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A Review on Fixed-Rank Representation for Supervised Learning Using Neural Network

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***Abstract*— This study focused on development and application of efficient algorithm for clustering and classification of supervised visual data. In machine learning clustering classification and clustering is most useful techniques in pattern recognition and computer vision. Existing techniques for subspace clustering makes use of rank minimization and spars based that are computationally expensive and may result in reducing the clustering performance. The algorithm called fixed rank representation based on matrix factorization is used to partially solve the problem of existing system. FRR perform classification using neural network algorithm. Neural network takes patterns as input from the FRR by performing rank minimization techniques in LRR and then performs classification. FRR can be able to solve the problem of multiple subspace clustering. Using neural network FRR can be able to give good classification of given pattern.**

***Keywords*— Supervised visual data classification, SSC, LRR, FFR, Neural Network**

I. INTRODUCTION

In machine learning algorithms are classified as supervised and unsupervised [1]. The difference in between these two is to be found from how the learner classifies the data. In supervised algorithm classes are predetermined. These classes are considered as finite set, In other words we can say that supervised learning uses external teacher, so that each output unit is told what desired output in response to input unit is, and during the learning process the global information is required, (decision tree induction, naive bayes) are the example of supervised learning techniques. The unsupervised learning algorithm uses no any kind of external teacher and is based on local information. K-mean clustering is the common example of unsupervised learning.

In machine learning clustering and classification are two of the most important techniques for visual data analysis. In the last decade, there has been an increasing interest in sparsity to visual learning, such as object classification [2], image/video processing [3] and motion segmentation [4]. Early studies usually presented on unsupervised visual learning. Recently subspace clustering uses spars-based techniques such as spars subspace clustering (SSC) [5-6] and Low-Rank Representation [7-8].

SSC uses the 1D sparsest representation vectors produced by l_1-norm [9] minimization to define the affinity matrix of an undirected graph and subspace clustering is performed by spectral clustering techniques, such as normalized cut (NCut) [10]. However, as SSC computes the sparsest representation of each point individually, there is no global structural constraint on the affinity matrix. This will degrade the clustering performance when data is grossly corrupted. Moreover SSC may over segment subspaces when dimension are more than 3-dimension.

Low-Rank Representation (LRR) is another technique for sparsity-based subspace clustering model. Low-Rank Representation is as same as Shape Interaction Matrix (SIM) [11] in absence of noise. LRR can perform true clustering when data sampling is sufficient and the subspaces are independent. However, LRR also have some limitations, first is the nuclear norm minimization in LRR typically requires calculating the singular value decomposition (SVD) at each iteration, which becomes computationally impractical as the problem is growing. Also if the observation is insufficient LRR may reduce clustering performance.

Previously the FRR is applied to unsupervised learning through the use of Normalized-Cut (N-Cut). FRR parameterizes the representation matrix as the product of two low-rank matrices. FRR having some benefits over LRR, when there is no noise and the data samples are sufficient FRR is the optimal solution to LRR, we can say that FRR solve the multiple subspace structure. Moreover when the data samples are insufficient the memberships of samples to each subspace determined by FRR. Also the singular value decomposition (SVD) is the most expensive computational part of LRR, FRR avoids the SVD computation and it can be applied to large scale problem.

In this study, we present the idea of matrix factorization with neural network into representation learning and improve functionality of Fixed-Rank Representation (FRR) to optimally solve the problems in supervised visual learning. Neural network [12-13] is the supervised learning technique that used to classify the given patterns. The pattern classification problem performed by feed forward neural network. If some of the output patterns in the pattern association problem are identical, then the number of distinct output patterns can be viewed as class labels, and the input patterns corresponding to each class can be viewed as samples of that class. If the pattern belongs to a class given as input, the network identifies the class label. During training, only a few samples of pattern for each class are given. In testing, the input pattern is usually different from the patterns used in the training set for the class.

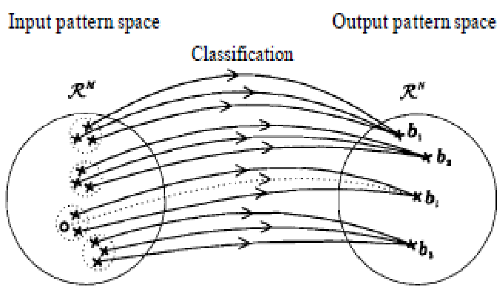

Fig. 1 Illustration of pattern classification task

Following is the example of pattern classification problem, labelling hand printed characters within a specified grid into the related printed character. Here the point is to be noted that the printed character patterns are unique and fixed in number, and serve as class labels.

