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A REVIEW ON MULTIPLE-FEATURE-BASED ADAPTIVE SPARSE REPRESENTATION (MFASR) AND OTHER CLASSIFICATION TYPES

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Abstract- A new technique Multiple-feature-based adaptive sparse representation (MFASR) has been demonstrated for Hyperspectral Images (HSI's) classification. This method involves mainly in four steps at the various stages. The spectral and spatial information reflected from the original Hyperspectral Images with four various features. A shape adaptive (SA) spatial region is obtained in each pixel region at the second step. The algorithm namely sparse representation has applied to get the coefficients of sparse for each shape adaptive region in the form of matrix with multiple features. For each test pixel, the class label is determined with the help of obtained coefficients. The performances of MFASR have much better classification results than other classifiers in the terms of quantitative and qualitative percentage of results. This MFASR will make benefit of strong correlations that are obtained from different extracted features and this make use of effective features and effective adaptive sparse representation. Thus, the very high classification performance was achieved through this MFASR technique.

Index Terms: Hyperspectral Images, Classification, Adaptive sparse representation, Feature extraction, Sparse representation.

I. INTRODUCTION

In recent years, Hyperspectral Image (HSI) plays an important role in the classification [1] - [5] field of remote sensing, which has involved in various applications and fields, such as Identifying of ground elements [6], Exploration of minerals [7] and Target detection. In Hyperspectral Images, the very high dimensional vector present in a each pixel and this represents the response of spectral in different spectral bands according to their entries. The pixels in Hyperspectral Images have been used in various applications, such as Anomaly detection [8], spectral unmixing [9] and classification [10]. The classification of Hyperspectral Images can be done with applying test pixels to each classes depends upon its characteristics of spectral information with a given training set.

The purpose of classification for the classes is to assign each test pixel in a given training set. To avail these functionalities, the two main approaches are Support Vector Machine (SVM) [11], [12] and multinomial logistic regression (MLR) [13] – [15]. The decomposition of an input pixel from an overcomplete dictionary is called as Sparse representation [16] – [20], which acts as an important classifier. To process an adaptive metric learning method and a novel technique for Hyperspectral image classification, a new technique called Metric Learning [21] is used. This method acts as object recognition. According to this classification method, the various classification techniques such as clonal selection feature extraction [22], semisupervised discriminative locally enhanced alignment [23], Principle Component Analysis (PCA) [24] and kernel discriminative analysis [25]. To enhance the class seperability problems [26], a kernel [27] method has been used in the above mentioned approaches.

The Extended Morphological Profiles (EMP) [28], [29] make use of pixels spatial information and this enhances the structure of neighbourhood pixels in Hyperspectral Images (HSI’s). In a local region, the spatial information of each test pixels are pre-processed efficiently [30]. The classification of Hyperspectral images can be done by using k-means clustering [31], [32] and these superpixels do not have the correlations among themselves. To make use of visual recognition [33] – [35], an analyse of superpixels has been made in computer vision. In order to slowdown the difference between the domains of both source and destination, an adaptation framework that is having multiple kernels is used [36].

In order to achieve good accuracy of HSI classification, the supervised classifiers are neural networks [37], kernel based methods [38], [39] and Bayesian [40]. If the number of training samples is limited and fixed, it increases the data dimensionality [41]. This causes high computational cost and to solve these problems, a feature reduction methods are used [42] – [47].

The spatial feature plays an important role in the field of classification of HSI’s [48], [49]. To improve the classification performance, the composite kernels combines spatial and spectral information [50].The combination of kernels can be represented as standard composite kernels and multiple kernel learning [51]. To solve the problem of optimization, the newly proposed method named generalized composite kernel is used [52]. In linear spatial-spectral features, the two methods maximum noise fraction [53] and independent component analysis [54] are used. In non-linear transformations, the manifold regularization methods [55] and extended multiattribute profile [56] are illustrated. To incorporate linear and non-linear multiple features, multiple feature learning (MFL) [57] and multinomial logistic regression (MLR) [58] are used in MFL and GCK methods.

