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A GUI Based Technique To Exploit Latency Towards Efficient Object Categorization

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Abstract—**Due to the advancement in technologies there is an increase in the number of digitized images, hence there is a requirement of large image dataset. to manage such a large dataset the most common method used is CBIR.In this system we obtain images which are most likely to be the same as the input image given by the user. Here retrieval is done based on different properties of the image, which will be represented as feature vectors. In our paper we resize the image, then extract features of the images and then the query feature vector is matched using different similarity measurements. At the output end images will be classified.**

Keywords—*Content-based image retrieval, image database, PCA, FLD, Manhattan distance, indexing, Euclidean distance, subspace mixture model, Minkowski distance.*

I. Introduction

Rapid increase in digital image collection due to development of internet and digital media technique has made classification necessary. Various techniques for storing, browsing, efficient indexing, searching & retrieving image becomes essential for large image archives. This leads to an existence of Image Retrieval System and has brought up a significant interest in the research community. In this system we obtain images which are most likely to be the same as the input image given by the user. Here retrieval is done based on different properties of the image, which will be represented as feature vectors. In this paper we resize the image, then extract features of the images and then we apply different similarity measurements.

Efficient indexing of visual feature vectors and similarity distance measure are important for image retrieval. As image retrieval is used the output images just does not is because of the key text given but it is the result of many features that are extracted and compared.

II. Methodology

The figure 1 shows the image retrieval methodology we have used in this paper. To create a data base first a group of images are collected and trained. This involves resizing of images. The features are extracted using FLD Mixture Model and the dimensionality is reduced using PCA. This forms feature vectors of each image and this is stored in feature vector data base.

The queryimage is selected by the user. To this image again resizing is done along with feature extraction using FLD mixture model. Feature vectors of this query image are compared withevery images of database. Comparison is done using six similarity measures.

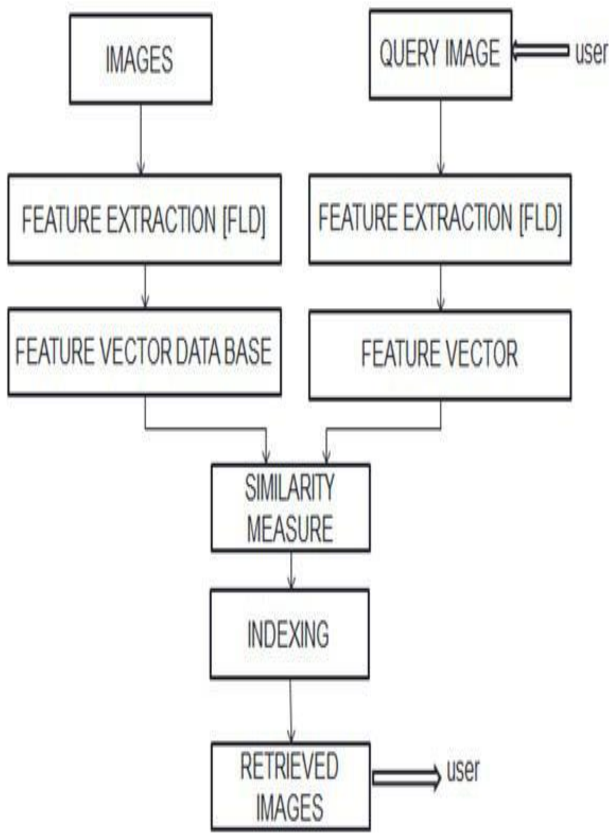

Figure 1: Typical image retrieval system

Extracting compact but semantically valuable information from images is feature extraction. We extract the features using FLD mixture model.

A. *Gaussian Mixture Model*

Representing normally distributed subpopulations within an overall population is Gaussian Mixture Models. Mixture models in general don't require knowing which subpopulation a data point belongs to this allows the model to learn the subpopulations automatically. Since subpopulation assignment is not known, this constitutes a form of unsupervised learning. It is parameterized by two types of values, the component means and variances/covariances and the mixture component weights.

