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Design and Implementation of Relevance Feedback for Content Based Image Retrieval System that use a Classifier

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Abstract - The objective of this paper to implement an effective algorithm for relevance feedback in Content Based Image Retrieval (CBIR) system that uses a classifier. The performance improvement of CBIR systems can be achieved by sequence of steps involving feature selection, optimization, selection of proper classifier, optimizing the classifier parameters and introducing highly efficient algorithm for relevance feedback. The proposed relevance feedback algorithm in this paper works in such a way that the retrieval results of the CBIR system is improved after the first trial of relevance feedback itself even if the classifier has classified the query image into the wrong class. The user feedback is given to the CBIR system in the form of scores ranging from 0 to 100. This score is given in the order of relevance of the retrieved images. It is customary that everybody prefers a CBIR system with good search results in minimum number of trials. The CBIR system with the proposed relevance feedback achieves this goal. In order to further reduce the number of trials of search, a memory log is also incorporated in the CBIR system which stores the previous search results. Thus, after each usage of the proposed CBIR with memory log, the retrieval speed and performance is improved. The CBIR system with the proposed relevance feedback algorithm and memory log is tested using standard data sets – MIT 8 scene category and Caltech data set.

Keywords: Feature Selection, Dimensionality Reduction (PCA, Fisher Score Based Feature Selection), SVM Classifier, Relevance Feedback, Distance Measures (Euclidian, Mahalanobis, Tanimoto), Performance Measures (Precision, Recall, Mean Opinion Score).

I. INTRODUCTION

The key technique used for retrieving images from a large-scale image collection or World-Wide Web is content-based image retrieval (CBIR) [27] which has the ability of searching digital images using image features (such as colour, texture, shape etc.) in large data base. CBIR system are widely used in the area of Art collections, Image search engines, medical diagnosis, military, face finding, textile industry etc. [27]. The major challenge CBIR system faces is the big gap between low-level image features and high-level image semantics.

Fig. 1 shows an image from Caltech data set [24]. Human beings may identify its semantics (ship floating on a river) effortlessly. However, computers only know it by the feature vector. Hence, if one user selects Fig. 1 as the query example, the CBIR system may retrieve Fig 2 (a flying aeroplane) in the retrieval results.

Fig 1. Query Image

Fig 2. One among the retrieved images

The more diverse the images in the database, the higher are the risk of retrieving false matches because of similarities in the visual primitives that have no equivalent in the semantics. This is called the semantic gap.

In order to solve the above problem, we provide user feedback for CBIR system. CBIR system can make use of relevance feedback or user feedback, where the user progressively refines the search results by marking images in the result as ‘relevant’, ’not relevant’ or ‘neutral’ to the images obtained from search results or giving some scores to these images based on their relative relevance, then repeating the search with the new information.

During the earlier stages, CBIR systems were making use of distance measures such as Manhattan distance [2], Euclidean distance [11] etc. for similarity computation without using a classifier. The larger the database, the more time it took for the retrieval [1,4]. Nowadays, a classifier is used to classify the query image into a particular class prior to the similarity matching process so that the retrieval speed is increased [28]. If the classification accuracy of the classifier is high, then the CBIR system with classifier will give better retrieval results.

The various techniques used nowadays for the implementation of the CBIR system that use a classifier are explained as follows. Features such as colour, texture, shape etc are extracted from the query image. Then they are classified using a classifier and the query image thus is classified into a particular class in the data base. The classifier used are Bayesian, classifier [28,29], Regularized least square classifier [28], SVM classifier [7,28] etc. Then, the matching process is done with respect to that class using any of the similarity measures such as Euclidean distance [11], Manhattan distance [11], Distance weighted (K-Nearest Neighbor) [11], Correlation [11], Cosine measure [11], Bayesian neural network [11] etc. Thus, the images with features similar to the query image are retrieved.

User feedback or relevance feedback [1,4,21,22] is an interactive process to incorporate human perception subjectivity into the query process and provide users with the opportunity to evaluate the retrieval results. Till now, relevance feedback was given to CBIR systems without using a classifier. Relevance feedback is given to the retrieval results of CBIR system in such a way that the user selects a set of positive and negative examples from the retrieved results. Based on this information given by user, the feedback algorithms works and retrieves another set of similar images from the data base. Formulation of feedback algorithm may be based on any of the following methods such as Bayesian learning [28,29], Support Vector Machines (SVM) [7,28], Boosting [1,4], Query Refining [1,4], Feature Re-weighing [1,4] etc. The retrieval performance is gradually improved after several feedback iterations. To further improve the performance of CBIR systems, memory learning by accumulating user feedback log is done. Its basic idea is to learn semantics from previous users' feedback knowledge instead of image contents.

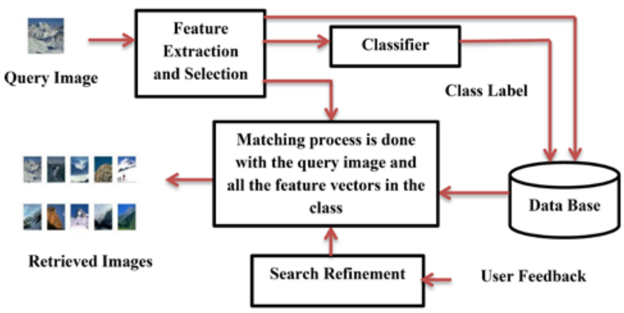

Fig 3. Block Diagram of a CBIR System with user feedback and classifier

The major disadvantage of CBIR system with classifier is that if the classifier classifies the query image into the wrong class, the retrieval results will be very bad. In this case, the present relevance feedback algorithms are of no use since that won't improve the retrieval results. If the classification accuracy of classifier is poor, then the overall performance of the CBIR system will be bad. So, CBIR system without classifier is preferred till now. In this paper, relevance feedback for CBIR system with classifier is proposed to eliminate the limitations of the CBIR system with classifier and take its advantage of increased retrieval speed with reduced number of trials.

The basic block diagram of the CBIR system with relevance feedback and classifier which is designed and implemented in this paper is shown below.

II. DATA SETS USED

The data sets used are MIT 8 scene category and Caltech data sets.