The distance weighted tikhonov regularization [59] and nearest subspace classifier are incorporated with the help of nearest regularized subspace (NRS). To overcome the drawbacks of NRS, the joint collaborative representation (JCR) [60] is proposed. The JCR works with surrounding pixels with same weights. To solve this issue, Weighted Joint Collaborative representation (WJCR) [61] is introduced to make use of different weights that lies in between neighbour pixels and the central pixel.

The HSI is used to achieve spectral pixels that are present in the spectral information with the help of various classifiers, such as Support Vector Conditional random classifier [62], neural network [63], adaptive artificial immune network [64], support vector machine [65] – [67], multinomial logistic regression [68], [69] and artificial deoxyribonucleic acid computing [70]. The composite kernel method is used to incorporate spectral and spatial information accordingly for each test pixel in HSI [71], [72]. Thus, a Bayesian-based approach is further used to make benefit of neighbouring pixels [73].

To increase the accuracy of ground object elements [74-77], HSI provides the acquisition of spectral information reflections simultaneously. To obtain the Hyperspectral Image classification performance [78-85], the representation based classification methods are used. In order to get good classification results, the various applications [86-92], are used for sparse representation classification (SRC) [93]. Collaborative representation classification (CRC) [94] is applied to get the good classification accuracy result. To avail a better result than the spectral information [95-98], spectral information is used in HSI.

Hyperspectral Images contains the hundreds of spectral bands that are reflected from ground elements and this can be applied to various domains, such as military [99], [100], Environmental monitoring [101], [102] and Agriculture [103-105]. In HSI, the categorization of test pixels obtained by using supervised HSI classification [106-112]. The various classification methods are used [113-115] in the field of spectral pixel-wise method. The spatial information provides the various pixels are present inside the local region that contains the spectral characteristics of information and ground objects similarly [116-124].

According to this spectral information, this produces the classification maps result with a result of very high noisy [125] [126]. To enhance the performance of classification, some techniques

[127] [128] have been examined to make use of spatial – spectral information. The method named region – based sparse representation [129] involves the region that contains some pixels always determines the same class. This representation defines the test pixel for the fixed region and then decomposes the various pixels related to the same region present in the same atom.

The region size is fixed, so that the Hyperspectral Images do not make the spatial information sufficiently. To improve the better classification performance, the neighbouring pixel which belongs to the central test pixels, the different weights are allocated [130]. The new approach named Batch – mode active learning was introduced to make use of spatial coherence Information [131]. The feature extraction method was approached to obtain the better classification results.

The main feature named Extended Morphological Profiles that are implemented with the help of Principle Component Analysis (PCA) [132]. In order to classify the HIS, morphological profiles can be set to create a transforms of both opening and closing from a very large feature set. The Hyperspectral Images data contains spectral information of the covered area, but it has no spatial information. The spatial information present in an individual image, since it has very low spectral data in that obtained image. If an original image contains in a profile, the base image acts as a principle component for an extended morphological profile.

A new approach called Multiple- feature learning algorithm is used for extraction of linear and non – linear features [133]. With this multiple feature learning classifier, HSI has achieved greater classification performance, but it is efficiently applied for fixed size window and it cannot make use of HSI spatial correlations [134]. This spatial correlations does not suitable for multiple feature based classifier [135].

