ISSN:2231-0711

Sarita Sharma et al | IJCSET |May 2013 | Vol 3, Issue 5, 194-199

Content Based Image Retrieval Based on Shape Feature using Accurate Legendre Moments and Support Vector Machines

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Abstract: **Legendre moments are continuous moments, hence, when applied to discrete-space images, numerical approximation is involved and error occurs. This paper proposes a method to compute the exact values of the moments by mathematically integrating the Legendre polynomials over the corresponding intervals of the image pixels. Experimental results show that the values obtained match those calculated theoretically, and the image reconstructed from these moments have lower error than that of the conventional methods for the same order. Although the same set of exact Legendre moments can be obtained indirectly from the set of geometric moments, the computation time taken is much longer than the proposed method.**

Content Based Image Retrieval is the application of computer techniques to solve the problem of searching for digital image in the large database. In Content Based Image Retrieval, images are retrieved based on color, texture and shape. The CBIR system uses these features for retrieval of images and the technique for getting these features is known as Feature Extraction. For image classification I have worked on the feature Shape.

Content Based Image Retrieval system using Accurate Legendre Moments (ALM) for gray scale images is proposed in my work. Further, the image classification efficiency is improved by employing Support Vector Machine (SVM) classifier.

*Keywords- **Content Based Image Retrieval, Legendre Moments, Accurate Legendre Moments, Gray images, Shape, Support Vector Machines.***

I. INTRODUCTION

The shape of an object is a binary image representing the extent of the object. Since the human perception and understanding of objects and visual forms relies heavily on their shape properties, shape features play a very important role in CBIR. Shape is one of the fundamental visual features in the Content-based Image Retrieval (CBIR) paradigm. Numerous shape descriptors have been proposed in the literature. These can be broadly categorized as region-based and contour-based descriptors. Contour based shape descriptors make use of only the boundary information, ignoring the shape interior content. Therefore, these descriptors cannot represent shapes for which the complete boundary information is not available. On the other hand, region-based descriptors exploit both boundary and internal pixels, and therefore are applicable to generic shapes. Among the region-based descriptors, moments have been very popular since they were first introduced in the 60's.

Moments of an image are region based shape descriptors. Accurate Legendre Moments (ALM) is a mathematical procedure to extract image shape features compactly and are continuous and orthogonal (based on exact data points), and computationally faster way to extract image shape features. They can be used to represent an image with minimum amount of information redundancy.

Support Vector Machines (SVMs) are supervised learning methods used for image classification. It views the given image database as two sets of vectors in an ' *n* ' dimensional space and constructs a separating hyper plane that maximizes the margin between the images relevant to query and the images not relevant to the query.

II. CONTENT BASED IMAGE RETRIEVAL (CBIR)

Content-Based Image Retrieval (CBIR), a technique which uses visual contents to search images from large scale image databases according to users' interests, has been an active and fast advancing research area since the 1990s. During the past decade, remarkable progress has been made in both theoretical research and system development.

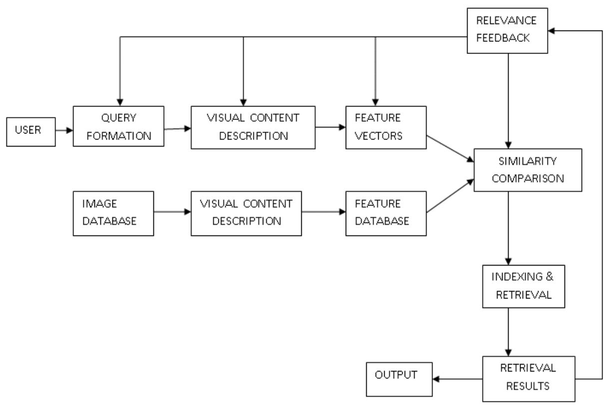

Fig 1. General diagram for content-based image retrieval system

III. SHAPE ANALYSIS

A. Introduction to Shape

The shape of an object is a binary image representing the extent of objects. Shape representations techniques used in similarity retrieval are generally characterized as being *region-based* and *boundary-based*. The former considers the shape being composed of a set of two-dimensional regions, while the latter presents the shape by its outline. Region-based feature vectors often result in shorter feature vectors and simpler matching algorithms. However, generally they fail to produce efficient similarity retrieval. On the other hand, feature vectors extracted from boundary-based representations provide a richer description of the shape. This scheme has led to the development of the *multi-resolution* shape presentations, which proved very useful in similarity assessment. The idea in multi-resolution techniques is to decompose a planar curve contour into components at different scales so that the coarsest scale components carry the global approximation information while the finer scale components contain the local detail information.