A. MIT 8 Scene Category Data Set

MIT 8 scene category data set [23] was developed by Massachusetts Institute of Technology. The Massachusetts Institute of Technology (MIT) is a private research university in Cambridge, Massachusetts. MIT 8 scene category has been used for experimentation and it contains images of coast, forest, highway, inside city, open country, street and tall buildings. Table I shows the number of images in each category. 2688 is the total number of images in the MIT 8 scene category dataset used for experimentation in this paper.

TABLE I : Table showing the Number of Images in each class for MIT 8 scene category data set

Class Label	Class Name	No . of Images
1	Coast	360
2	Forest	328
3	Highway	260
4	Inside city	308
5	Mountain	374
6	Open country	410
7	Street	292
8	Tall Building	356

B. Caltech Data Set

Caltech data set [24] was developed by California Institute of Technology. The California Institute of Technology (Caltech) is a private research university located in Pasadena, California, United States., Out of 101 categories in the Caltech data sets, 4 categories are used for experimentation in this paper. Table II shows the class name and the number of images in each category. Category 'Anims' contains images of different kind of animals including birds and reptiles. Category 'Cars' contains images of different types of cars. 'Distras' contains images of sceneries including sunset, sunrise, mountains, and open country. 'Trans' contains images of transportation vehicles such as aeroplanes, helicopters, trains, bus and boats.

We selected 3979 images from Caltech dataset for experimentation in this thesis work. Caltech is a more complicated data set compared to that of MIT 8 scene category since categories like Anims, Distras and Trans contains more diverse variety of images.

TABLE II: Table showing the Number of Images in each class for Caltech data set

Class Label	Class Name	No . of Images
1	Anims	1322
2	Cars	771
3	Distras	1123
4	Trans	763

III. FEATURE EXTRACTION

Features are extracted using Wndchrm [5]. Weighted Neighbor Distance using a Compound Hierarchy of algorithms Representing Morphology [5] is abbreviated as Wndchrm. Wndchrm is software which extracts features including and excluding colour features depending upon the user's choice. The input images given to the Wndchrm should be in 'tiff' format. It extracts 4059 features including colour features and 2919 features excluding colour features. The extracted features include some general (raw) features, transform of these features, transform of transform of features edge features and their transform. The raw features extracted by the Wndchrm are Radon Transform Features [12], Chebyshev Statistics [13], Gabor Filter coefficients [14], Multiscale histograms [13,9], Tamura Texture Features [15], Edge Statistics [16], Object Statistics [17], Zernike Features [18], Haralick Features [19], Chebyshev Fourier Features [20] and first 4 Moments [5,18]. The command used for feature extraction in Wndchrm is:

% wndchrm train [options] input_image output_feature_file

IV. DIMENSIONALITY REDUCTION TECHNIQUES USED

Principal Component Analysis (PCA) [25] and Fisher score based method of feature selection [8] are the 2 dimensionality reduction techniques used.

A. Principal Component Analysis (PCA)

The following steps are performed to obtain principal components [25,26].

1. Find the mean (A) of the feature set(F). Feature set, 'x' is obtained by taking all the feature vectors of all the class and concatenating each class one below the other.
2. Find 'F-A'.
3. Find the covariance of 'F'.
4. Find the Eigen values and Eigen vectors of the covariance matrix [26].
5. Sort the Eigen values in descending order [26].
6. Set a threshold for Eigen value and take the Eigen vector above this threshold value. Project the data in the direction of the Eigen vectors to get the reduced dimensional representation of a high dimensional data [26].

i.e (x-m)*(Eigen vectors above the threshold value).

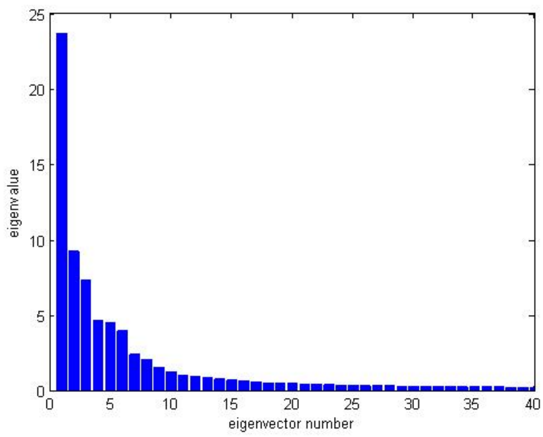

Fig 4. Graph showing the variation of Eigen values in decreasing order for the experiments done on all classes in MIT 8 scene category data set

Threshold is found out from graph (Fig 4) showing the variation of Eigen values in decreasing order. The point at which the sharp decrease of Eigen value ends and attains a constant value is selected as the threshold value for PCA.

B. Fisher Score Based Feature Selection Method

In Fisher score based feature selection method [8,26], the feature vectors of all the images in all the classes are concatenated one below the other and a score is given to each column of features. Let 'M' be the total number of classes.

Fisher Score is given to each column of feature using the following equation:

Fisher score, $F_j = \frac{\sum_{k=1}^{M} n_k(\mu_k^j - \mu^j)}{(\sigma^j)^2}$

where, .μ_k^j is the mean of j-th feature for the examples of the k-th class, n_k is the number of examples in k-th class,

μ^j and σ^j are the mean and standard deviation of the j-th feature over the whole data set.

The total variance for the j-th feature,

$$(\sigma^j)^2 = \sum_{k=1}^{M} n_k (\sigma_k^j)^2$$

where, $(\sigma_k^j)^2$ is the standard deviation of j-th feature for the examples of the k-th class.

Feature columns are arranged in the order of their descending fisher scores. Features with top fisher scores are selected to form the reduced dimensional representation of a high dimensional data.

V. CLASSIFIER USED

Support Vector Machine (SVM) based classifier is used in the CBIR system. SVM [7] is a binary learning machine which constructs a hyperplane as the decision surface in such a way that the margin of separation between positive and negative class of examples is maximized. The separation between the hyperplane and the closest data point (support vector) is called the margin of separation. The objective of SVM is to find the particular hyperplane for which the margin of separation is maximized.