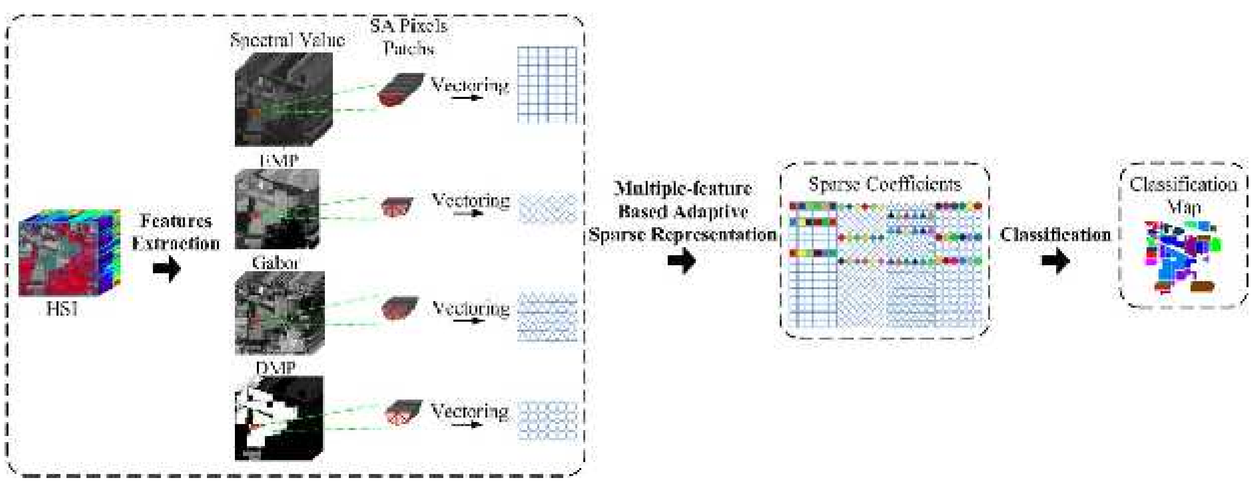


Figure. 1. MFASR Architecture

To avoid these circumstances, a new technique named Multiple -feature- based adaptive sparse representation (MFASR). This MFASR has involved in four steps. Each step process the HSI data on its own way. A shape adaptive (SA) region is used for the window in a fixed size range, so that it can make use of its neighbouring pixels. The usage of adaptive sparse representation is implemented in the shape adaptive region will break the pixels effectively. This exploits all the correlations among themselves in the four features mentioned above in an effective way. To get the good classification map results, it joints all the correlations in a single way for each test pixels in a given obtained class label.

II. CLASSIFICATION TYPES

a. Support Vector Machine (SVM)

Machine learning algorithms are widely used in classification of HSI in agriculture field. This algorithm is implemented in various fields, such as KNN [136], Artificial Neural Networks [137], [138] and Decision tree [139]. To understand the concept of Statistical learning theory, the Support vector machine (SVM) is introduced [140], [141]. This SVM is applied to various emerging fields, such as cancer recognition [142], text classification [143], [144], credit scoring [145-147] and Image retrieval [148].

Support vector machines are also known as Support vector networks, which is a supervised learning used in machine learning. This SVM approach can be used to analyze the data that are used for HSI classifications and the regression analysis. The supervised learning is not at all possible to implement, when the data are not labelled. In such cases, an unsupervised learning method is required to organize the clustering data into groups and then gives the new data. This automatically improves the SVM clustering algorithm and this process is called Support Vector Clustering. SVM is applied to the training sets of any classes so that a hyperplane with good separation is achieved. The data was mentioned as p – dimension vector and the separation can be addressed in such a vector p with a p-1 dimensional hyperplane. This process is called as Linear Classifier.

b. Sparse Representation Classification (SRC)

To overcome the problem of optimization, the various pursuit methods are Basis pursuit [149], orthogonal matching pursuit [150], matching pursuit [151], K-SVD method [152] and LARS/ homotopy methods [153]. To apply the sparse representation to various applications, such as image inpainting, signal separation and coding. [154-158]. This SRC representation also applied to the field of digital image processing like face recognition [159], fusion [160] and Interpolation [161]. This sparse classifier (SR) [162-167] is widely used in HSI classification for acquiring better classification results.

The Sparse representation classification has implemented in various fields, such as Target detection [168] [169], Denoising [170], reconstruction [171] – [173] and Tracking [174]. A pixel in Hyperspectral Image is denoted by ‘X’, which is referred as $X=[X_1, X_2 \ldots X_N] \varepsilon R^{Nx1}$, where N is the Number of Spectral bands.

SRC [175] framework takes a pixel X form a particular class C to obtain the Dictionary D from a linear combination of all the atoms selected. Therefore, $D = [D_1, D_2 \ldots D_C] \varepsilon R^{NxM}$, where C is a class and M is the Training samples.

c. Joint Sparse Representation Classification (JSRC)

The JSRC is implemented in a fixed size region for each test pixels and thus construct a form of matrix along with the neighbouring pixels. This determines the class label for each test pixel by jointly adopted coefficients in the broken dictionary of all the atoms. [176], [177].

d. Collaborative Sparse Representation (CRC)

Collaborative sparse representation classification is mainly used for HSI classification. This CRC effectively enhance the classification efficiency of SRC. The CRC is then applied to the kernel technique to enhance the classification results and this indicates the KCRC (Kernel CRC).