B. *Shape Attributes*

- **Area:** can be measured as the count of internal pixels.
- **Bounding rectangle :** is the minimum rectangle enclosing the object.
- **Aspect ratio:** is invariant to the scale of the object, since it is computed as the radio of the width and length of the rectangle.
- **Roundness (also called circularity)** is defined as:

  Roundness = $\frac{1}{Form\ Factor} = \frac{P^2}{4\pi a}$

  where P is the perimeter of a contour and A is the area of the enclosed region.
- **compactness:** is very similar to roundness defined above. It is defined as the ratio of the perimeter of a circle with an area equal to the area of the original object, i.e.

  Comp = $\frac{P_{circle}}{P} = \frac{2\sqrt{A\pi}}{P}$
- **Elongation:** is defined as the ratio between the squared perimeter and area.
- **Convexity:** a convex hull is the minimal cover able to encase the object. It can be thought as an elastic ribbon stretched around the contour of an object. Convexity can be thus be defined as the ratio of perimeters of the convex hull and the original contour.

  Conv= $\frac{P_{covexhull}}{P_{contour}}$

IV. MOMENTS IN IMAGE PROCESSING

There are two ways of viewing moments, one based on statistics and one based on arbitrary functions such as $f(x)$ or $f(x, y)$. As a result moments can be defined in more than one way.

A. *Statistical View*

Moments are the statistical expectation of certain power functions of a random variable. The most common moment is the mean which is just the expected value of a random variable: where f(x) is the probability density function of continuous random variable X. More generally, moments of order p = 0, 1, 2, … can be calculated as $m_p = E[X^p]$. These are sometimes referred to as the raw moments. There are other kinds of moments that are often useful. One of these is the central moments $\mu_p = E[(X–\mu)^p]$. The best known central moment is the second, which is known as the variance. Two less common statistical measures, skewness and kurtosis, are based on the third and fourth central moments. Moments are easily extended to two or more dimensions.

B . *Non-Statistical View*

This view is not based on probability and expected values, but most of the same ideas still hold. For any arbitrary function $f(x)$, one may compute moments as or for a 2-D function. To find the mean value of $f(x)$, one must use m_1/m_0, since $f(x)$ is not normalized. Likewise, for higher order moments it is common to normalize these moments by dividing by m_0 (or m_{00}). This allows one to compute moments which depend only on the shape and not the magnitude of $f(x)$. The result of normalizing moments gives measures which contain information about the shape or distribution (not probability dist.) of $f(x)$. This is what makes moments useful for the analysis of shapes in image processing, for which $f(x, y)$ is the image function. It may be a gray-level function or binary (0 for background, 1 for foreground). Most often moments are computed for connected components of binary images for the analysis of shape. In this situation and depending on the application, moments may be computed for several orders, not just orders 2 to 4 used in statistics. Also, since they are 2-D moments, quite a few will be needed. The moments computed are usually used as features for shape recognition. Such methods have been in use for at least 40 years.

C. *Orthogonal Moments*

Orthogonal functions have been around for a very long time. The best known are the sine and cosine. Two functions or vectors are orthogonal if their inner product (defined as the sum of the product of their corresponding elements) is zero. An important class of orthogonal functions is orthogonal polynomials, which are orthogonal over various intervals of the real axis. Important orthogonal polynomials include Legendre, Hermite, Chebyshev, etc. Legendre polynomials, which are orthogonal over [-1, 1], can be taken as a product $P(x).P(y)$, and the result is an orthogonal set of polynomials over a square. Orthogonal moments are computed similar to regular moments, except that the set of orthogonal polynomials replaces the x^p or x^py^q monomial. That is, where $h_{pq}(x, y)$ is the pq-th orthogonal polynomial, and R is the region over which the polynomials are defined.