For a given training example $\{(x_i, d_i)\}_{i=1}^{n}$ (x_i is the input pattern for the i-th example and d_i is the corresponding desired response.), equation for optimal hyperplane for linearly separable patterns is given as:

$$w_o^T x + b_o = 0$$

where, 'w_o' is the optimum weight vector, 'x' is the input vector and 'b_o' is the optimum bias.

Here, $w_o^T x + b_o \geq 1$ for $d_i = +1$ (positive class)

$$w_o^T x + b_o \leq 1 \text{ for } d_i = -1 \text{ (negative class)}$$

The particular point for which the above 2 equations satisfies with equality is known as support vectors. In order to maximize the margin of separation, Euclidian norm vector should be minimized. To find the optimal value of weight vector and bias we use Lagrangian optimization. In the case of non-linearly separable classes, the margin of separation is soft if data point (x_i,d_i) violates the following condition.

$$d_i\,(w_o^T x + b_o) \geq 1$$

Violation is of 2 types. The data point (x_i, d_i) falls inside the region of separation but on the correct side of the decision surface. Here, there is no misclassification. Data point (x_i, d_i) falls inside the region of separation. but on the wrong side of the decision surface. Here, there is misclassification. So, a new set of non-negative scalar variable known as slack variables $\{\xi\}_{i}{}_{i=1}^{n}$ are introduced.

$$d_i\,(w_o^T x + b_o) \geq 1 - \xi_i$$

where, ξ_i measure the deviation of the data point from the ideal condition of pattern separation.

Instead of constructing a complex curve for separating the objects, we can use a set of mathematical functions known as kernels. Kernels create decision region with high dimension (it might be hyperplane, hypersphere, hyperellipsoidal etc.) by mapping the support vectors into a high dimensional feature space. Thus, the mapped objects become linearly separable. There are number of kernels that can be used in SVMs models. Here we use linear, polynomial and radial basis function (Gaussian) kernels.

SVM Torch [6] is a decomposition algorithm used for implementing SVM classifier. It is suitable for classification of multiclass data. *SVM Torch* is the training machine and *SVM Test* is the testing machine.

The command line used for training data is:

% svm_torch [options] [training file] [model file].

The command line used for testing the data is;

% svm_test [options] [model file] [testing file].

VI. DISTANCE MEASURES USED

3 distance measures are used in this project to find the distance between 2 feature vectors. They are Euclidean distance [11], Mahalanobis distance [2] and Tanimoto [3] distance. If 'A' and 'B' are any 2 feature vectors then,

Euclidian distance between 'A' and 'B'

$$= \sqrt{\sum_{i=1}^{n}(A_i - B_i)^2}$$

where, 'i' represents the i-th feature and 'n' is the total number of features.

Mahalanobis distance between 'A' and 'B'

$$= \sqrt{(A - B)^T \Sigma^{-1} (A - B)}$$

where, 'Σ' is the covariance matrix.

Tanimoto distance between 'A' and 'B' = $\frac{A.B}{||A||^2 + ||B||^2 - A.B}$

where, A.B is the dot product of A and B, A.B= $\sum_{i=1}^{n}(A_i \times B_i)$, || || is the norm of the vector,

$$||A|| = \sqrt{\sum_{i=1}^{n}(A_i)^2},\ ||B|| = \sqrt{\sum_{i=1}^{n}(B_i)^2}.$$

VII. PERFORMANCE MEASURES USED

For analyzing the performance of the proposed CBIR system, the performance measures used are precision, recall and mean opinion score (MOS).

A. Precision and Recall

Precision [21] (also called positive predictive value) is the fraction of retrieved instances that are relevant, while recall [21] (also known as sensitivity) is the fraction of relevant instances that are retrieved. Maximum value of precision is 1.

$$\text{Precision}= \frac{\text{Number of Retrieved Relevant Images}}{\text{Number of Retrieved Relevant Images} + \text{Number of Retrieved not Relevant Images}}.$$

$$\text{Recall}= \frac{\text{Number of Retrieved Relevant Images}}{\text{Number of Retrieved Relevant Images} + \text{Number of not Retrieved Relevant Images}}$$

B. Mean Opinion Score (MOS)

Human observers can be used to perform subjective evaluation in order to access performance of the retrieval system. Mean Opinion Score (MOS) [26] is the mean value of scores given by human observers based on the retrieval results of the proposed CBIR system. The MOS is generated by averaging the results of a set of standard, subjective tests where a number of observers rate the retrieval results of the CBIR system for different query images. The opinion and the corresponding scores are tabulated in the table shown below.

TABLE III : Table showing the score for the opinions given by the user

Opinion	Full Form	Score
E	Excellent	5
G	Good	4
F	Fair	3
P	Poor	2
B	Bad	1

VIII. DESIGN OF THE CBIR SYSTEM WITH THE PROPOSED RELEVANCE FEEDBACK

For the design of the CBIR system (that use SVM classifier) with the proposed relevance feedback, the following steps are performed.

A. Feature Extraction and Grouping (Step 1)

Features are extracted using Wndchrm. 4059 features including colour features are extracted [5,9]. They are grouped into 4 feature sets. Feature Set 1 includes general features. Column 1 to 963 of the features extracted from Wndchrm is grouped as feature set 1. Feature Set 2 includes transform of these general features. Column 964 to 2363 is grouped as feature set 2. Feature Set 3 includes transform of transform of general features. Column 2364 to 3219 is grouped as feature set 3. Feature Set 4 includes edge features and their transforms. Column 3220 to 4059 is grouped as feature set 4.

The features extracted using Wndchrm may contain ‘inf’ and ‘NaN’ values. The columns containing ‘inf’ or ‘NaN’ values are removed. If all the row values in a column are same, that column is also removed. Then the resulting features are normalized between -1 and +1. Step 1 is implemented using MATLAB.

The equation for normalization is:

$$X(i,j)= \frac{(class(i,j)-Min}{(Max-Min)*(d-c))}+c$$

where, Max and Min is the maximum and minimum values of each column of the given data respectively, d and c are +1 and -1 respectively.

B. Determination of Classification Accuracy of Each Feature Set using SVM Classifier (Step 2)

For each feature set, 70% of the data is taken from each class and used as training set. The remaining 30% from each class is used as the testing set. SVM Torch is used as the training machine and SVM test is used as the testing machine. Feature set which gives maximum classification accuracy is selected for further dimensionality reduction.

