Sparse Representation For Image Classification

Arockia Panimalar.S [1], Thanga Balu.A[2], Aswin George Willy[3], Barath.A[4]

[1] *Assistant Professor, Department of BCA & M.Sc SS, Sri Krishna Arts and Science College, Tamilnadu, India*
[2,3,4] *III BCA, Department of BCA & M.Sc SS, Sri Krishna Arts and Science College, Tamilnadu, India*

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Abstract - *The primary target of this paper is to give a complete report on Sparse Representation based feature extraction techniques in the image classification domain. Sparse Representation (SR) assumes a fundamental part in both theoretical research and practical applications. The Sparse Representation being image dependent has turned into a comprehensively utilized feature extraction technique that speaks to the signal or image under study. Considering the feature extraction techniques, this article incorporates the work including Multikernel Fusion Sparse Representation. An effective grouping of remote sensing data is a colossal test on the grounds that many components have a place with the proper selection of remote sensing data, image pre-processing and processing methods may result in improper results. This issue requests a point by point gathering of information extraction algorithms which would be strikingly valuable for the researchers who are new to the field of high resolution remote sensing data in choosing an appropriate classification technique. This paper focuses on restating all the possible information extraction techniques for image classification in remote sensing images.*

Key Words: **Sparse Representation, Kernel Sparse Representation, Multi Kernel Sparse Representation, and Image Classification.**

1. INTRODUCTION

Sparse Representation (SR) is a signal representation in a smaller vector space comprising of very few non zero entries. In the recent image processing and signal processing applications SR has become an unavoidable concept of feature extraction because of its ability to represent higher dimensional data[1]. SR is the extension of underdetermined linear system solutions. Some SR is also named as Compressive Sensing, which is defined as a compact representation of the signal or image by finding the solution for underdetermined linear systems. Underdetermined linear system is the group of linear equations for a system, which has the number of variables more than the number of equations that may lead to nontrivial solution along with the trivial one. In order to get those non-trivial solutions the matrix regularization algorithms is carried out [2].

Sparse Representation is the projecting function that projects a higher dimensional data on a lower dimensional feature space. The matrix regularization is carried out predominantly using the algorithms for optimization[2]. Sparse Representation is widely used in the applications like Biometrics [3], Video Tracking [4], Source Separation [1] and Image Classification [5]. Support Vector Machine has the capability of handling the higher dimensional feature space for training and testing, which makes it suitable for Hyper spectral image classification [6]. In many SR based classification implementation it is assumed that the test samples can be represented sparsely by using the structured dictionary of the training samples. A pixel is a linear combination of some basis vectors, which is taken from the dictionary while applying sparse representation [7].

Classification algorithm performed learning while training and classifying while testing. Learning based classification algorithms need a large amount of data for the system to learn, which amplifies the memory requirement and also the computational complexity. In order to get rid of these disadvantages the active learning methods is introduced. Some of the primary Active Learning (AL) methods are discussed in [9-11].

2. IMAGE CLASSIFCATION METHODS IN REMOTE SENSING

Classification between objects is found to be difficult for machines because of the increase in higher version computers, high quality video cameras. Image classification methods get importance in the field of military, agriculture and mineralogy [12-14]. Visible light belongs to the electromagnetic spectrum, and any material would reflect, absorb and emit the electromagnetic energy according to its molecular property [8]. Electromagnetic energy emission of the materials is used by the Hyperspectral sensors, which acquire the digital images having spectral bands. The images thus captured are called Hyperspectral Images (HSI) and the application of HSI is to identify the materials taking in to account its reflectance spectrum. Another challenge that HSI applications come across is the spatial resolution of the sensor and the spatial variation found in the ground scene. This challenge is overcome by methods like likelihood ratio detectors, Adaptive Matched Filter algorithm, Linear Discriminant Analysis and Structured and Unstructured Background models[8]. Another Hyperspectral image application of target detection is dealt in [9] with the name of Anomaly detection. A variant of Reed- Xiaoli (RX) algorithm known as Dimension Reduction RX (DRRX) algorithm is used for Anomaly detection. Different target detection techniques based on the Hyperspectral images like anomaly, signature based, change detection and Airborne Real-time Cueing Hyperspectral Enhanced Reconnaissance (ARCHER) are discussed in detail with experimental implementation on civilian search and rescue application [10]. Methods such as Optimal Margin Classifiers apply the idea of increasing the margin between the training space and the decision space. Optimization of the capacity of the classifier includes capacity tuning of the classification function, extracting only few supporting patterns from the training patterns for classification and distinctiveness of solutions. This method was later called as Support Vector Machine (SVM).