D. *Accurate Legendre Moments*

Image moments and their functions have been utilized as features in many image processing applications, viz., pattern recognition, image classification, target identification, and shape analysis. Moments of an image are treated as region-based shape descriptors. Legendre Moments (LM) are continuous and orthogonal moments, they can be used to represent an image with minimum amount of information redundancy. Many algorithms are developed for the computation of LM , but these methods focus mainly on 2D geometric moments. When they are applied to a digital image, a numerical approximation is necessary. Error due to approximation increases as the order of the moment increases. An accurate method for computing the Accurate Legendre Moments (ALM) proposed by Hosney is as follows. Legendre moments of order $g = (p + q)$ for an image with intensity function (x, y) are defined as :

$$L_{pq} = \frac{(2p+1)(2q+1)}{4}\int_{-1}^{1}\int_{-1}^{1} Pp(x)Pq(y)\ f(x,y)\,dxdy \quad (1)$$

where, $P_p(x)$ is the p^{th} order Legendre polynomial defined as

$$P_p(x) = \sum_{k=0}^{p} a_{k,p}\, x^k = \frac{1}{2^p\, p!}\left(\frac{d}{dx}\right)^p [(x^2-1)]^p \quad (2)$$

where, x Є [-1,1] and $P_p(x)$ obeys the following recursive relation

$$P_{p+1}(x) = \frac{(2p+1)}{(p+1)}\, x\, P_p(x) - \frac{(p)}{(p+1)}\, P_{p-1}(x) \quad (3)$$

with $P_0(x) = 1$, $P_1(x) = x$ and p > 1

The set of Legendre polynomials { $P_p(x)$ } forms a complete orthogonal basis set on the interval [-1, 1]. A digital image of size *N* x *N* is an array of pixels. Centers of these pixels are the points (x_i, y_j). In order to improve accuracy, it is proposed to use the following approximated form :

$$L_{pq} = \frac{(2p+1)(2q+1)}{4}\sum_{i=1}^{N}\sum_{j=1}^{N} h_{pq}\,(x_i, y_j)\ f(x,y) \quad (4)$$

where $x_i = -1 + (i - \frac{1}{2})\,\Delta x$ and $y_j = -1 + (j - \frac{1}{2})\,\Delta y$ with *i*, *j* = 1,2,3...*N*

$$h_{pq}(x_i, y_j) = \int_{x_i - \frac{\Delta xi}{2}}^{x_i + \frac{\Delta xi}{2}}\int_{y_i - \frac{\Delta yi}{2}}^{y_i + \frac{\Delta yi}{2}} P_p(x)P_q(y)\,dxdy \quad (5)$$

This double integration is required to be evaluated exactly to remove the approximation error in computation of Legendre moments. A special polynomial is given as follows:

$$\int P_p(x)\,dx = \frac{P_{p+1}(x) - P_{p-1}(x)}{2p+1} \quad (6)$$

where, p≥ 1, The set of Legendre moments can thus be computed exactly by:

$$\hat{L}_{pq} = \sum_{i=1}^{N}\sum_{j=1}^{N} I_p(x_i) I_q(y_j) f(x,y) \quad (7)$$

$$I_p(x_i) = \left\{\frac{(2p+1)}{(2p+2)}\right\}[x P_{p(x)} - P_{p-1}(x)]_{u_i}^{u_{i+1}} \quad (8)$$

$$I_q(y_j) = \left\{\frac{(2q+1)}{(2q+2)}\right\}[y P_{q(y)} - P_{q-1}(y)]_{v_i}^{v_{i+1}} \quad (9)$$

where,

$u_{i+1} = x_i + \frac{\Delta x_i}{2} = -1 + i\Delta x$

$u_i = x_i - \frac{\Delta x_i}{2} = -1 + (i-1)\,\Delta x$

similarly,

$v_{i+1} = y_j + \frac{\Delta y_{j_i}}{2} = -1 + j\Delta y$

$v_i = y_j - \frac{\Delta y_j}{2} = =-1 + (j-1)\,\Delta y$

Equation (7) is valid only for p≥1, q≥1. Further, moment kernels can be generated using (8) and (9). Computation of Accurate Legendre Moment (ALM) using (7) is time consuming. Hence, ALM can be obtained in two steps by successive computation of 1D *qth* order moments for each row as follows. By rewriting (7) in separable form