C. Dimensionality Reduction of the Feature Set with Maximum Classification Accuracy (Step 3)

Dimensionality reduction is important in the sense that it saves memory space and thereby, reduces the cost and increases the speed of retrieval. Dimensionality reduction methods are done in such a way that the high dimensional data (features) is reduced to a low dimensional feature set that captures most of the variability in the original data. The dimension of the original data must be reduced in such a way that the low dimensional data gives the same retrieval results as that of the original data set. Also the classification accuracy of the feature set before and after dimensionality reduction must be same. PCA and Fisher score based feature selection are the 2 dimensionality reduction technique used here. The better dimensionality reduction method among the 2 methods is chosen to reduce the dimension of the feature set. The reduced feature set is further used in this project as feature vectors to represent the images.

D. Design of the CBIR System that use SVM Classifier and the Proposed Relevance Feedback (Step 4)

Query image is given as input to the CBIR system. Features are extracted from the query image using Wndchrm. Then, features are grouped into 4 and the feature set which gives highest classification accuracy among the 4 feature set is selected and suitable dimensionality reduction is done on these features to get the optimal reduced feature set. Thus, the feature vector corresponding to the query image is obtained. The query image is classified to a class using SVM classifier. The Euclidean distance between the feature vector of query image and each feature vector of that class is calculated. 10 images whose feature vectors have least Euclidean distance between the feature vector of the query image is displayed. The precision and recall is found out.

Feedback is given to the system in the form of scores varying from 0 to 100. The proposed relevance feedback algorithm works based on this score given by user. Relevance feedback algorithm designed in this paper is for the retrieval of 10 images similar to the query image. The working of the algorithm is explained for 3 different cases.

Case 1-: When the highest score is between 50 and 100

1. Class label and feature vector of the image with the highest score are taken. Matching process is done with all the feature vectors in the class using any of the 3 distance measure and 20 similar feature vectors are taken.

2. The above process is repeated for the images with the 2nd and 3rd highest score. Thereby, we get 3 sets of 20 image feature veciors.

3. 6 common image feature vectors (we can name it as set C1) from the first 2 sets are taken and 4 common image feature vectors (which are not in C1) from the 2nd and 3rd feature sets are taken. The images corresponding to these feature vectors are displayed. Thus, a total of 10 images are displayed.

If the feature vectors of common images got from the first 2 sets of 20 feature vectors is less than 6 then, the algorithm works in such a way that the remaining feature vectors are taken from the feature vectors of common images got from the 2nd and 3rd sets of 20 retrieved feature vectors. If the feature vectors of common images got from the 2nd and 3rd sets of 20 feature vectors is less than 4 then, the algorithm works in such a way that the remaining feature vectors are taken from the feature vectors of common images got from the first 2 sets of 20 retrieved feature vectors. If for any case there is a shortage of feature vectors of common images and the images to be displayed are less than 10 then, the remaining feature vectors will be taken from the first set of 20 retrieved feature vectors and their corresponding images will be displayed.

Case 2-: When the highest score is 100

1. Class label and feature vector of the image with the highest score are taken. Matching process is done with all the feature vectors in the class using any of the 3 distance measure and 20 similar feature vectors are taken.

2. The above process is repeated for the images with the 2nd and 3rd highest score. Thereby, we get 3 sets of 20 image feature veciors.

3. First feature vector (name it as C1) from the 1st set is taken. 6 common image feature vectors (we can name it as set C2 which is not similar to C1) from the first 2 sets are taken and 3 common image feature vectors (which are not in C1 an C2) from the 2nd and 3rd feature sets are taken. The images corresponding to these feature vectors are displayed. Thus, a total of 10 images are displayed.

If the feature vectors of common images got from the first 2 sets of 20 feature vectors is less than 6 then, the algorithm works in such a way that the remaining feature vectors are taken from the feature vectors of common images got from the 2nd and 3rd sets of 20 retrieved feature vectors. If the feature vectors of common images got from the 2nd and 3rd sets of 20 feature vectors is less than 3 then, the algorithm works in such a way that the remaining feature vectors are taken from the feature vectors of common images got from the first 2 sets of 20 retrieved feature vectors. If for any case there is a shortage of feature vectors of common images and the images to be displayed are less than 10 then, the remaining feature vectors will be taken from the first set of 20 retrieved feature vectors and their corresponding images will be displayed.

Case 3-: When the highest score is below 50

1. Feature vector of the query image is taken. And matching process is done with all the feature vectors in all the classes using any of the 3 distance measure.

2. First retrieved feature vector and its class label is taken and matching process is done with all the feature vectors in that class and 10 similar image

feature vectors are taken and their corresponding images are displayed.

3. The algorithm works in such a way that no 2 images in the images displayed are same. The 10 images displayed may be similar to that of the input query image given to the CBIR System. The retrieval results of the 3 distance measures (Euclidean, Mahalanobis and Tanimoto distance) are compared here in this paper through Mean Opinion Score (MOS).

In this paper, comparison of the CBIR system that uses SVM classifier along with the proposed relevance feedback is compared with the following 2 CBIR system.

- CBIR without a classifier which simply retrieves 10 images (irrespective of classes) with the least Euclidian distance to the query image.
- CBIR system that use SVM classifier and no relevance feedback, which retrieves 10 images with the least Euclidian distance to the query image from the class to which the query image was classified by the classifier.

E. Design of Memory Log for the CBIR System with the Proposed Relevance Feedback

A memory log is incorporated in the CBIR with the proposed relevance feedback so that the previous search results can be viewed by the user. Incorporation of a memory log increases the retrieval speed. 2 memory spaces are created – Memory 1 and Memory 2. In Memory 1, feature vectors of the searched query images along with their class label of the previous search results are stored and in Memory 2, the image numbers of previous search results are stored.

Features are extracted from the query image using Wndchrm to form a feature vector and dimensionality reduction is done on the feature vector. It should be noted that the same method of dimensionality reduction must be done as that done for the feature vectors in the data base. Then the query image is searched in memory 1. The working of the CBIR system with memory log for 2 different cases is explained below.