This Kernel CRC will classify the HSI with the small number of complexity issues and this provides the greater performance compared with SRC. Then this will applied in a different direction with the training samples obtained, since it was extracted from SVM. The Kernel CRC might avoid the data distribution in the same direction.

e. Shape Adaptive Joint Sparse Representation (SAJSR)

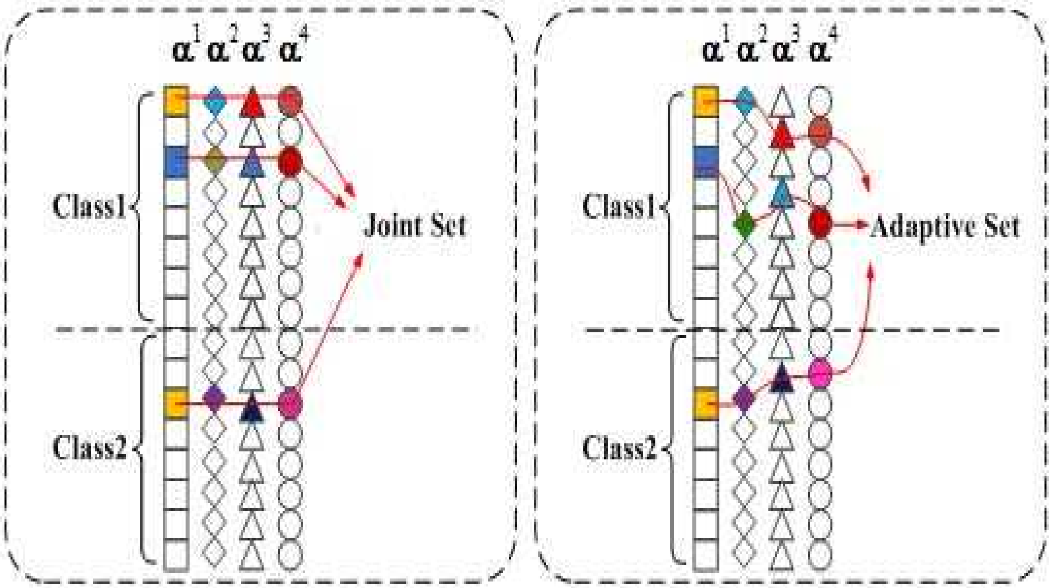
The method named SAJSR classifies the HSI in the various steps. Initially, the Principle Component Analysis (PCA) is applied to the Hyperspectral Images. Then the Shape Adaptive algorithm is applied to each test pixel in a form of region.

Finally apply the Joint Sparse Representation classifier to the Shape Adaptive region within a set of pixels to outcomes the good classification results. This representation is widely used in major applications, such as Fusion, Interpolation, face recognition, etc.

f. MFASR – pixelwise

Each pixel ‘x’ in a multiple feature can be denoted as $x^{MF}=\{x^k\}$, k=1,2,3,4 where $x^k$is thefeature vector. Similarly, the dictionaries for different features can be defined as $D^{MF}=\{D^K\}$, k=1,2,3,4 which is obtained by four features that extracts he pixels accordingly.

Orthogonal Matching Pursuit (OMP) – For each iteration, the OMP adds a new atom at the existing atom. It will not pick the same atom again and again, once it used the atom before. Thus the linear combination of all atoms is projected in the active set.



(a) (b)

Figure. 2. (a) Pixel-wise multiple-feature-based joint sparse model (b) Pixel-wise Multiple-feature-based Adaptive sparse model.

III. REVIEW OF LITERATURE

Ping Zhong et al., has suggested that the diversity regularization to improve the HSI classification in Deep Belief Networks to both the procedures of pretraining and fine tuning methods. To improve the further computational efficiency, Deep belief networks hidden units has introduced to promote other diversities.

Jiangtao Peng et al., exploits the method named Ideal Regularized Composite Kernel (IRCK) to improve the various information, such as spectral, spatial and label information. This improves the state - of -the - art kernels that contains various information and this regularized all the above information.