$$\hat{L}_{pq} = \sum_{i=1}^{N} I_p(x_i)\quad Y_{iq} \quad (10)$$

where ,

$$Y_{iq} = \sum_{i=1}^{N} I_q(y_j)\ f(x_i, y_j) \quad (11)$$

where, Y_{iq} is the q^{th} order moment of i^{th} row

Since, $I_0(x_i) = 1/N$. Substituting this in (10) results the following

$$\hat{L}_{oq} = \frac{1}{N}\sum_{i=1}^{N} Y_{iq} \quad (12)$$

The number of ALM of order *g* is given by

$$N_{total} = \frac{(g+1)(g+2)}{2}$$

These ALM features are used for CBIR.

E. Support Vector Machines

Support Vector Machines (SVMs) are supervised learning methods used for image classification. It views the given image database as two sets of vectors in an ‘ *n* ’ dimensional space and constructs a separating hyper plane that maximizes the margin between the images relevant to query and the images not relevant to the query.

There are many pattern matching and machine learning tools and techniques for clustering and classification of linearly separable and non separable data. Support vector machine (SVM) is a relatively new classifier and it is based on strong foundations from the broad area of statistical learning theory .

It is being used in many application areas such as character recognition, image classification, bioinformatics, face detection, financial time series prediction etc. SVM offers many advantages over other classification methods such as neural networks. Support vector machines have many advantages in comparison with other classifiers:

- They are computationally very efficient as compared with other classifiers, especially neural networks.
- They work well, even with high dimensional data and with less number of training data.
- They attempt to minimize test error rather than training error.
- They are very robust against noisy data.
- The curse of dimensionality and over fitting problems does not occur during classification.

Fundamentally, SVM is a binary classifier, but can be extended for multi-class problems as well. The task of binary classification can be represented as having, (x_i, y_i) pairs of data where x_i Э x_p, a p dimensional input space and y_i Э $[-1, 1]$ for both the output classes. SVM finds the linear classification function *g*(*x*) = w. x + b, which corresponds to a separating hyperplane w. x + b = 0, where w and *b* are slope and intersection.

SVM usually incorporates kernel functions for mapping of non-linearly separable input space to a higher dimension linearly separable space. Many kernel functions exist such as radial bases functions (RBF), Gaussian, linear, sigmoid etc.

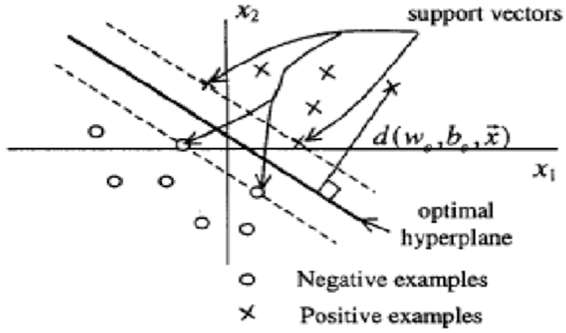

Fig 2. Hyperplane through two linearly separable classes

The basic principle of SVMs is a maximum margin classifier. Using the kernel methods, the data can be first implicitly mapped to a high dimensional kernel space. The maximum margin classifier is determined in the kernel space and the corresponding decision function in the original space can be non-linear. The non-linear data in the feature space is classified into linear data in kernel space by the SVMs.

The aim of SVM classification method is to find an optimal hyper plane separating relevant and irrelevant vectors by maximizing the size of the margin (between both classes). Image classification or categorization is a machine learning approach and can be treated as a step for speeding-up image retrieval in large databases and to improve retrieval accuracy.

Similarly, in the absence of labelled data, unsupervised clustering is also found useful for increasing the retrieval speed as well as to improve retrieval accuracy. Image clustering inherently depends on a similarity measure, while image classification has been performed by different methods that neither require nor make use of similarity measures.