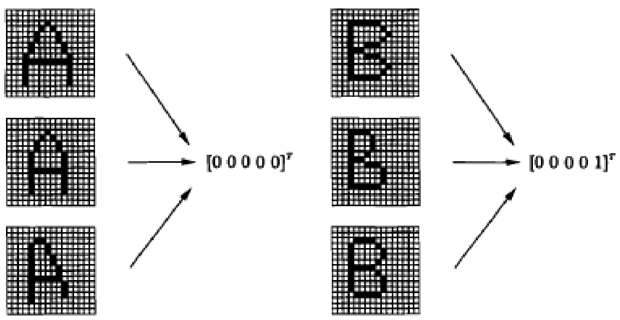

Fig. 2 An example of pattern classification problem

The performance of the network for the given pattern classification problem depends on the characteristics of the samples associated with each class. Thus, performance is determined by, grouping of the input patterns by the class label. Following section II gives literature survey, and in section III FRR using neural network for supervised learning is described.

II. LITERATURE SURVEY

This section consists of brief description of some techniques used for subspace clustering.

A. *Sparse subspace clustering.*

Ehsan Elhamifar et.al [5], Centre for Imaging Science, Johns Hopkins University, Baltimore MD 21218, USA. He proposed the method to solve problem of subspace clustering, Sparse Subspace Clustering (SSC) clusters the collection of data points from union of subspace using sparse representation. SSC uses the 1-dimensional spar set representation vectors produced by $l_1$norm minimization to define the affinity matrix of an undirected graph. Then subspace clustering is performed by spectral clustering techniques, such as normalized cut (NCut) based on subspaces whether they are in linear or affine subspaces.

B. *Robust subspace segmentation by low-rank representation.*

Guangcan Liu, Zhouchen Lin, and Yong Yu [7], they present another approach for subspace clustering, the Low-Rank Representation is as same as Shape Interaction Matrix (SIM) in absence of noise. LRR clusters data taken from a union of multiple linear (or affine) subspaces. Given a set of data vectors, LRR used the lowest- rank representation among all vectors as the linear combination of the bases in a dictionary. Unlike the sparse subspace clustering (SSC), which computes the sparsest representation of each data vector individually, the goal of LRR is attending the lowest-rank representation of a collection of vectors jointly. LRR better captures the global structure of data, giving a more effective tool for robust subspace clustering from corrupted data.

C. *Normalized Cuts and Image Segmentation.*

jianbo shi et.al. [10], member of IEEE. He propose the theory related to graph for finding out the image partition known as normalized cut (N-Cut). By simply removing edges from two different parts of the graph and dissimilarity is calculated between two parts as total weight of edges that have been removed. In graph theory is known as *cut*.

$$cut(A,B) = \sum_{u \in A, v \in B} w(u,v)$$

Fig. 3 indicates that minimizing the cut in the graph gives bad partitioning.

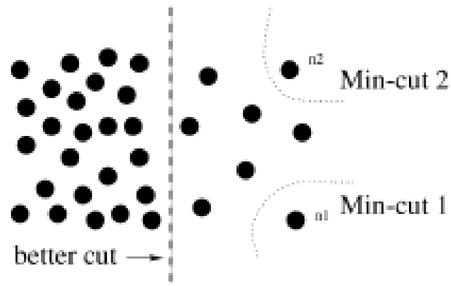

Fig.3 Minimum cut gives a bad portioning.

Wu and Leahy et. al. [16] present a clustering method based on the minimum cut criteria. They partition the graph into k-sub graph such that maximum cut of sub graph is minimized. They compute the cut cost as the fraction of total edge connections to all nodes in the graph.

$$Ncut = 2 - Nassoc(A,B)$$

The above equation gives the normalized cut in the graph. Hence, the tow partition criteria, minimization the disassociation in the groups and maximizing the association within the groups.

D. *Motion segmentation via Robust Subspace Separation in the presence of outlying, incomplete or Corrupted Trajectories.*

Shankar R. Rao, et.al. [15]. He studied the problem of segmentation of moving objects in an image sequence. They proposed the methods that solve the problem of sparse representation, low-rank minimization and lossy compression. They test their method and compare performance with other methods on Hopkins 155 database.

E. Fixed-Rank Representation for unsupervised visual learning.

Risheng Liu, Zhouchen Lin, Fernando De la Torre and Zhixun Su et.al [8], They uses the factorization idea into representation learning and propose fixed rank representation for unsupervised visual learning. They prove that if data sampling is insufficient, the membership of each sample to each subspace determined by FRR. They propose the FRR algorithm for subspace clustering using normalized cut (N-Cut). FRR can be used for unsupervised feature extraction by considering the transpose version of FRR (TFRR) analyzing the column and row space of data. They create a dataset by combining the images with face from the FRGC version 2 and non-faces images from Catletch-256.