For a Gaussian mixture model with K components, the k^{th}component has a mean of μ_k and variance of σ_k for the univariate case and a mean of μ_k and covariance matrix of σ_k for the multivariate case. The mixture component weights are defined as $\emptyset_k$ for component C_k, with the constraint that $\sum_{i=1}^{k} \emptyset_i = 1$ so that the total probability distribution normalizes to 1 . If the component weights aren't learned, they can be viewed as an a-priori distribution over components such that p(x generated by component C_k) = $\emptyset_k$. If they are instead learned, they are the a-posteriori estimates of the component probabilities given the data.

One Dimensional model:

$$p(x) = \sum_{i=1}^{K} \emptyset_i N(x/\mu_i, \sigma_i) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

$$N(x/\mu_i, \sigma_i) = \frac{1}{\sigma_i\sqrt{2\pi}} \exp(-\frac{(x-\mu_i)^2}{2\sigma_i{}^2}) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

$$\sum_{i=1}^{k} \emptyset_i = 1 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3)$$

Multi Dimensional model:

$$p(\vec{x}) = \sum_{i=1}^{K} \emptyset_i N(\frac{\vec{x}}{\mu_i}, \sigma_i) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

$$N(\frac{\vec{x}}{\vec{\mu_i}}, \Sigma_i) = \frac{1}{\sqrt{(2\pi)^K|\Sigma_i|}} \exp(\frac{-1}{2}(\vec{x} - \overrightarrow{\mu_i})^T \Sigma_i^{-1}(\vec{x} - \overrightarrow{\mu_i})) \ldots\ldots(5)$$

$$\sum_{i=1}^{k} \emptyset_i = 1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(6)$$

If the number of components is k known, expectation maximization is the technique most commonly used to estimate the mixture model's parameters. In frequentist probability theory, models are typically learned by using maximum likelihood estimation techniques, which seek to maximize the probability, or likelihood, of the observed data given the model parameters. Unfortunately, finding the maximum likelihood solution for mixture models by differentiating the log likelihood and solving for 0 is usually analytically impossible.

B. Expectation Maximisation

This is a way of implementing maximum likelihood estimation for this problem. Closed-form expressions are possible where EM of particular appeal for finite normal mixtures. Expectation maximization (**EM**) is a technique for highest likelihood estimation, and mostly used when closed form expressions are calculated. Expectation maximization is an iterative algorithm and has the easy property that the maximum likelihood of the data strictly increases with each subsequent iteration.

Expectation maximization for mixture models has two steps.

- **E** step, consists of calculating the expectation of the component assignments C_k for each data point $x_i \in X$ given the model parameters $\emptyset_k$,μ_k , and σ_k.

Calculate for all i , k:

$$\widehat{\gamma_{ik}} = \frac{\emptyset_k N(x_i|\widehat{\mu_k},\widehat{\sigma_k})}{\sum_{j=1}^{k} \widehat{\emptyset_j} N(x_i|\widehat{\mu_j},\widehat{\sigma_j})} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(7)$$

$\widehat{\gamma_{ik}}$is the probability that x_i is generated by component C_k . Thus, $\widehat{\gamma_{ik}}$ =$p({}^{C_k}/_{x_i}, \widehat{\emptyset}, \hat{\mu}, \hat{\sigma})$

- **M** step, which consists of maximizing the expectations calculated in the E step with respect to the model parameters. This step consists of updating the values$\emptyset_k$,μ_k , and σ_k.

Using the $\widehat{\gamma_{ik}}$ calculate in the Expectation step, calculate in the following order for all k:

$$\widehat{\emptyset_k} = \sum_{i=1}^{N} \frac{\widehat{\gamma_{ik}}}{N} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(8)$$

$$\widehat{\mu_k} = \frac{\sum_{i=1}^{N} \widehat{\gamma_{ik}} x_i}{\sum_{i=1}^{N} \widehat{\gamma_{ik}}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(9)$$

$$\widehat{\sigma_k} = \frac{\sum_{i=1}^{N} \widehat{\gamma_{ik}}(x_i - \widehat{\mu_k})\text{^}2}{\sum_{i=1}^{N} \widehat{\gamma_{ik}}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(10)$$

The entire iterative process repeats until the algorithm converges, giving a maximum likelihood estimate. Intuitively, the algorithm works because knowing the component assignment $C_k$for each x_i makes solving for$\emptyset_k$, μ_k, and σ_k easy, while knowing $\emptyset_k$, μ_k, andσ_k makes inferring easy. The expectation step corresponds to the latter case while the maximization step corresponds to the former. Thus, by alternating between which values are assumed fixed, or known, maximum likelihood estimates of the non-fixed values can be calculated in an efficient manner.

