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SPARSE REPRESENTATION AND COMPRESSION DISTANCE FOR FINDING IMAGE SIMILARITY

Dipali S.Matre and Prof. P. S. Mohod
Department of Computer Science and Engineering
G. H. Raisoni College of Engineering and Technology for Women Nagpur, India
Department of Computer Science and Engineering
G. H. Raisoni College of Engineering and Technology for Women Nagpur, India

ABSTRACT
For the image similarity sparse representation is widely used because of it's simplicity and easiness. Sparse representation and compression distance plays an important role in finding the similarity between the two images. For image similarity we create an overcomplete dictionary. Dictionary may be complete or over complete depending upon the elements contain in it. Overcomplete means the basic element or atoms in dictionary is greater than the vector space of that element. For the feature extraction we classify all the images into different classes and perform clustering on that so that it is easy to match the different images with the original one. Sparse Representation simply create a dictionary of the respective images and extract feature from it and perform matching on it.

KEYWORDS:- Sparse Representation,Dictionary Learning,Overcom-plete dictionary,Compression distance.

INTRODUCTION
The assumption of sparse representation is developed mainly to address the problems like signal denoising, reconstruction and compression. In recent times, it has been shown that sparse representation can also be useful in addressing classification problems. This is because sparse representation is naturally discriminative - it selects from many basis vectors, only those that most compactly represent a signal. The success of the sparse reconstruction-based classification algorithms largely depends on the choice of the dictionary. predefined dictionaries such as curvelets and variants of wavelets can be used. But the success of these dictionaries depends on their suitability in capturing the structures in the signal under consideration. Another approach to building a dictionary is by concatenating the vectorized training samples of all classes together. This approach is successfully used in face recognition. However, constructing such a dictionary requires a good number of training samples to be available for each class. Such a dictionary learning approach has been employed in texture classification and segmentation. A recent work proposes learning a dictionary by jointly optimizing an energy formula containing both sparse reconstruction and class unfairness components. This work reported prelude results on image segmentation. However, the joint optimization approach proposed in introduces further difficulty to the already complicated optimization task. A work on object recognition moved from pixel domain to feature domain and obtained sparse decomposition of the Scale Invariant Feature Transform (SIFT) features. This method creates a dictionary of SIFT features using sparse coding, but sticks to the traditional Support Vector Machine for classification. The area of sparse representation-based classification, though rapidly growing, is still at an early stage. Prior work on classification using sparse representation has mainly dealt with images. Videos, being functions of space and time, pose a bigger challenge. There also exist the need for developing more efficient and discriminative classification frameworks. The work that we present in this chapter, explores the utility of sparse representation obtained using learnt dictionaries in the context of image-based face recognition.

Compression-based similarity methods
The compression-based similarity methods rely on a new mathematical theory of similarity which is in turn based on the idea of the Kolmogorov complexity. The work of Kolmogorov and others on how to measure data complexity

has been influential in many areas of knowledge, across multiple disciplines. The notion of complexity of a string is related to its randomness.

Compression-based image similarity

The compression-based similarity measures have been shown to be highly effective in clustering and classifying uni-dimensional data such as protein and text. The success of the compression-based distances heavily depends on the availability of a normal compressor. A compressor is said to be normal only if it satisfies certain conditions such as monotonicity , symmetry, etc. The existing compression-based methods either approximate the conditional compression or use a simplified definition so as not to include any conditional term Direct evaluation is usually bypassed mainly to retain the simplicity of the compression-based measures since evaluating accurately requires delving into the complicated standards and algorithms of data or image compression.

The last few years the area of sparse representation has become one of the most active areas in multimedia, signal and image processing. Other than denoising, restoration and in painting, there are a number of tasks, such as encryption, watermarking, scrambling and target detection, that can benefit from sparse analysis. Recently, sparse representation has been used to address classification problems such as face recognition, object recognition, texture classification. The application of sparse representations obtained by learning over complete dictionaries for two types of application areas that require compatibility with human visual perception. These applications involve Classification of image signals information relevant to human observation, such as the type of object, scene, activity or uniqueness of a person, needs to be extracted from given data.

RELATED WORK

Feature extraction methods for color image similarityR.Venkata Ramana Chary, Dr.D.Rajya Lakshmi a Dr. K.V.N Sunitha,[1].Feature Extraction Methods.Content Based Image Retrieval, means it extracting a range of images which is relevant with the given image from a large data base of images. In Content Based Image Retrieval we arrange data in table row-column format. Then we perform any similarity measurement algorithm to find the similar kind of image data. Feature means some visual similarity which can uniquely an image from others. There exist many image features like color, shape, texture etc. We need to extract these features from image. Here we get another term “feature extraction” which means mapping the image pixels into the feature space.