Case 1-: When the query image feature vector is present in Memory 1

1. The class label corresponding to the query image is taken. The image numbers of the corresponding query image from memory 2 is taken. Row number of the query image in memory 1 and image numbers in memory 2 are same.
2. The images corresponding to the image numbers from the class shown by the class label are displayed.

Case 2-: When the query image feature vector is not present in

Memory 1

1. The query image is classified to a class using SVM classifier. Matching process is done with all the feature vectors in the class using Euclidian distance measure and the images corresponding to the 10 feature vectors with the least Euclidian distance is displayed.
2. The query image feature vector along with the class label is stored in memory 1. The image numbers corresponding to the retrieved images are stored in memory 2.

Relevance scores can be given to these retrieved images if desired. Then, the image numbers in memory 2 will be updated according to images retrieved based on the relevance feedback.

IX. EXPERIMENTAL STUDIES

Experimental studies are done on MIT 8 scene category data set and Caltech data set. The CBIR systems are designed for a retrieval of 10 images.

TABLE IV: Table showing the number of features in each feature set after doing Step 1 for MIT 8 scene category data set

Feature Set	No. of features
1	631
2	694
3	234
4	367

TABLE V: Table showing the number of features in each feature set after doing Step 1 for Caltech data set

Feature Set	No. of features
1	709
2	1019
3	591
4	463

Table IV and V shows the number of features obtained after doing step 1 for MIT 8 scene category data set and Caltech data set respectively.

From Table VI and VII, it is observed that feature set 1 (General features) has got the maximum classification accuracy compared to that of all the other 3 feature sets. Gaussian kernel in SVM classifier has got the maximum classification accuracy compared to that of the other 2 kernels. So, feature set 1 is taken for further dimensionality reduction and SVM classifier with Gaussian kernel is used to train the training set for classification.

TABLE VI: Table showing the comparison of classification accuracy of SVM classifier for different feature sets for MIT 8 scene category data set

Classification Accuracy → / SVM Kernels ↓	Feature Set 1 (%)	Feature Set 2 (%)	Feature Set 3 (%)	Feature Set 4 (%)
Linear	72.33 (c=0.08)	54.9 (c=1)	50 (c=0.01)	42.42 (c=0.002)
Polynomial (d=2)	73.33 (c=0.0002)	57.94 (c=0.0001)	50.74 (c=0.005)	43.05 (c=0.001)
Gaussian	73.68 (c=55,st=25)	58.06 (c=31,st=25)	50.87 (c=0.001,st=25)	43.92 (c=1000,st=10)

TABLE VII: Table showing the comparison of classification accuracy of SVM classifier for different feature sets for Caltech data set

Classification Accuracy → / SVM Kernels ↓	Feature Set 1 (%)	Feature Set 2 (%)	Feature Set 3 (%)	Feature Set 4 (%)
Linear	66.42 (c=0.08)	64.49 (c=3)	59.89 (c=1)	57.35 (c=0.001)
Polynomial (d=2)	66.75 (c=0.00009)	65.83 (c=0.0001)	61.29 (c=0.0001)	60.13 (c=0.005)
Gaussian	67.34 (c=9,st=25)	66.5 (c=1000,st=25)	62.67 (c=1,st=25)	61.34 (c=10,st=25)

TABLE VIII: Table showing the comparison of classification accuracy of SVM classifier and the resulting number of features in feature set 1 after dimensionality reduction for MIT 8 scene category data set

Dimensionality Reduction Method	Classifier Used	Classification Accuracy (%)	No. of feature after dimensionality reduction
PCA (Threshold= 0.005)	SVM classifier with Gaussian kernel (c=15, st=10)	73.57	263
Fisher Score based feature selection method	SVM classifier with Gaussian kernel (c=15, st=20)	71.46	333

TABLE IX: Table showing dimensionality reductions done on feature set 1 when Tanimoto distance is used as the distance measure in the matching process (MIT 8 scene category data set)

Dimensionality Reduction Method	Classifier Used	Classification Accuracy (%)	No. of feature after dimensionality reduction
Fisher Score based feature selection method	SVM classifier with Gaussian kernel (c=15, st=20)	71.33	518

TABLE X: Table showing the comparison of classification accuracy of SVM classifier and the resulting number of features in feature set 1 after dimensionality reduction for Caltech data set

Dimensionality Reduction Method	Classifier Used	Classification Accuracy (%)	No. of feature after dimensionality reduction
PCA (Threshold= 0.005)	SVM classifier with Gaussian kernel (c=100, st=50)	67.09	289
Fisher Score based feature selection method	SVM classifier with Gaussian kernel (c=10, st=18)	66.42	324

TABLE XI : Table showing dimensionality reductions done on feature set 1 when Tanimoto distance is used as the distance measure in the matching process (Caltech data set)

Dimensionality Reduction Method	Classifier Used	Classification Accuracy (%)	No. of feature after dimensionality reduction
Fisher Score based feature selection method	SVM classifier with Gaussian kernel (c=15, st=10)	66.1	589

From Table VIII and X, we observe that PCA is a better dimensionality reduction method compared with Fisher Score based feature selection method because PCA gives the same classification accuracy as that of the original feature set with reduced number of features when compared to that of Fisher Score based feature selection. So here in this paper, when Euclidean and Mahalanobis distance measures are used in the feedback section, PCA is used to reduce the dimensionality.

TABLE XII : Table showing the comparison of average precision of different CBIR systems as tested with MIT 8 scene category data set (40 query images) and Caltech data set (20 query images)

Data Sets Used	No. of Query Images Tested	Average Precision of a CBIR without a classifier	CBIR System that use SVM classifier (for all 3 distance measures in the feedback section)		
			Average Precision of the CBIR System without Relevance Feedback	Average Precision of the CBIR System after 1st trial of Relevance Feedback	Average Precision of the CBIR System after 2nd trial of Relevance Feedback
MIT 8 Scene Category	40	0.5925	0.925	1	1
Caltech	20	0.74	0.8	1	1

When Tanimoto distance measure is used in the feedback section, Fisher Score based feature selection method of dimensionality reduction is done since Tanimoto distance is highly sensitive to any kind of transformations. The retrieval results may be affected by PCA transformations. Dimensionality reduction for Tanimoto distance is shown in table IX and XI.