Zhixi Feng et al., states that to understand the data in all dimensions to get accurate and rapid HSI in order to achieve images using Supervised Tensor Sparse Coding (STSC). The HSI can rapidly cluster the various images and obtained the result as superpixels tensors. The various accuracies levels, such as overall accuracy (OA) and kabba coefficient (KC) in order to achieve good HSI in a very good performance level.

Junshi Xia et al., has suggested that a method named Rotation random forest via kernel principle component analysis (RoRF – KPCA). This divides into several subsets on the feature space and those subsets were combined with the help of RF classifiers. This method gives the good performance compared with earlier methods, such as SVM, random forest, Etc.

Zengmao Wang et al., states that to get the better training samples quality, a method named Active learning is used. To improve the training samples quality, a semisupervised learning method is approached. To get the high classification of HSI, the supervised method is used.

Lixia Yang et al., has suggested that to obtain a good accuracy and efficiency of HSI, a method named Sparse Spatio - Spectral – LapSVM is implemented. This performs on both labeled and unlabeled of spatial and spectral information to get the regularized spectral and spatial information to get high accuracy, since they perform on few labeled samples.

Sen Jia et al., illustrates that to improve the classification of HSI, the images can be segmented into various different homogenous sections that are referred as Superpixels. To extract the discriminative features, the techniques called 2-D Gabor filters are implemented. The Gabor cube is further used to reduce dimensionality with the help of spatial – spectral schroedinger eigenmaps (S^4E). The further Gabor - S^4E- MTL_{SVM} is applied to reduce the complexity problem of computational issues compared with previous techniques.

Haoliang Yuan and Yuan Yan Tang have suggested that to reduce the pixels dimensions, Subspace Learning (SL) method is used. To extract the feature representation, a framework called Ridge Linear Regression (RLR) method for SL is used.

Chunjuan Bo et al., states a two main techniques called point to set distance and local weight assignment to obtain a good consistency in the spatial information within a nearby neighboring pixels. To improve a further performance of Weighted Generalized Nearest Neighbour (WGNN), a novel label refinement is implemented. Further to improve classification performance, a set based classification will be approached.

Bushra Naz Soomro et al., illustrates a two main classification approaches called Sparse representation classification (SRC) and Collaborative representation classification (CRC) exploits a labeled samples and processes all the queries of all the classes. The context- aware elastic net (ELN) further approached to develop the neighbouring graph with the help of image dispatch distance. In future, it focuses on dictionary of both feature and spectral space to acquire good accuracy of HSI.

Lin He et al., has suggested a method named Discrete Space method (DSM) in order to reduce the computational complexity compared with support vector machine (SVM). This approach gets a result of discrete features from continuous spectral signatures. Thus improves the SVM classification accuracy with the help of discrete space method.

Li Xie et al., states a method to decrease the computational complexity and accuracy of HSI classification, when compared with 3D spectral – spatial Gabor filter. This combines a various rank filters that is low pass and band pass filters to obtain a good results of HSI classification. This decomposes the various filters into eight subfilters to achieve a good accuracy level.

J. L. Crespo et al., illustrates the process of decision module used to provide a probability vector that uses a Hyperspectral image segmenter and multi image segmenter gives an application of both parallel and concurrent application of Artificial Neural Network (ANN). These ANN uses an algorithm called Gaussian Synapses back propagation that incorporates Gaussian Synapses.

M. Fauvel et al., states the process of spectral and spatial information for Hyperspectral Image classification. The spatial information uses a set of pixels that are extracted from an object than a normal pixel level. The spatial structure of an image includes size, orientation and contrast that provides the Morphological profiles named as Mathematical Morphology. The Support Vector Machine (SVM) used for applying classification on both spatial and spectral information. This method obtains the better classification result of Hyperspectral image by using spectral and spatial functionalities.

H. R. Kalluri et al., has suggested to deal with high-dimensional feature space in both single and multiple classifiers. This paper proposes a new technique for spectral information for the classification for robust land cover with a method of decision-level fusion. The spatial derivatives reduce the problem of over-dimensionality by the means of classification of Hyperspectral images (HSI's). This method gives the overall qualified classification accuracy with the help of reflectance information.