Image Similarity Measure using Color Histogram,Color Coherence Vector, and Sobel Metho Kalyan Roy, Joydeep Mukherjee[2]. on feature extraction is to extract the color histogram value from an image. The color histogram for an image is constructed by quantizing the colors within the image and counting the number of pixels of each color. Color is one of the most outstanding features of the image, it is most important human visual substance and it is very easy to calculate. It is widely alarmed by many researchers because it does not effected by natural rotation, scaling and translation of an image.The color distributions in the images can be represent educing the Color Histograms. The histogram of the query image and the database images are compared for there rival. But this method fails if two different images have the same color distributions. To avoid this color coherence vectors can be used which store spatial information of an image in vector format.

Sparse Representation for Image Similarity Assessment using SIFT Algorithm Shanmugam C,Nandhini K,Poovizhi ,Priyadharshni **C[3].**SIFT is one of the most persistent and robust image features, and it has been widely used in several multimedia applications, such as image recognition, copy detection ,retrival and near-duplicate detection. In addition, in a recent performance evaluation, the SIFT descriptor has been shown to outperform other local descriptors. Current SIFT-based image retrieval approaches are usually based on building indices for SIFT feature descriptors that are extracted from local image regions. Then, the descriptors are quantized into visual words defined in a pre-constructed expressions. Finally, image retrieval can be achieved through a text retrieval technique Moreover, for SIFT-based image recognition, an efficient architecture, called a vocabulary tree, was proposed .

A Novel Algorithm for View and Illumination Invariant Image Matching Yinan Yu, Kaiqi Huang, Wei Chen and Tieniu Tan.affine(ASIFT)[7].They simulate the original image to discrete poses. The simulations are controlled by two variables: horizontal angle and vertical angle. Choosing a group of values for the two variables, they construct simulations of the image to cover the whole affine space. Finally, SIFT is used to extract features from these simulations. It turns out that the SIFT is not fully affine invariant, whereas ASIFT is fully affine invariant, which is credited to the framework. ASIFT can find the association between the matching pair, even if they are much different in vision. The improvement by the novel ASIFT image-matching frame work gives us a new viewpoint to image matching. Real-time applications are constantly proposed as many Different detectors and descriptors have been developed to extract illumination invariant local features.

PROPOSED WORK

A natural way of measuring the similarity between two given images is to quantify how well each image can be represented using the information of the other. The more similar the images, the better is the representation of one image in terms of the other.Sparse representation-based complexity functions. We define two quantities that measure the compressibility of an image i.e. how much can an image be compressed. These two quantities use (i) the dictionary learnt from the image itself, and (ii) the dictionary extracted from the other image.
In our approach, the first step is to extract suitable features from the available training data. The dimensionality of those features is reduced if necessary. Overcomplete dictionaries are then learnt from the lower-dimensional features. When a new query data is available, similar features are extracted from the query. Image-based face recognition Face recognition experiments are performed on the AT&T face database. This benchmark dataset contains 400 grayscale images of 40 individuals in 10 poses.The images were taken at different times, with varying illumination, facial expressions and details. Each image is of dimension 92_112.

Figure 3.1: Sample images from the AT&T face database

For feature extraction, 1000 random patches of size 24_24 are extracted from each image. Each patch is converted to a vector of dimension 576. These high dimensional patch vectors are projected onto a random 64-dimensional subspace using RP. The shared dictionary FS 2 R64_256 is learnt using k = 8 and 20 KSVD iterations. Each of the class-specific dictionaries Fi 2R64_128 where i 2 is learnt with k = 8 and 20 KSVD iterations. The concatenated dictionary is FC 2 R64_5120.A training set is constructed by randomly selecting 7 images per class and the rest is used for testing.

