Retrieval Of Digital Images Based On Shape Feature Using Support Vector Machines And Self Organizing Maps

Sarita Sharma, Avinash Dhole

Abstract— **Legendre moments are continuous moments, hence, once applied to discrete-space images, numerical approximation is concerned and error happens. This paper proposes a technique to work out the precise values of the moments by mathematically desegregating the Legendre polynomials over the corresponding intervals of the image pixels. Experimental results show that the values obtained match those calculated in theory, and therefore the image reconstructed from these moments have lower error than that of the standard ways for constant order. Though constant set of tangible Legendre moments are often obtained indirectly from the set of geometric moments.**
Content Based Image Retrieval is the application of computer techniques to resolve the matter of checking out digital image within the giant information. In Content Based Image Retrieval, images are retrieved based on color, texture and shape. The CBIR system uses these options for retrieval of images and therefore the technique for obtaining these options is understood as Feature Extraction. For image classification I actually have worked on the feature Shape. Content Based mostly Image Retrieval system exploiting Accurate Legendre Moments (ALM) for grey scale images and color images is projected in my work. Further, the image classification potency is improved by using Support Vector Machine (SVM) and Self organizing Maps (SOM) classifiers.

Index Terms— **Content Based Image Retrieval, Legendre Moments, Accurate Legendre Moments ,Active Contour Without Edges, Shape, Support Vector Machines ,Self Organising Feature Maps.**

I. INTRODUCTION

Shape is one amongst the elemental visual features within the Content-based Image Retrieval (CBIR) paradigm. In designing a shape-based retrieval system needs the shape descriptors that's accustomed to have the subsequent four necessary characteristics:
Discrimination: Features ought to have considerably completely different values for objects belonging to completely different classes.
Reliability: Features ought to have similar values for all objects belonging to a similar class.
Independence: If multiple shape descriptors are getting used, then one ought to make sure that they're unrelated.
Small in Number: Limit the quantity of options that's being used. Adding excess features degrade the performance of the retrieval system.

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Invariance: The features ought to have invariance properties such as scaling, rotation and translation.

Numerous shape descriptors have been projected within the literature. These will be broadly classified as region-based and contour-based descriptors. Contour based mostly shape descriptors make use of solely the boundary info, ignoring the shape interior content. Therefore, these descriptors cannot represent shapes that the whole boundary information isn't accessible. On the opposite hand, region-based descriptors exploit each boundary and internal pixels, and so are applicable to generic shapes. Among the region-based descriptors, moments are extremely popular since they were 1st introduced within the 60's.Moments of an image are region based shape descriptors.

Accurate Legendre Moments (ALM) may be a mathematical procedure to extract image shape features compactly and are continuous and orthogonal (based on actual data points), and computationally quicker way to extract image shape features. They can be used to represent an image with minimum quantity of information redundancy.

Support Vector Machines (SVMs) are supervised learning strategies used for image classification. It views the given image database as 2 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.

One notably attention-grabbing category of unsupervised system is based on competitive learning, during which the output neurons compete amongst themselves to be activated, with the result that just one is activated at anyone time. This activated neuron is named a winner-takesall neuron or just the winning neuron. Such competition will be induced/implemented by having lateral inhibition connections (negative feedback paths) between the neurons. The result's that the neurons are forced to organize themselves. For obvious reasons, such a network is termed a **Self Organizing Map (SOM)**.

Measurement of image similarity is very important for variety of image processing applications. Image similarity assessment is closely associated with image quality assessment therein quality is predicated on the apparent variations between a degraded image and also the original, unmodified image. Automatic analysis of image compression systems depends on correct quality measurement. Current algorithms for measuring similarity embrace Mean Square

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Error (MSE), Peak Signal-to-Noise Ratio (PSNR) and Entropy (E).

Mean Square Error (MSE): It measures the amount of change per pixel due to the processing on image. It is the cumulative squared error between the compressed and the original image.

Peak Signal to Noise Ratio (PSNR): The ratio between the maximum potential power to the ability of corrupting noise is recognize as Peak Signal to Noise ratio. It affects the fidelity of its illustration .It may be also aforesaid that it's the logarithmic function of peak value of image and mean square error.

Entropy: Entropy could be a statistical measure of randomness which will be used to characterize the texture of the input image. The entropy of an image is that the measure of information content. It's the average number of bits needed to quantize the intensities within the image.