S. Li and L. Fang have stated the process of signal denoising with the help of Random Refined Orthogonal Matching Pursuit (RROMP) by the means of an effective algorithm called Sparse recovery. This algorithm was applied for multi-selection approach and a control of false discovery rate (FDR) with several sparse representations. This method gives more accurate result by the means of mean-square-error (MSE) technique.

H. Liu et al., has stated a new technique named Principle Component Analysis (PCA) and Local Sparse Representation (LSR) for robust object tracking. In Principle Component Analysis, the patches are obtained from the error map gives the combination of target and blockage of candidate. To find the error and detect the blockage, the method called LSR is used. This provides the effective object tracking method for the sequences of an image.

J. Wright et al., illustrates the two main approaches named Feature extraction and blockage to robustness in face recognition technique. In feature extraction, the sparse representation feature is comparably very large and this is computed very correctly. The Sparse representation is mainly used to maximize the robustness due to blockage while choosing the training images. This method will efficiently verify the available database publicly.

S. G. Mallat and Z. Zhang have stated the new concept for obtaining the waveforms through by separating signals from a required dictionary is called Matching Pursuit. This Matching Pursuit is used to calculate adaptive signals by the means of general procedures. The obtained waveforms are collected accordingly to the signal structures matches.

T. C. Bau et al., has stated a new model named 3D-Gabor filters for spectral and spatial information. The Hyperspectral images are processed by 3D- Gabor filters to obtain the wavelength properties, scale and directions in an effective way. The large number of spectral and spatial information is processed by these filters and thus improves the performance and efficiency of an image region. These filters are first applied to Airborne visible and Infrared imaging Hyperspectral data to obtain the better classification result.

M. Fauvel et al., illustrates the approaches of spatial and spectral information for Hyperspectral Image classification. The Morphological profiles used to overcome an issue to obtain one feature vector from two vector attributes. Once the dimensionality of an image is reduced, the Support Vector Machine (SVM) is applied to get the better classification result. This approach gives the better result of feature reduction upto 79% to 83%.

L. Shen and S. Jia have stated a new approach for Hyperspectral Image classification named 3D-Gabor-Wavelet for pixel-wise images. This 3D-Gabor-Wavelet is used to extract spectral and spatial domains jointly and separately. This usually extracts the appropriate information from an each test pixel. This approach applied to real datasets of Hyperspectral Images (HSI's) and achieves a good accuracies result of 96.04% and 95.36% appropriately.

X. Huang and L. Zhang have stated a method for pixels and objects to combine the different features of spatial and spectral information called Support Vector Machine (SVM) Ensemble approach. This approach works with feature extraction, composite kernels and vector stacking while compared with other SVM multifeature methods. This method parallel improves the accuracy level from 1 – 4% on three datasets.

L. Fang et al., has stated an efficient tool named sparse representation for Hyperspectral Image Classification (HIC). This Sparse representation test with each pixel and defines a local region of an image. These regions are jointly represents from a given set of training samples. This approach allows the atoms to be selected from various pixels and provides an improved classification representation method. This Sparse representation classifier gives the classification method in both Qualitative and Quantitative results by the means of accuracy.

IV. CONCLUSION

The different classification methods and Multiple-feature-based Adaptive Sparse Representation (MFASR) were discussed in this paper to obtain the good classification results. The various methods of classification are used in Hyperspectral Images (HSI's) to identify the ground elements, minerals and Skin imaging. The method Adaptive sparse representation was mainly implemented to make use of various correlations obtained from different features. Furthermore, a Shape-adaptive region exploits the spectral and spatial information of Hyperspectral Images (HSI's) for each test pixel in four different features.

An MFASR method process the Hyperspectral Images in four different stages. First, the spatial and spectral information obtained from an original HSI's. Then, the shape adaptive (SA) spatial region is tested in each test pixel. Then, the coefficients are obtained from each test pixels by using Adaptive sparse representation. Finally, the class label is obtained from each test pixels by combining the obtained coefficients. This MFASR method gives n effective quantitative and qualitative results in the form of classification maps.

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