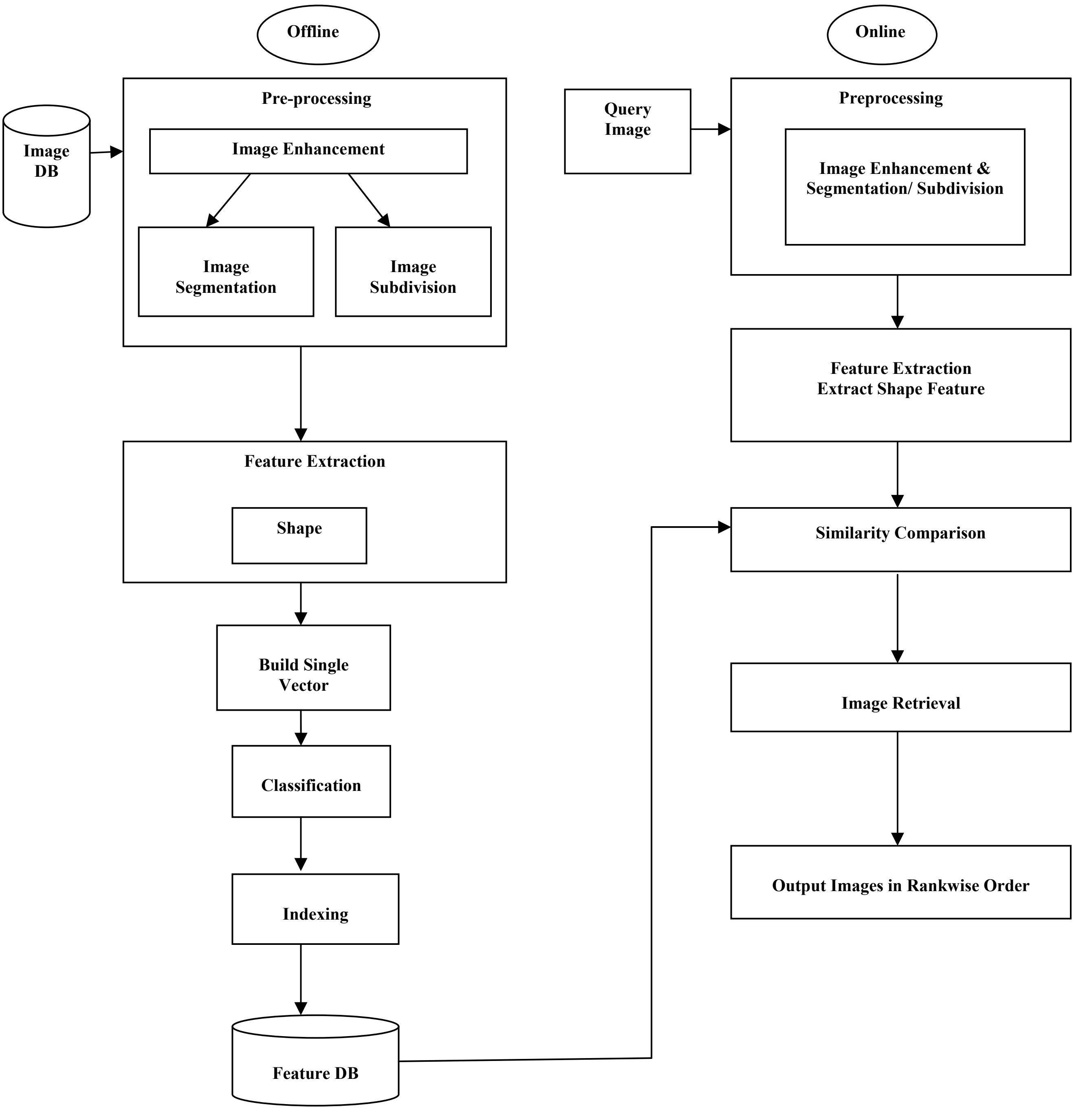

Fig 3. Proposed Architecture of CBIR System

V. PROBLEM IDENTIFICATION

Shape representation compared to other features, like texture and colour, is much more effective in semantically characterising the content of an image. However, the challenging task of shape descriptors is the accurate extraction and representation of shape information. The construction of shape descriptors is even more complicated when invariance, with respect to a number of possible transformations, such as scaling, shifting and rotation, is required. The overall performance of shape descriptors can be divided into qualitative and quantitative performances. The qualitative characteristics involve their retrieval performance based on the captured shape details for representation. Their quantitative performance includes the amount of data needed to be indexed in terms of number of descriptors, in order to meet certain qualitative standards as well as their retrieval computational cost. Various shape descriptors exist in the literature, mainly categorised into two groups: contour-based shape descriptors and region-based shape descriptors.