In Table XII, five images from each class in MIT 8 scene category data set are taken as query images for the test which makes a total of 40 images from MIT 8 scene category data set. Similarly, five from each class in Caltech data set are taken for the test which makes a total of 20 images from Caltech data set. Here, images are considered as relevant or irrelevant based on class label.

TABLE XIII : Table showing the comparison of MOS of different CBIR systems for the 3 distance measures (MIT 8 scene category data set)

Distance Measure used in the Relevance Feedback section	Mean Opinion Score (MOS)		
	CBIR System without Relevance Feedback	CBIR System after the 1st trial of Relevance Feedback	CBIR System after the 2nd trial of Relevance Feedback
Euclidian distance	4.725	5	5
Mahalanobi's distance	–	4.775	4.775
Tanimoto distance	_	5	5

From Table XII, it is observed that the average precision is higher for a CBIR system with SVM classifier compared to that of CBIR system without classifier. The average precision is increased to 1 after trial 1 of relevance feedback and it is maintained as such in the 2nd trial. Maximum recall is also achieved after trial 1 of feedback.

From Table XIII, it is observed that the Mean Opinion Score for feedback with Tanimoto distance and Euclidian distance is higher than Mahalanobis distance. Mean Opinion Score for feedback with Mahalanobis distance is slightly lower than Tanimoto and Euclidian distance. Mean Opinion Score is higher for CBIR system with feedback compared to that of without feedback.

TABLE XIV: Table showing the comparison of MOS of different CBIR systems for the 3 distance measures (Caltech data set)

Distance Measure used in the Relevance Feedback section	Mean Opinion Score (MOS)		
	CBIR System without Relevance Feedback	CBIR System after the 1st trial of Relevance Feedback	CBIR System after the 2nd trial of Relevance Feedback
Euclidian distance	3.35	4.3	4.3
Mahalanobi's distance	–	3.7	3.8
Tanimoto distance	_	4.3	4.3

From Table XIV, it is observed that the Mean Opinion Score for feedback with Tanimoto distance and Euclidian distance is higher than Mahalanobis distance. Mean Opinion Score is higher for CBIR system with feedback compared to that of without feedback. Mean Opinion Score for feedback with Mahalanobis distance has slightly increased after trial 2 compared to that with trial 1.

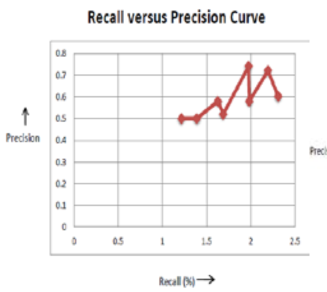

Fig 5(a)

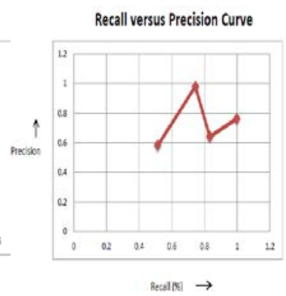

Fig 5(b)

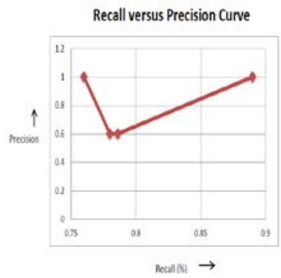

Fig 5(c)

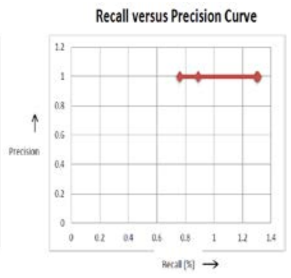

Fig 5(d)

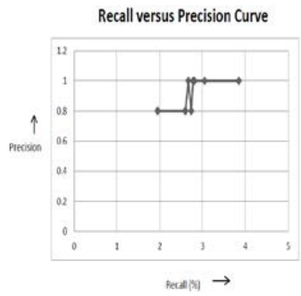

Fig 5(e)

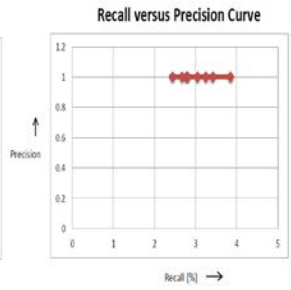

Fig 5(f)

Fig 5. Recall versus Precision Curve for CBIR system (a) without classifier and without relevance feedback for MIT 8 scene category data set (b) without classifier and without relevance feedback for Caltech data set (c) with SVM classifier and without relevance feedback for Caltech data set (d) with SVM classifier and relevance feedback for Caltech data set.(Trial 1/Trial 2) (e) with SVM classifier and without relevance feedback for MIT 8 scene category data set (f) with SVM classifier and relevance feedback for MIT 8 scene category data set (Trial 1/ Trial 2).

Figure 5 shows the Recall versus Precision curves. These curves are plotted with recall (here recall is expressed in percentage) on x- axis and precision on y- axis. Five images from each class are given as input to the CBIR system and average precision and average recall of each class are calculated and plotted to draw these curves. From figure 5(a) and 5(d), it is observed that the precision has increased to 1 irrespective of the recall values (similar to an ideal recall versus precision curve) for the 1st trial of relevance feedback itself and this precision is maintained in the successive trials. The same observations can be made from the bar graphs shown in figure 6.

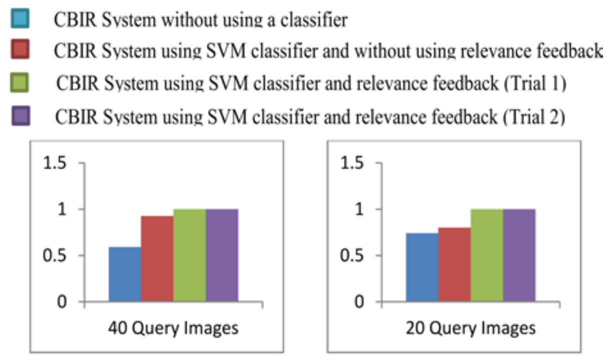

Fig 6(a) Fig 6(b)

Fig 6. Bar graph showing the average precision for all classes (a) MIT 8 scene category data set (b) Caltech data set

Figure 7 shows the query image and their corresponding retrieval results of a CBIR system before giving relevance feedback and after giving relevance feedback (for all the distance measures) for MIT 8 scene category data set when the classifier has correctly classified the query image. Figure 8 shows the query image and their corresponding retrieval results of a CBIR system before giving relevance feedback and after giving relevance feedback (for all the 3 distance measures) for Caltech data set when the classifier has incorrectly classified the query image.