A. Implementation details

Practically, there are 4 parameters to be set: the patch size (n) the number of patches to be extracted from each image (s), the number of dictionary elements (m) and the reconstruction error (d). Unfortunately, there is no theoretical guidelines to determine values of parameter, so we depend on the previous work. We have used the same parameter values for all experiments. Below, we describe how the parameter values are chosen for this particular work. Patch size and automatic scale selection: The patch size determines the spatial scale at which an image is analyzed. For simplicity and speed, we analyze each image at a single scale, but use a simple technique to automatically select the optimal scale. A 2D LOG filter is applied to each image to detect the local maxima points at four different scales. The scale at which the maximum number of keypoints are detected is chosen as the optimal scale for that image. The image is downsampled accordingly and a set of patches are extracted. This particular patch size is chosen in order to be consistent with most of the compression based algorithms which process 8_8 blocks.

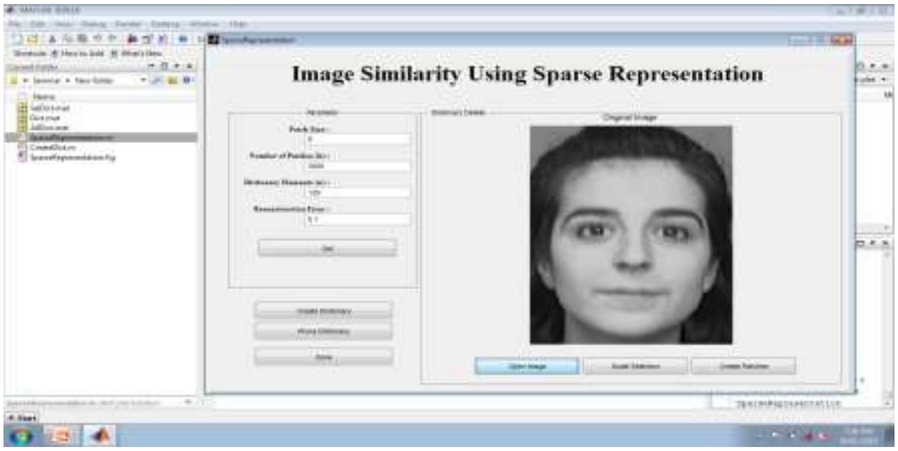

Figure3.2 Image from the database

In the AT&T Dataset we use different sets of images for finding the accuracy.we classify the different sets of images into different classes and make them to form the cluster so that the similarity finding between a pair of images is easy and also we use an OMP algorithm in the dictionary learning so that it is flexible and it takes less computation time for matching.