The tool that is broadly used for the image classification of Hyper-spectral image has been Support Vector Machine (SVM)[11]. The SVM method uses the kernel method, which could map the training patterns to the higher dimensional space with a linear separation (hyperplane) between the two classes [11].

A modified SVM method to improve the classification rate, defined as percentage of correct classification, is conducted in [12] where both the labelled and the unlabelled samples involve in the semi-supervised learning. A novel method called Transductive SVM (TSVM) is introduced in [12] based on the theory called transductive inference. . TSVM exhibited higher classification accuracy and very good stability [12]. In [13] Context Sensitive SVM (CS-SVM) is implemented by considering the spatial context information of the pixel to be trained. A context dependent term is introduced in the objective function of the SVM with the minimization criteria. The CS- SVM outperformed SVM on different data sets [13].

Classification method involves both the pixel wise SVM and the segmentation map obtained from the partitional clustering using majority voting. To improve classification further in [14] decision rules to accept or reject the labelled samples is carried out. Randomly selecting pixels and labelling would create a preliminary classification map called as the markers. These markers are used to build the minimum spanning forest (MSF) [14].

In [15] a saliency driven nonlinear diffusion filter is applied on the images for classification. A multiscale fusion of foreground features is collected, which constitutes medium scale and the final scale where diffusion process converges, is amalgamated. Accuracy of classification has improved in this method [15]. The work proposes a genetic algorithm based multi objective genetic programming (MOGP) for generating domain adaptive global feature. Classification error rate and the tree optimization are considered as the objectives. Testing and training the dataset with SVM obtain the best solution and classification error rate is calculated by averaging the error obtained for the datasets. The two features based classification algorithms uses two features instead of single feature which would be used as the input for the classification algorithms. Classification accuracy has worked better than many two feature based classification implementations.

The recent work deals with the sparse representation that would go beyond just feature extraction. This implementation is carried with the idea that any real world problem will set itself into a manifold, which is a manifold learning problem. Instead of implementing the SR on the objects or image, this implementation would apply the SR of the manifold defined in the object or image. The classification model is such that it would create a SR, which would manipulate the underlying manifold of the signal. The manifold is exploited indirectly using regularization.

3. FEATURE EXTRACTION TECHNIQUES BASED ON SPARSE REPRESENTATION

In classification, feature extraction techniques play a critical role. In general, to distinguish the objects in feature space, visual feature should exhibit uniqueness property. Gradient features have been preferred for human detection which uses shape or contour, statistical information of the gradient. Colour features are preferred where robustness is required against certain illumination changes. By varying the intensity of the surface, smoothness and regularity properties can be calculated which represents texture features. For action recognition and visual detection, spatio-temporal features are used.

SR from over complete dictionary has been viewed as the successive principle of signal processing and image processing. Sparse representation has become the popular approach in the context of remote sensing data processing such as spectral immixing and classification. If an image is sparse or compressive, the original image can be reconstructed from few measured value [17]. The three basic components of compressed sensing are sparse representation, encoding measuring and reconstruction algorithm. Sparse representation is a signal sampling technique used for the compressed image and has been efficiently applied for remote sensing applications. The categories of sparse representation methods can be learned from various perspectives[17]. One such perspective is norm minimizations used in sparse constrains, the methods norm minimization based sparse representations are l0-norm minimization, lp-norm ($0 < p < 1$) Minimization, l1-norm minimization, l2-norm minimization and l2-norm minimization.