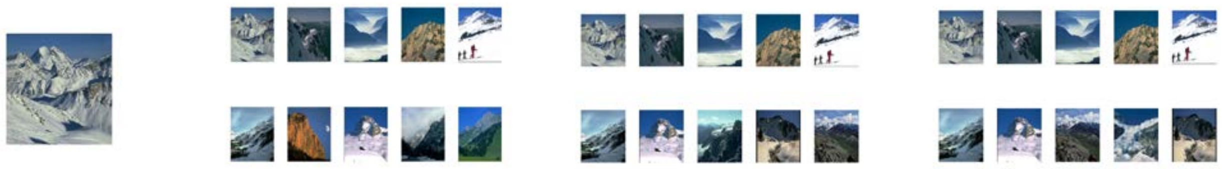

Fig 7(a) Fig 7(b) Fig 7(c) Fig 7(d)

Fig 7(e) Fig 7(f) Fig 7(g) Fig 7(h)

Fig 7. (a) Query Image from MIT 8 scene category data set (b) Retrieval Results before giving relevance feedback (c) Retrieval Results after giving relevance feedback using Euclidian distance measure (Trial 1) (d) Retrieval Results after giving relevance feedback using Euclidian distance measure (Trial 2) (e) Retrieval Results after giving relevance feedback using Mahalanobis distance measure (Trial 1) (f) Retrieval Results after giving relevance feedback using Mahalanobis distance measure (Trial 2) (g) Retrieval Results after giving relevance feedback using Tanimoto distance measure (Trial 1) (h) Retrieval Results after giving relevance feedback using Tanimoto distance measure (Trial 2)

Fig 8(a) Fig 8(b) Fig 8(c) Fig 8(d)

Fig 8(e) Fig 8(f) Fig 8(g) Fig 8(h)

Fig 8. (a) Query Image from Caltech data set (b) Retrieval Results before giving relevance feedback (c) Retrieval Results after giving relevance feedback using Euclidian distance measure (Trial 1) (d) Retrieval Results after giving relevance feedback using Euclidian distance measure (Trial 2) (e) Retrieval Results after giving relevance feedback using Mahalanobis distance measure (Trial 1) (f) Retrieval Results after giving relevance feedback using Mahalanobis distance measure (Trial 2) (g) Retrieval Results after giving relevance feedback using Tanimoto distance measure (Trial 1) (h) Retrieval Results after giving relevance feedback using Tanimoto distance measure (Trial 2)

X. CONCLUSION

By incorporating the proposed relevance feedback in the CBIR system, the search results have improved thereby, increasing the performance of the CBIR system. The average precision and average recall is high for CBIR system that use SVM classifier compared to that of CBIR system without a classifier. The average precision and recall has got the maximum value for CBIR system that incorporates both SVM classifier and relevance feedback. The precision is increased to 1 after giving relevance feedback even if the precision was 0 before giving the relevance feedback.

The Mean Opinion Score for CBIR system with Euclidian distance or Tanimoto distance based relevance feedback is slightly high compared to that of CBIR system with Mahalanobis distance based relevance feedback. From the Mean Opinion Score, it is observed that the CBIR system with the proposed relevance feedback gives excellent retrieval results when tested with MIT data set and gives good retrieval results when tested with Caltech data set. It can be concluded that relevance feedback using Euclidian distance is better than with the other 2 distance measures used in this paper because relevance feedback using Euclidian distance measure gives good retrieval results with reduced number of features in feature vector. Relevance feedback using Tanimoto distance measure also yields retrieval results as good as Euclidian distance but Tanimoto distance is highly sensitive to any type of transformations. So, the number of features in the feature vector can be reduced to a small extend only. By incorporating the memory log to the proposed CBIR system, the retrieval speed and performance of the CBIR can be increased.

Based on the MOS obtained, the retrieval results of Caltech data set is good but not excellent since the classes like Anims, Distras and Trans in Caltech data set contains diverse variety of images in the respective classes. Unlike the classes in MIT data set which is more specifically grouped. So, it is concluded that excellent retrieval results can be obtained when proper grouping of images into classes are done during the creation of a data set.

Here, in this paper the advantage of increased retrieval speed by the use of classifier is being utilized and also the problems encountered while giving relevance feedback to a CBIR that use a classifier is being solved efficiently with good retrieval results after the first trial of relevance feedback.

XI. FUTURE WORK

In this paper, SVM classifier was implemented using *SVM Torch* which works on ‘one versus the rest’ concept of classification. We can implement the same in *lib SVM* instead of *SVM Torch* which works on ‘one versus one’ concept of classification thereby, increasing the classification accuracy of SVM classifier.

CBIR systems can be incorporated in various systems to enhance the performance. One such application is the use of CBIR system with the proposed relevance feedback and memory log, along with expert systems in a specified domain of interest. An additional camera can be used to capture images and augment the knowledge base of the expert system thereby increase the precision and accuracy of their prediction. A camera can be incorporated in the CBIR system to capture the image. The image captured by the camera will be given as query image to the CBIR system which will in turn decide to which class the query image should be categorized and images similar to the query image is identified and displayed. Here, the camera acts as an eye and the CBIR system acts as a human brain which has the decision making ability. So, a system with artificial intelligence can be implemented.

For real world data sets (images), the classification accuracy of a classifier is never 100%. So, the CBIR system after implementation will be in a state similar to ‘childhood’ as in the case of human beings where the CBIR may sometimes fail to classify correctly. In that case, the proposed relevance feedback with memory log works to retrieve the desired accurate retrieval results. There should be a ‘learning period’ for this CBIR system.

