Performance of K-Means Algorithm on 2D-DWT Compressed Image Data

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ABSTRACT

A simple recognition system is proposed which clusters the gray scale images using K-means algorithm based on wavelet features. The method is based on information extracted from the images known as features extraction. The features are extracted by using the following process: the image is decomposed by applying 2D- discrete wavelet transform (DWT) for one, two, three and four levels. The dimensionality of the image data is reduced up to desired level by the application of wavelets. The decomposed coefficients of an image are considered as the feature sets. The four methods of reducing dimensions are applied on a specific set of images to obtain four different data sets which serve as input to the k-means algorithm for clustering. The number of clusters is fixed prior to the experiments. The relative performances of k-means based on four different data sets are evaluated in terms of clustering accuracy and CPU time consumed.

Keywords

k-means, DWT, clustering, feature extraction, normalization.

1. INTRODUCTION

Clustering the images is an important area of research in Pattern recognition around the globe which involves image processing [1]. Clustering is an unsupervised way of representing data into groups based on a given similarity measure and clustering algorithms organize the feature vectors into groups such that the samples inside the cluster are more similar to each other than to samples belonging to different clusters [2]. One of the popular algorithm for cluster analysis is K-means [3-5], which aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest. The K-means algorithm is unsupervised clustering method, widely used by the researchers in image segmentation [3-8]. K-means is popular for its implementation and is commonly applied for grouping pixels in images and video sequences [6]. The disadvantage of K-means is that the number of clusters should be defined in advance [9].

The wavelet transforms [10-14] have found numerous applications in signal processing, image processing and pattern recognition and other related areas. The Discrete Wavelet Transform (DWT) is approximating a signal through a set of basic mathematical functions and detailed description is found in [13]. The multiresolution decomposition of the signal into four sub bands is obtained by wavelets. Daubechies family is used in multiresolution analysis [13]. In [15-16] researchers have used the wavelets to compress the moment's coefficients and Fourier coefficients. The wavelets decomposition provides the important information from the original data used for feature extraction. The data set (feature vectors) obtained by using DWT is processed using k-means algorithm which decides to which cluster the particular feature vector belongs to. The performance of the k means algorithm is evaluated on four data sets in terms of classification accuracy and CPU time. The remainder of this paper is organized as follows: section II describes the methodology adopted. Section III presents experiments and section IV presents results obtained. Finally a summary of observations and future scope of the work is given in section V as conclusion.

2. METHODOLOGY

The proposed design consist of two phases: the first phase is to extract the required information from the image by means of feature extraction. The extracted features serve as input data sets and are stored in a file. The second phase, K-means algorithm clusters the data sets into respectively categories. Consider a gray level image of size P x Q. The following feature extraction methods are considered for the simulation studies.

In method 1, the wavelets are applied for image compression based on multiresolution representation property. The wavelets decomposition coefficients provide the important information from the original data and hence used as extracted features. The multiresolution wavelet decompositions are carried out on the original image up to one level. The features obtained from decomposition of each image are normalized and stored in a vector form in a file. The wavelets decomposition method is applied up to two levels for method 2, up to three levels for method 3 and up to four levels for method 4 respectively. The decomposed features serve as data sets are stored in different files. The features are normalized and store in [1 x a] matrix where 'a' stands for columns. The feature extraction method is represented in Fig.1.

The feature vectors obtained by the above methods are given as input to the K-means algorithm. Given a set of observations (x1, x2, …, xn), where each observation is a d-dimensional real vector, then k-means clustering aims to partition the n observations into k sets (k < n) S={S1, S2, …, Sk} so as to minimize the within-cluster sum of squares (WCSS):

$$\mathbf{arg}_{s}\, \mathbf{min} \sum_{\mathbf{i=1}}^{\mathbf{k}} \sum_{\mathbf{x_j \epsilon S_i}} \| \mathbf{X_i} - \boldsymbol{\mu}_\mathbf{i} \|^2$$

Where μi is the mean of points in Si.

The complete flowchart of the methodology adopted is as shown in Fig. 2.