Based on the perspective of atoms (image pixel with linear combination of a small of number elementary samples), it is of two types: 1) Native sample based and Dictionary learning based sparse representation. Based on the labels of atoms, sparse representation with learning methods are divided into supervised learning, Semisupervised learning and unsupervised learning Methods. On the basis of sparse constraint, Sparse Representation Methods can be splitted into Structure constraint based sparse representation and sparse constraint based sparse representation. For image classification, holistic representation based method and local representation based method are preferred.

By taking into account of different methodologies, the sparse representation method can be typically divided as pure sparse representation and Hybrid sparse representation. Grouping all the existing methodologies of sparse representation together, they are further classified into 1) Greedy algorithm 2) Constrained optimization algorithm 3) Proximity algorithm 4) Homotopy algorithm.

A. Kernel Sparse Representation

Kernels are able to learn non-linear functions with a limited number of training samples. Kernel transforms the non-linear features into linearly separable features in higher dimensional feature space [27, 28]. It provides effective discriminative information, by offering higher classification accuracy compared to conventional sparse representation. KSR may minimize the feature quantization error and improve the sparse coding performance to a particular extend. Thus it outperforms sparse coding in both Image classification and face recognition. One main advantage of kernel is that one can use the same algorithm with numerous different kernel functions, and the same kernel function with numerous different algorithms.

Composite Kernels is a combination of both the spatial and the spectral information by simultaneously using more than one kernel of the images are used for the HSI classification [6]. It shows great success in solving many real-world problems with non-linear data structures. One of the primitive works in which the Kernel space is developed using SR is [27, 28]. The SR on nonlinear features is successful by the use of the kernel trick on the image. This is called the Kernel Sparse Representation (KSR). It has proved to be effective in image classification techniques [27, 28]. However a Simple kernel method is not suitable for tedious applications due to its kernel function and feature selection problem when kernel SRC methods are used for classification. Incorporating Spacial Pyramid Matching (SPM) with Kernels is proposed to reduce the information loss in feature quantization steps. It can be treated as both an extension of Sparse Coding SPM and the generalization of Efficient Match Kernel (EMK) which can evaluate between local features accurately.

B. Multi Kernel Sparse Representation

In applications like multimedia, computer vision and audio-visual speech processing, improving the system performance and robustness draw the attention of the researchers. Feature fusion pays a solution for this task because of the emergence of various feature descriptors. Nowadays there is a need to deal with more tricky learning problems, therefore there is an increasing need for algorithms that efficiently require more refined forms of prior knowledge. Examples are the group Lasso problem, Multikernel learning, Multiclass prediction, and Multitask learning.

Multikernel learning methods enables us to use multiple kernels instead of using a single kernel function. Multiple Kernels are merged to obtain a better result. In this method multiple descriptors are in general adopted to describe various features of the image and allow us to use multiple sophisticated features such as spatial colour histogram and spatial orientation histogram inorder to improve the performance of complex image processing applications[18]. Descriptors of different features are combined together into a unified feature space using kernel methods. Feature descriptors provide good discrimination for all classes of image.

A Multikernel Sparse Representation method has been used for the visual tracking of the moving objects. A particle filter based framework is introduced to create the training templates and the testing templates are searched on the search space with reference to the Kernel sparseness with the training templates [18]. The adoptions of multi kernel fusion allow us to incorporate multiple features to achieve complementary effect in image representation.

4. CONCLUSION

This paper is an effort to provide a brief knowledge about the different feature extraction methods for image classification. Sparse representation has become a basic tool which has been used into various learning systems. Sparse representation due to its understandability and controlling approach, it has seen a recent surge of interest in the classification community. For image classification, the robustness to random corruptions, varying illuminations, outliers, occlusion and complex backgrounds is a critical issue which has to be considered. Kernel Sparse representation methods and Multi Kernel Sparse Representation methods are also taken into consideration in this review, motivated by the reality that kernel trick can detain the nonlinear similarity of features, which helps in finding a sparse representation of nonlinear features, based on the recent advancement. Thus, developing an efficient and robust sparse representation method for sparse representation is still a major challenge.

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