During this period, different users’ must give their feedback (in this paper the feedback is given in form of score varying from 0 to 100) to the CBIR system. This will improve the performance and retrieval speed of the CBIR system making it a self- annotated system which can be used in almost every field like shops, textile industry, military applications, art gallery, image search engines etc. CBIR systems with the proposed relevance feedback and memory log can be used in military application to detect mines and bombs safely even without detonating them. Similar images of mines and bombs are retrieved from the data base and if the images are tagged in a way to retrieve the history and information along with the images then, user will get the complete information and guidance so as to how to handle the situation.

To reduce the ‘learning period’ and improve the performance of CBIR system, focus must be on feature selection and design of classifier which gives 100% classification accuracy for real world data sets. The algorithm of relevance feedback can be varied depending on the necessities arising in the application level.

REFERENCES

[1] Dr. Ananthi Sheshasaayee, Jasmine C, *Relevance Feedback Techniques Implemented in CBIR: Current Trends and Issues*, International Journal of Engineering Trends and Technology (IJETT), Volume 10 Number 4, pp.166-175, April 2014.

[2] B. S. Shajee Mohan and C.Chandra Sekhar, *Class-Specific Mahalanobis Distance Metric Learning for Biological Image Classification*, Springer lecture Notes in Computer Science - Image Analysis and Recognition, vol. 7325, pp.240-248, 2012.

[3] Kumar Vaibhav, Vikas Pratap Singh and C..Patvardhan, *Towards better retrievals in CBIR system using Tanimoto distance measure,* International Journal of Advances in Engineering & Technology, Vol. 7, Issue 2, pp.477-487, May, 2014.

[4] Ritendra Datta, Dhiraj Joshi, Jia Li, and James Z Wang, *Image Retrieval: Ideas, Influences, and Trends of the New Age* ACM Computing Surveys, Vol. 40, No. 2, Article 5, pp. 1-60, April 2008.

[5] Lior Shamir, Nikita Orlov, D Mark Ekley, Tomasz Macura, Josiah Ohnston, Ilya G Goldberg, Wndchrm- *An Open Source Utility for Biological Image Analysis*, Source *code for Biology and Medicine,* 3:13, 2008.

[6] *A Small User Guide for SVM Torch,* pp.1-5, August 9, 2000.

[7] Simon O. Haykin, *Neural Networks and Learning Machines*, pp.318-344, 1999.

[8] Quanquan, G. Zhenhui, L, Jiawei H., *Generalized Fisher Score for Feature Selection*. Proceedings of the International Conference on Uncertainty in Artificial Intelligence, pp.21-32, 2011.

[9] Nikita Orlov, Lior Shamir, Tomasz Macura, Josiah Johnston, D. Mark Eckley, Ilya G. Goldberg, *WNDCHRM: Multi-purpose image classification using compound image transform*s, Pattern Recognition Letters 29, pp.1684–1693, 2008.

[10] Xiang Sean Zhou, Thomas S. Huang, *Relevance feedback in image retrieval: A comprehensive review,* Xiang Sean Zhou, Thomas S. Huang, Multimedia Systems 8: pp.536–544, 2003.

[11] Simone Santini and Ramesh Jain, *Similarity measures*, IEEE Transactions on Pattern Analysis and Machine Intelligence, 21(9):pp.871-883, 1999.

[12] Lim J S, *Two-dimensional signal and image processing*, New Haven, Prentice Hall, pp.42-45, 1990.

[13] Gradshtein I, Ryzhik I, *Table of integrals, series and products* 5th edition, Academic Press, pp.45-55, 1994.

[14] Gabor D, *Theory of communication*, Journal of IEEE, 93:429-457, 1946.

[15] Tamura H, Mori S, Yamavaki T, *Textural features corresponding to visual perception*, IEEE Trans On Systems, Man and Cybernetics, 8:460-472, 1978.

[16] Prewitt J M, *Object enhancement and extraction,* In Picture Processing and Psychopictoris, Edited by: Lipkin B S, Rosenfeld A, New York: Academic, pp.75-149, 1970.

[17] Otsu N, *A threshold selection method from gray level histograms*, IEEE Trans Systems, Man and Cybernetics, 9: pp. 62-66, 1979.

[18] Teague M, *Image analysis via the general theory of moments*, Journal of the Optical Society of America, 70: pp.920-930, 1980.

[19] Haralick RM, Shanmugam K, Dinstein I, *Textural features for image classification*, IEEE Trans on Systems, Man, and Cybernetics, 6: pp.269-285, 1973.

[20] Orlov N, Johnston J, Macura T, Shamir L, Goldberg I, *Computer vision for microscopy applications*, In Vision Systems – Segmentation and Pattern Recognition Edited by: Obinata G, Dutta A. Vienna: ARS Press, pp.221-242, 2007.

[21] Seema H.Jadhav, Dr. Shah Aqueel Ahmed, *A Content Based Image Retrieval System using homogeneity Feature extraction from Recency-based Retrieved Image Library,* IOSR Journal of Computer Engineering (IOSRJCE), Volume 7, Issue 6, pp. 13-24, Nov-Dec 2012.

[22] Pushpa B. Patil, Manesh B. kokare, *Relevance Feedback in Content Based Image Retrieval: A Review*, Journal of Applied Computer Science & Mathematics, no.10 (5), pp.41-47, 2011.

[23] http://web.mit.edu/ir/cds/ -MIT office of the Provost International Research.

[24] http://www.vision.caltech.edu/Image_Datasets/Caltech101/ -Caltech 101.

[25] Ali Ghodsi, *Dimensionality Reduction A Short Tutorial*, pp.1-5, 2006.

[26] Siji K.K,Binitha Sara Mathew,Rakhi Chandran,Shajeemohan B.S,Shanthini K.S, *Feature Selection, Optimization and Performance Analysis of Classifiers for Biological Images*, Proceedings of IEEE National Conference on Communication, Signal Processing and Networking (NCCSN) at NSS Palakkad, pp. 1-5, October 2014.

[27] http://en.wikipedia.org/wiki/Content-based_image_retrieval.

[28] Neera Lal, Neetesh Gupta, Amit Sinhal, *A Review of Image Classification Techniques in Content Based Image Retrieval*, International Journal of Computer Science and

Information Technologies, Vol. 3 (5), pp.5182 – 5184, 2012.

[29] Richard O. Duda, Peter E. Hart, David G. Stork, *Pattern Classification* 2nd Edition, pp.3-25, 2000.