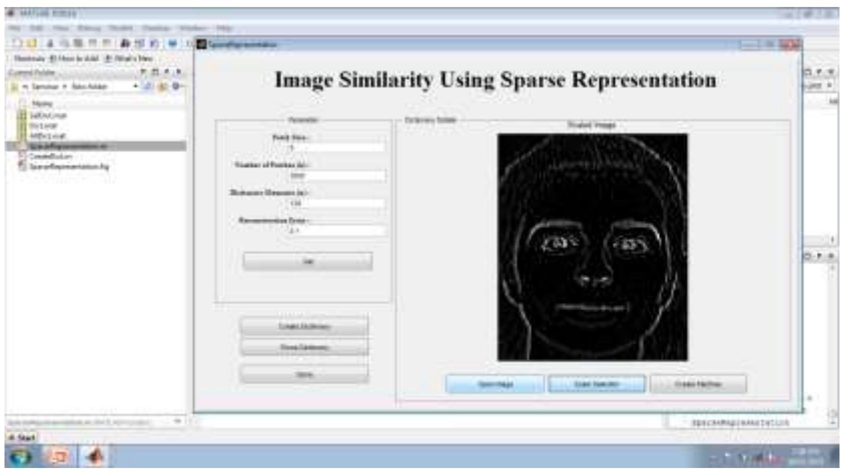

Figure3.3 Scaling of image

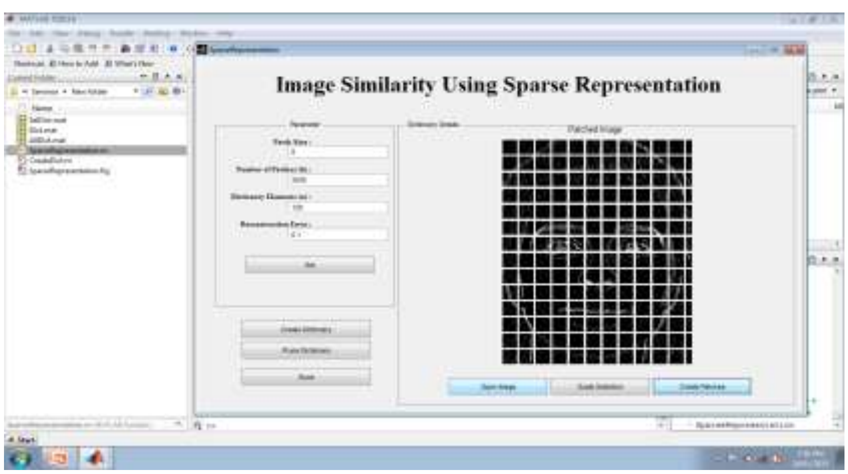

Figure3.4 Create patches to the image

Number of patches (s): In order to train a dictionary, a large number of patches need to be extracted. The color images are first converted to grayscale to achieve color invariance. It is also important that the randomly extracted patches contain important structural information of the image and do not come from the homogeneous regions of the image only. This is accomplished by selecting the patches whose energy levels are above an empirically set threshold.

B. Dictionary learning

The discovery by Olshausen and Field, promotes the idea of learning an overcomplete dictionary i.e. learning a set of overcomplete basis functions from the given data. This idea apparently mitigates the difficulty of selecting the right basis function that would lead to a sparse representation of a given signal. An overcomplete dictionary can be formed i) by combining multiple orthogonal bases (such as the Identity and Fourier matrices) or ii) by selecting one of the predefined overcompletebases, such as bandlets. However, the success of an overcomplete dictionary with predefined bases is often limited by how suitable its basis functions are in representing the structure in the signal under consideration. The dictionary learning approach, on the other hand, is more generalized as its basis vectors could be adapted to fit the structures in the given data. overcomplete case. Earlier approaches to learning overcomplete dictionaries.

These methods have successfully shown that an overcomplete set of bases yield a better approximation of the underlying statistical distribution of the data and can lead to
a more compact representation. Thanks to the recent progress and the growing interest in the areas of sparse optimization, dictionary learning has become an important topic of research in the last few years. Several practical dictionary learning algorithms have now been developed. These methods have been shown to outperform prespecified dictionaries like wavelets and produce state-of-the-art results in several real world applications such as in image and video denoising and color image restoration.The idea of fitting bases to a particular data distribution however is not new to the signal processing community. The well-known Principal Component Analysis (PCA) learns orthogonal bases from a particular data by finding the directions in the data with the largest variance - the principal components. An extension of 10 PCA, called the Independent Component Analysis (ICA), allows the learning of nonorthogonal bases from the data.

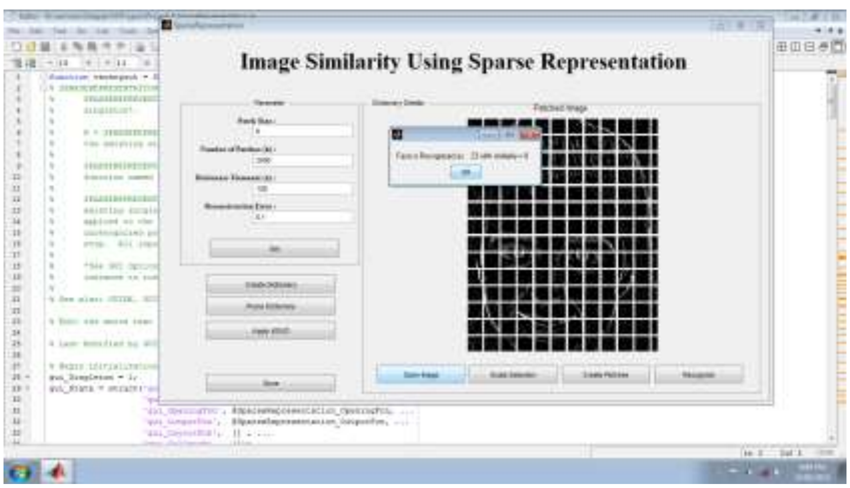

Figure3.5 Matching of images

RESULT AND ANALYSIS

In this we compare the two different datasets i.e. AT&T and Yale face dataset then we compare their accuracy and find out the best similarity between the pair of images.