Contour-based methods need extraction of boundary information which in some cases may not available. Region-based methods, however, do not rely on shape boundary information, but they take into account all the pixels within the shape region. Therefore for generic purposes, both types of shape representations are necessary. Content Based Image Retrieval (CBIR) systems based on shape using invariant image moments, viz., Moment Invariants (MI) and Zernike Moments (ZM) are available in the literature. MI and ZM are good at representing the shape features of an image. However, non-orthogonality of MI and poor reconstruction of ZM restrict their application in CBIR. Therefore, an efficient and orthogonal moment based CBIR system is needed. Legendre Moments (LM) are orthogonal, therefore, an efficient and orthogonal moment based CBIR system is needed. Legendre Moments (LM) are orthogonal, computationally faster, and can represent image shape compactly.

CBIR system using Accurate Legendre Moments (ALM) for gray scale images is proposed in this work. Superiority of the proposed CBIR system is observed in terms of retrieval efficiency and retrieval time. Further, the classification efficiency is improved by employing Support Vector Machine (SVM) employed as classifier.

VI . PROPOSED METHODOLOGY

Faster and accurate CBIR algorithms are required for real time applications. This can be achieved by employing a classifier such as Support Vector Machine (SVM). The basic procedure involved in the proposed CBIR system is as follows:

- Create the feature vector for the images in the image data set.
- Accurate Legendre Moments (ALM) computation for the given image to form the feature vector.
- Calculation of distance measure between the feature vectors of query image and data base image.
- Retrieval of similar images based on minimum distance.
- Use SVM classifier to classify the images in the database.
- Increase the number of training samples to improve the classification efficiency**.**

The steps of proposed CBIR algorithm are as follows:

- Accurate Legendre moments for the database images are computed by using equations (10) - (12) to form the feature database.
- Feature database is created by feature vector $f_{database} = (f_1, f_2, \ldots, f_M)$ for the image database consisting of M images. Each feature vector f_i, for $i = 1,2 \ldots M$, is a set of ALM of order $(p + q) = g$

$$\mathbf{f_i = \{L_{00} L_{01} \ldots L_{pq}\}_{database}} \quad \mathbf{(13)}$$

- A feature vector comprising of ALM of order $(p + q) = g$ for the query image is formulated.

$$\mathbf{f_q = \{L_{00} L_{01} \ldots L_{pq}\}_{query}} \quad \mathbf{(14)}$$

- Distance measure between the feature vector f_q of the query image and each feature vector of the database images f_i is calculated by using Canberra distance d_{qi}^c

$$\boldsymbol{d_{qi}^c} = \sum_{i=1}^{M} \frac{|f_q - f_i|}{|f_q| + |f_i|} \quad \mathbf{(15)}$$

where, g is the order of moments.

- Retrieve all the relevant images to the query image based on minimum distance d_{qi}^c .
- Train the SVM by selecting proper samples of the database from each class. All the classes of the image database are labeled.
- Pass the class labels with their features to the SVM classifier with the chosen kernel. The Gaussian Radial Basis Function kernel is considered as defined in equation [5].
- Classify all the images from the database by considering each image in the database as the query image.

A query image may be any one of the database images. This query image is then processed to compute the feature vector as in equation (14). The distance d_{qi}^c is computed between the query image (‘q’) and image from database (‘i’). The distances are then sorted in increasing order and the closest sets of images are then retrieved. The top “ N ” retrieved images are used for computing the performance of the proposed algorithm. The retrieval efficiency is measured by counting the number of matches.

