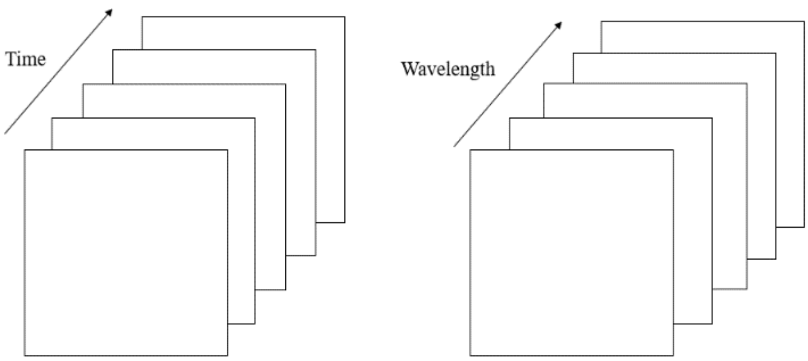

Fig. 1. A multivariate image is an array of images, each captured for a different variable.

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Multivariate images have rich information, but it possesses great challenges due to abundant data [6]. The inability of linear approaches, such as PCA, to identify the curved and nonlinear structure of the data is one of its drawbacks [6],[7]. 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 [8]. Also, the spatial features are taken into consideration when PCA is used for dimensionality reduction. So, to improve classification accuracy, spectral features along with spatial features must be considered [9]. To overcome the issue of non-linearity, Geodesic distance measure as illustrated in Fig. 2 must be implemented during feature extraction instead of Euclidian distance.

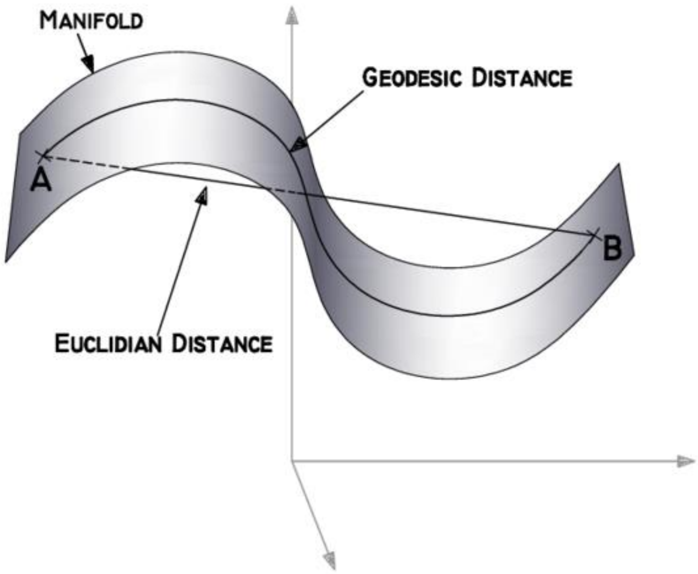

Fig. 2. Geodesic distance vs Euclidian distance

II. PROPOSED METHOD

GGPS Method

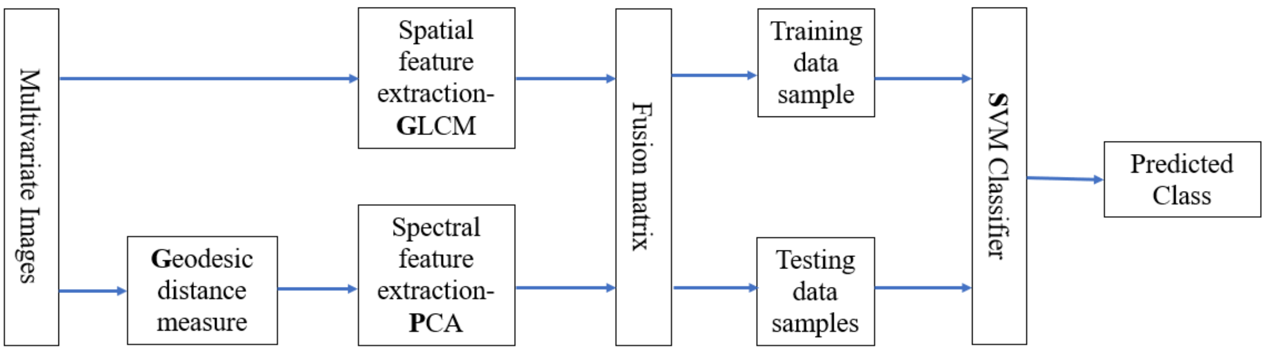

Fig. 4. GGPS method which involves Geodesic distance measure for spectral feature extraction using PCM, GLCM for spatial feature extraction, SVM as classifier