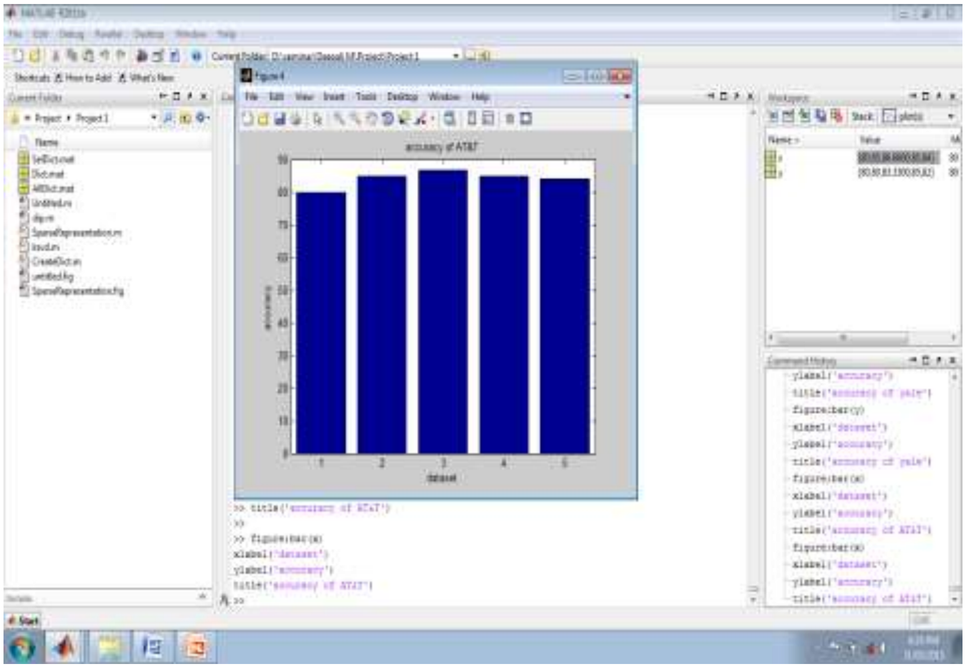

Figure3.6 Accuracy of AT&T Dataset

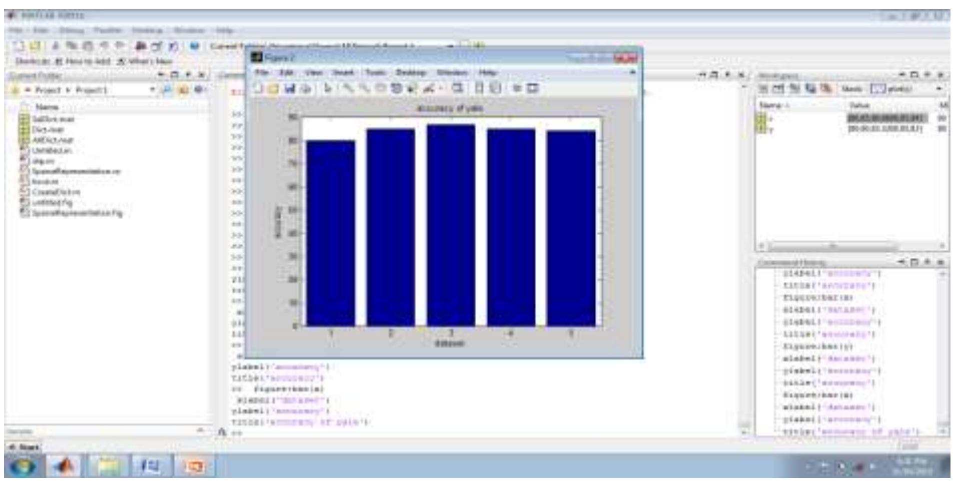

Figure3.7 Accuracy of Yale Dataset

Datasets / No. of images in class	AT&T accuracy(%)	Yale Accuracy(%)
10	80	80
20	85	80
30	86.66	83.33
40	85	85
50	84	82

Figure 3.8 Accuracy comparision between two datasets

FUTURE SCOPE

In the dictionary learning method we can use different greedy algorithm for increasing the accuracy of dataset. Future research will focus on using the measure more efficiently to classify and cluster larger datasets. This will require exploiting sophisticated machine learning techniques. Applications can also be extended to problems such as copy detection and data mining.

CONCLUSION

In This paper we proposed a dictionary learning by using the K-SVD Algorithm for improving the efficiency of the similarity between two images that it assumes no prior knowledge of the data or the application. The dictionary learning process takes only a few seconds; for example, with the abovementioned parameter values, a MATLAB implementation takes 2 secs to learn a dictionary per image including the patch extraction process on a standard PC e.g. intel quad @2.67GHz. In order to obtain a dictionary a large number of patches need to be extracted from the each image. but the proper selecting dictionary is not an easy task it require many trials, domain knowledge and previous experience.our method match the images with 86% of accuracy.

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