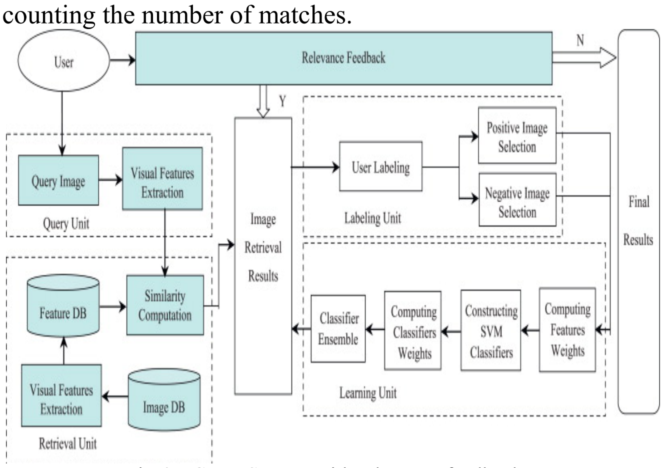

Fig 4. CBIR System with relevance feedback

VII. PROPOSED OUTCOME

Retrieval performance of the proposed CBIR system would be tested by conducting experiments on Corel shape database, COIL-20. It consists of 20 classes of images with each class consisting of 72 different orientations resulting in a total of 1440 images. All these gray scale images in the database are of the size 128×128. All images of all the 20 classes would be used for experimentation. Experiments would be conducted using MATLAB 7.6.0 with Pentium-IV, 3.00 GHz computer.

As SVM is a kernel method, the kernel function used in SVM is very crucial in determining the performance. A kernel function needs to be chosen with appropriate parameters. The kernel is tuned with a pre-defined ideal kernel matrix. As a kernel method, SVMs can efficiently handle nonlinear patterns. However, the choice of kernel and tuning of appropriate parameters, adapting SVMs for specific requirements of CBIR such as learning with small sample is a challenging problem.

Improved image classification efficiency is desired to be obtained by employing SVM classifier. The image classification efficiency of the proposed CBIR system should increase with the increase in the number of training samples.

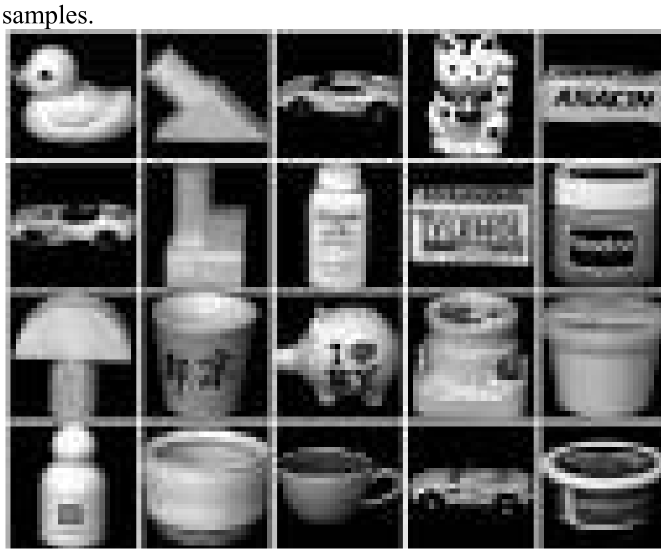

Fig 5. COIL-20 Database

Classifier	Features Extraction method	Annotation Rate	Error Rate
Support Vector Machines	Moment Invariant	61.53%	38.47%
	Fourier Descriptor	68.42%	32.57%
	Zernike Moment	69.70%	30.30%
	Accurate Legendre Moment	79.91%	20.09%

Table 1. Various Feature Extraction Methods with varying Annotation Rate and Error Rate

VIII. CONCLUSION AND SCOPE FOR FUTURE WORK

A CBIR system using Accurate Legendre Moments (ALM) is proposed in this work. Performance of the proposed CBIR system is expected to be superior when practiced on COIL- 20 database in terms of average retrieval efficiency and average retrieval time. Further, improved classification efficiency would also be obtained by employing SVM classifier. It is assumed that the average retrieval efficiency increases as the moment order increases. It is also assumed that the classification efficiency of the proposed CBIR system increases with the increase in the number of training samples.

In future for image classification we can emphasize on the analysis and usage of different advanced classification techniques like Artificial Neural Networks, Support Vector Machines, Fuzzy Measures, Genetic algorithms and their combinations for digital image classification .

In digital image classification the conventional statistical approaches for image classification use only the gray values. Different advanced techniques in image classification like Artificial Neural Networks (ANN), Support Vector Machines (SVM), Fuzzy measures, Genetic Algorithms (GA), and Genetic Algorithms with Neural Networks can be developed for image classification for better and efficient retrieval results.

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