They selected 20 images for the first 180 subjects of the FRGC database, having a total of 3600 images. For catletch-256 database, which contains 257 image categories, then they select 1 image from 257 non-facial images. All images are resized into 32×36 and the pixel values are normalized to 0, 1. The goal is to extract facial features and use them for classification.

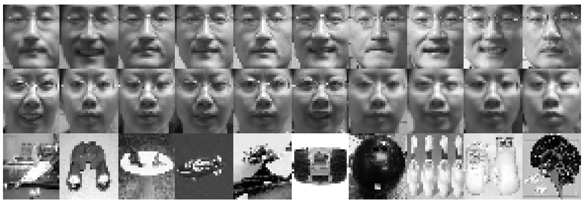

Fig. 4 The top two rows corresponds to face images and the bottom row corresponds to non-face images.

III. Fixed Rank Representation using neural network

In this section the fixed rank representation algorithm based on idea of matrix factorization for supervised visual learning is described. Previously the FRR applied on unsupervised visual data using normalized-cut (N-Cut) algorithm to obtain clusters. FRR can also be applicable to classify the supervised visual data using neural network. The algorithm works is described as follows:

A. Algorithm:

Step 1: Apply FRR for subspace clustering

In first step we have to apply analysis on LRR for forming the affinity matrix of set of data points sampled from k subspaces. Then we can construct the graph by using $(|Z^*| + |Z^{*T}|)$ as the affinity matrix, here Z is spar set representation coefficient, $|Z|$ represent a matrix whose entries are the absolute values of Z and $|Z| + |Z|^T$ graph on which we apply neural network to obtain true memberships of data points.

Step 2: Apply neural network to graph to obtain classification.

The pattern classification in neural network is best for linear associative network. But if the units in the output layer are nonlinear, then the network is limited by the linear separability constraint on the function relating the input-output pattern pairs. We need a way of updating these weights when each input-output pattern presented to network. To update the weight in supervisory mode, it is necessary to know desired output for each unit in the hidden and output layers. We used back propagation algorithm [15] to solve this problem. Back-propagation algorithm is based on principle of gradient descendent along error surface. This approach is used to find the error (square difference between the desired output and the actual output obtained at the output layer of the network).

The output is calculated using the current setting of the weights in all the layers. The optimum weights may be obtained if the weights are adjusted in such a way that the gradient descent is made along the total error surface. The objective is to determine the weight update for each presentation of an input-output pattern pair.

$$\Delta w_{ij}(m) = -\eta \frac{\partial E(m)}{\partial w_{ij}} \qquad (1)$$

Where $\eta >= 0$ is the a learning rate parameter, and to update the weight is given by

$$w_{ij}(m+1) = w_{ij}(m) + \Delta w_{ij}(m) \qquad (2)$$

Apply the back-propagation algorithm to the input-output pattern pair one by one, in some random order and update the weights until the total error reduces to an acceptable value.

The fixed rank representation with neural network algorithms flowchart is shown below:

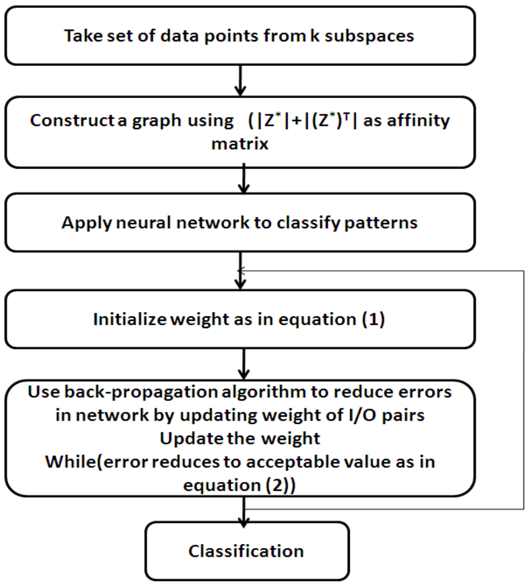

Fig. 4 Flowchart of Fixed-Rank Representation with Neural Network

IV. Conclusions

In this study we learn FRR algorithm for supervised visual learning. FRR uses the neural network to classify the given patterns. Pattern classification problem in neural network is solved by Back propagation algorithm that corrects the errors by updating the weight between each pair of input-output unit in the graph. Hence, we can obtain better classification of given pattern from FRR using neural network for supervised visual data. Remain direction to Future work: To Provide a deeper analysis on LRR for subspace clustering.

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