C. FLD Mixture Model

Fisher Linear Discriminant analysis (LDA) is useful in searching a linear combination of features. These features separate two or more classes of objects present. This feature extracted is used for dimensionality reduction also.

We calculate Ck by applying PCA mixture model for the set of mean μi of each class with K-different mixtures. We use transformed matrix T_k& diagonal matrix $U_k$along with eigen values λ_{kd} as diagonal elements. This is the d_{th} largest eigen value of co-variance matrix. We obtain scatte matrix between the classes with the results obtained . The within-class scatter matrix for k_{th} mixture component can be written as

$$S_{B_k} = T_k U_k T_k^T \ldots\ldots\ldots\ldots\ldots\ldots\ldots(11)$$

$$S_{W_k} = \sum_{l=L_k} \frac{1}{n_l} \sum_{x \in Cl} (x - m_l)(x - m_l)^T \ldots\ldots\ldots(12)$$

With the help of above two scatter equations, we compute transformation matrix Wk for kth mixture component .here we get generalized eigen vectors corresponding to largest eigen values.

$$SJ_k(U) = \frac{|U^T S_B U|}{|U^T S_{W_k} U|} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(13)$$

The extracted feature vectors of the images in the data base as well as that of the query image feature vector is given to the similarity measure block where six different distance matrix are applied. If in one particular distance matrix the object is correctly recognized we consider that particular object to be classified. The different distance matrix that we have used are

- Manhattan distance
- Euclidean distance
- Modified square Euclidean distance
- Angle based distance measure
- Correlation coefficient distance measure
- Minkowski distance measure

III. EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

Here we use the MALAB software for execution of the algorithm. The dataset used in the paper is that of Corel-1k and Caltech 101. Caltech 101 has 101 different categories of images. Each category might have 30 to 800 numbers of images inside it.

A. COREL-1K

The experimental output of Corel-1K with proposed methodology is shown in Fig 2.Proposed methodology is 83 percentages efficient for Corel-1k.

Figure 2Few example images of Corel-1K.

B. CALTECH101

The performance analysis of Caltech -101 compared with the existing methods is 47% efficient. The images having accuracy greater than or equal to 90% are shown. The proposed methodology is 83 percentages efficient for Corel set being used and 47 percentages for Caltech used.

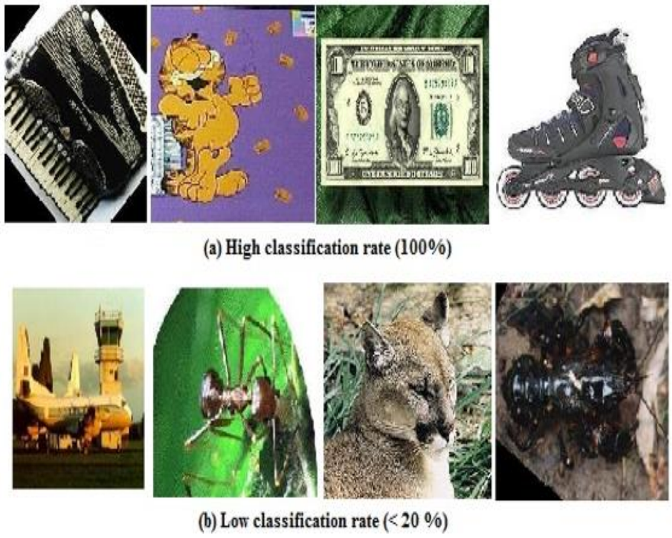

Figure 3. Few example images of Caltech 101 datasets with (a) High & (b) Low classification rates.

C. GUI OUTPUT

In this paper the GUI is prepared to make it easier for the users.