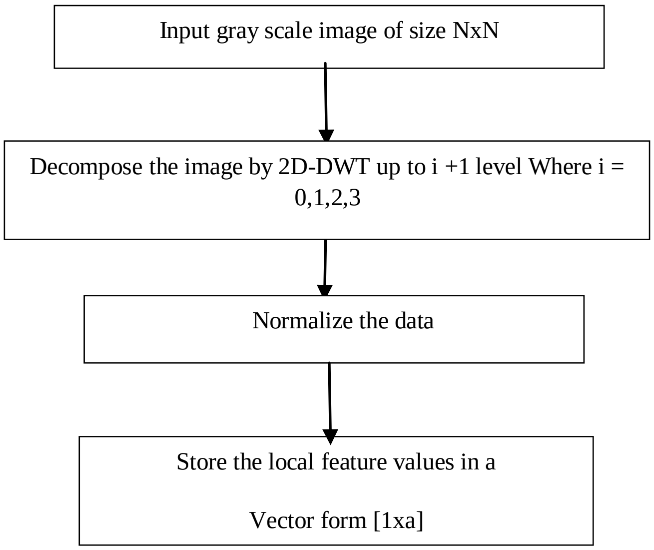

Fig. 1 Flowchart of Feature Extraction by 2D-DWT decomposition upto i-level

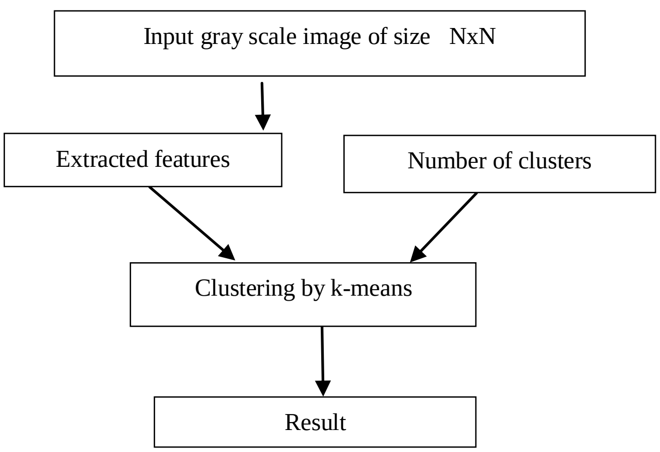

Fig. 2 The block diagram of the complete clustering process by k-means method

3. EXPERIMENTS

For the simulation process, the standard data-set of gray scale images obtained from database [17]. The experiments are implemented in Matlab on Intel core 2 Duo,2.10 GHz, 3 GB RAM machine. It is assumed that the images are free from noise and hence no preprocessing technique is used. The data-set consists of two classes: face images and non-face images. Some of the sample gray scale images are shown in Fig. 3.

Fig. 3 The standard data-set of gray scale images obtained from MIT database [16]

The image set consists of 100 gray scale images including 50 face images and 50 non-face images like forests. The images are re sized to 64 x 64 for the experiments. In the experiment number 1, the one level of 2D-DWT is applied to the image to get four sub bands. Each sub band is of size 32 x 32 i.e. dimension of data is 1024. The approximate coefficients are only considered for the data set. The data obtained is normalized in the range of [-1, 1] and stored in a file. The above process is repeated for all 100 images. The input size is of 100 x 1024. The normalized feature vectors obtained serve as input to K-means algorithm for clustering. The number of cluster (K) is fixed to 2. The K-means algorithm exactly clusters the data set into two clusters face and non-face categories without error. The CPU time consumed by the machine to do the processing is 0.6292 Seconds.

In the experiment 2, experiment 3 and experiment 4, images as mentioned in experiment 1 are decomposed by means of 2D-DWT up to two levels, third levels and four levels and the reduced dimensions of feature vectors in terms of approximate coefficients obtained are 16 x 16, 8 x 8, 4 x 4 respectively. The k-means algorithm is fed with input data sets of size 100 x 256, 100 x 64 and 100 x 16 that are stored in different files for clustering. The k-means algorithm clusters the data sets into 2 clusters face and non-face accurately for experiment number 2 and experiment number 3 which uses 100x256 and 100x64 sized data-sets respectively with reduced CPU processing time. In the experiment 4, 100x16 input one face data is wrongly clustered with non-face images. It is evident from the Table 1 that the experiment 4 takes less time to process the data compared to data sets as mentioned above with cluster misclassification. The results obtained from the experiments above are summarized in Table 1.

Table 1. Results Of The Experiments Performed on Different Data Sets By K-Means Algorithm.

Exp No	Dimensions in feature vector	CPU time in seconds	Percentage Recognition
1	one level decomposition = 1024	0.6292	100
2	two level decomposition = 256	0.2203	100
3	three level decomposition= 64	0.0702	100
4	four level decomposition = 16	0.0445	99

4. DISCUSSION

From the results, it is evident that the clustering performance of the algorithm varies from 100% to 99% as the dimensions of feature vector reduce from 1024 to 16 and also CPU time consumed is reduced from 0.6292 Secs to 0.0445 Secs. In the cases discussed above, the third experiment is the best optimized process for the practical applications. The experiments show that reducing the dimensions in data sets reduces the processing time without any effect on the clustering performance up to a certain level. The further reduction in dimensions of feature vector results in misclassified clusters. K-means algorithm performance degrades due to the loss of information in feature data. The dimension of feature vector becomes too small to provide the valuable information for clustering. Hence the proper selection of dimensions in features is an important factor for the classifiers to produce accurate results as outputs.

The DWT helps in better identification of which data is relevant to human perception and higher compression ratio and hence useful to obtain reasonable clustering performance results while maintaining a low number of computations. The number of iterations performed by k-means algorithm is less for feature set extracted using 2D-DWT up to three levels than one and two level. Some important information is lost when the image is decomposed by 2D-DWT up to four levels resulting in errors.

5. CONCLUSION

The K-means algorithm is evaluated on four different features extracted data sets. The feature extraction techniques for the experiments are based on the decomposition of the images up to one, two, three and four levels using 2D-DWT. The features serve as input to the K-means algorithm. The simulation results predict that the features extracted by three level decomposition using 2D-DWT gives better clustering result and takes less computing time when compared to the features extracted by the first and second levels of wavelet decomposition. The fourth level wavelet decomposition takes lesser processing time than third level with classification error. Hence, the third experiment is the optimized solution for the given problem as discussed above. In future, other feature extraction algorithms like statistical features, Fourier coefficients etc. may be tried with other type of classifiers for more than two class of problem. The proposed result is encouraging and show possible potential use for industrial application in future.

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