III. METHODOLOGIES

1. Gray Level Co-Occurrence Matrix (GLCM)

The GLCM has been proved to be a powerful approach for image texture analysis. It describes how often a pixel of gray level i appears in a specific spatial relationship to a pixel of gray level j. The GLCM defines a square matrix whose size is equal to the largest gray level Ng appearing in the image.

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The element *Pij* in the (*i*, *j*) position of the matrix represents the co-occurrence probability for co-occurring pixels with gray levels *i* and *j* with an inter-pixel distance δ and orientation θ . Haralick *et al.* [10] proposed 14 original statistics (e.g., contrast, correlation, energy) to be applied to the co-occurrence matrix to measure the texture features.

The most widely used textural measures (Table 1) are considered in this study: energy (ENE), contrast (CON), entropy (ENT), and inverse difference (INV). Energy is a measure of the local uniformity [16]. Entropy is inversely related to the energy, and it reflects the degree of disorder in an image. Contrast measures the degree of texture smoothness, which is low when the image has constant gray levels. The inverse difference describes the local homogeneity, which is high when a limited range of gray levels is distributed over the local image[10].

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)[11]. 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 [12].

Data cube of multivariate image has resolution M x N x L where M x N is spatial resolution of spectral band and L is total number of bands in cube. Let $Z_n = [Z_{1L}, \; Z_{2L}, Z_{3L}, \dots, Z_{nL}]^T$ 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,

$$J_n = Z_n - \bar{J} \tag{1}$$

$$\bar{J} = {}^{1}\!/_{MN} \sum Z_n \tag{2}$$

Covariance matrix cov is obtained using eq,

$$cov = E\{J_n {J_n}^T\} \tag{3}$$

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

$$cov = VDV^T \tag{4}$$

where D is a diagonal matrix obtained by arranging the Eigen values of cov and it given as $D = [\lambda_1, \lambda_2 \dots, \lambda_L]$, and Eigen vectors constitutes orthonormal matrix V [13].

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

$$v_n = V^T J_n \tag{5}$$

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

$$PC = [C_{n1}, C_{n2}, C_{n3}, \dots, C_{nP}]^T \tag{6}$$

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 [14]. So for multiclass model, SVM requires concurrent discrimination which can be achieved by combining number of binary classifiers. 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].

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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 [15]. 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.

IV. EXPERIMENTAL SETUP AND RESULTS

The experimental data used and its description such as number of bands, spectral range, number of classes is summarized in Table I. 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. False colour image and groundtruth image with different classes.

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 GGPS is applied on filtered data cube separately, which yields the reduced dimensionality of feature space. In GGPS method, after preprocessing the multivariate data, spatial features are extracted using the GLCM. Then spatial features are extracted using Geodesic distance measure. Because of this distance measure, issue of nonlinearity in multivariate image is resolve. Then fusion matrix is formed which contains spatial as well as spectral features. Finally SVM classifier is applied for classification of data.

Overall accuracy (OA) of classification using both the methods is calculated. OA values using GGPS on Indian Pines HSI database for several number of components is mentioned in Table I. OA has increased in GGPS approach as local structures are preserved as compared to other approaches which uses Euclidian distance measure.

TABLE I. Overall accuracy (OA) in %

Number of components	PCA	LLE	GGPS
10	76.6	80.4	83.23
20	78.3	82.4	84.78
30	80.7	83.2	85.88
40	81.2	85.7	86.12
50	81.8	85.4	87.98
60	79.4	85.3	88.26
70	78.6	84.1	88.62

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. Geodesic distance based spectral feature extraction along with spatial features is able to overcome the problem of nonlinearity in data. These proposed methods not only reduce the dimensionality but also improves the classification accuracy.

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