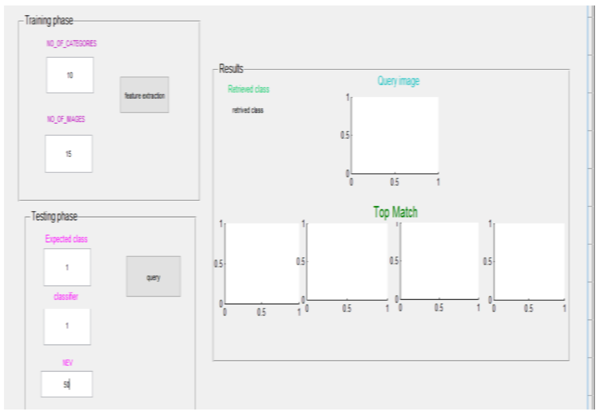

Figure4 Training the images

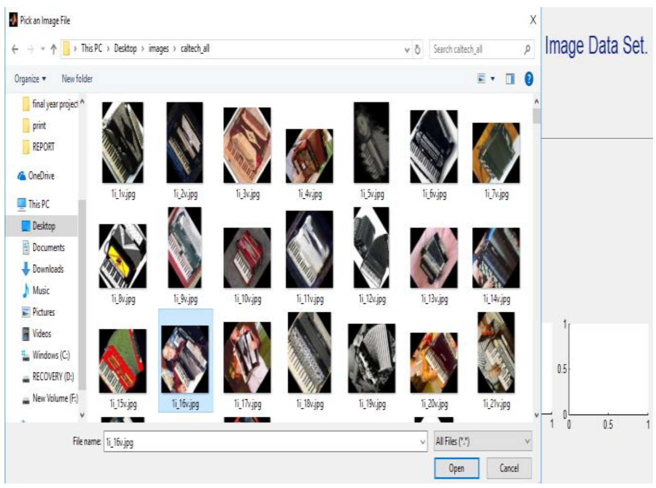

Figure 5Loading the query image

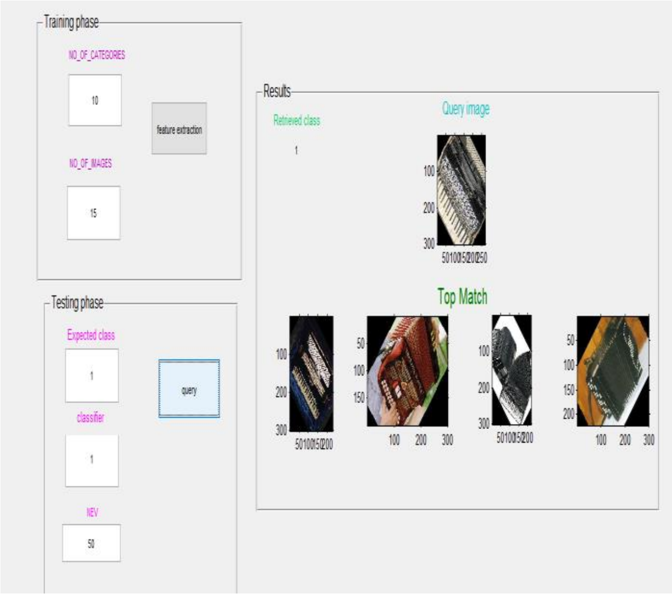

Figure 6 Results showing the top four best match for the given query

Figure 4, 5 and 6 shows the three phases of GUI part of the experiment. They include training the algorithm by taking 15 images from each category. Loading the query image from the images in any folders. The top four best match will be displayed to the user and the classification of image is done .

IV. CONCLUSION AND FUTURE SCOPE

There has been various works done on pattern recognition. In this paper we have done an effective analysis of subspace mixture model, FLD Mixture model, Expectation Maximization to extract features hence increasing the performance of image retrieval systems.

The usual method of text based input to search for images is quiet a tedious job. Also the results obtained from them are not efficient. Hence retrieving images using features are more efficient. However the features extracted and implementing in distance measure is basic, further works can be done using features extractions from shape, texture and color.

In near future, focusing upon different classifiers such as neural networks and SVM's to reduce the false recognition rate and the use of multimodal discriminating features (mixture of multiple features) may increase the performance of retrieval system.

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