II. CONTENT BASED IMAGE RETRIEVAL (CBIR)

Content-Based Image Retrieval (CBIR), a method that uses visual contents to search images from giant scale image databases in keeping with users' interests, has been an active and quick advancing research space since the Nineteen Nineties. Throughout the past decade, exceptional progress has been created in each theoretical analysis and system development.

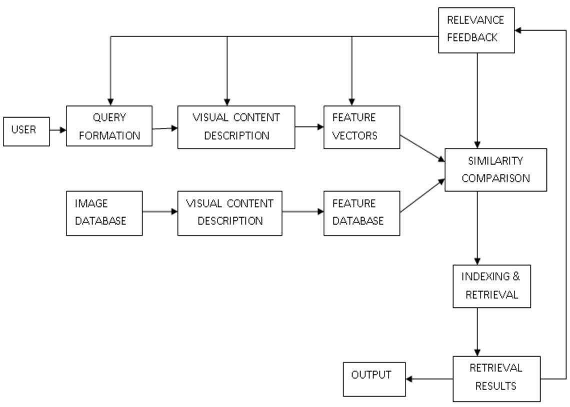

Fig 1. General diagram for content-based image retrieval system

To measure the performance of any retrieval system, precision and recall are still the foremost outstanding techniques to use.

$$\text{Precision} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of images retrieved}}$$

$$\text{Recall} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of relevant images in the database}}$$

PR graphs might not contain all the required info associated with the performance of a CBIR system. many different measures are employed in the current literature, viz., retrieval efficiency, retrieval time, and Error rate. Each of these performance measures is outlined as follows.

$$\text{Retrieval efficiency} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of images retrieved}} * 100\%$$

Retrieval time is outlined as the average time needed by CBIR system to retrieve images from the database relevant to query image by considering every image within the database as query image.

$$\text{Error rate} = \frac{\text{Number of non-relevant images retrieved}}{\text{Total number of images retrieved}}$$

Content primarily based Image Retrieval (CBIR) could be a outstanding area in image processing owing to its numerous applications in net, multimedia, medical image archives, and crime hindrance. Improved demand for image databases has redoubled the necessity to store and retrieve digital images. Extraction of visual features, viz., color, texture, and shape is a vital part of CBIR. Out of those, shape is one amongst the primary visual features in CBIR. Shape descriptors comprise 2 classes i.e., contour-based and region-based.

Contour-based shape descriptors like Fourier descriptors, curvature scale space and shape signatures exploit solely boundary info, they can not capture shape interior content. Besides, these strategies cannot handle disjoint shapes wherever boundary might not be available, therefore, they need restricted applications. In region based techniques, all the pixels within a shape region are taken under consideration to get the shape illustration. Region-based shape descriptors are often applied to more general shapes. However, contour-based shape descriptors have limitations of extracting complicated shapes. Hence, region based mostly shape descriptor viz., Legendre Moments (LM) is most well-liked to represent the shape content of an image. An efficient shape descriptor ought to be affine invariant, robust, compact, simple to derive, and match. The usefulness of image moment, viz., LM as image shape features is explored for CBIR during this work.

III. ACCURATE LEGENDRE MOMENTS

Image moments and their functions are used as features in several 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 will be accustomed represent an image with minimum amount of information redundancy. Several algorithms are developed for the computation of LM , however these strategies focus chiefly on 2D geometric moments. When they are applied to a digital image, a numerical approximation is critical. Error owing to approximation will increase because the order of the moment will increase. An accurate technique for computing the Accurate Legendre Moments (ALM) projected by Hosney is as follows. Legendre moments of order $g = (p + q)$ for an image with intensity function (x, y) are outlined as :

$$L_{pq} = \frac{(2p+1)(2q+1)}{4} \int_{-1}^{1}\int_{-1}^{1} P_p(x) P_q(y) \; f(x, y)\, dx dy \qquad (1)$$

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

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

where, x Є [-1,1] and $P_p(x)$ obeys the subsequent 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 an entire 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). So as to boost accuracy it's planned to use the subsequent 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 $i, j = 1,2,3...N$

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

This double integration is needed to be evaluated specifically to get rid of 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, $p \geq 1$, The set of Legendre moments will so be computed specifically by:

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

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

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

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,

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

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

Equation (7) is valid only for $p \geq 1$, $q \geq 1$. Further, moment kernels may be generated using (8) and (9). Computation of Accurate Legendre Moment (ALM) using (7) is time overwhelming. Hence, ALM may be obtained in 2 steps by following computation of 1D *qth* order moments for each row as follows. By rewriting (7) in separable form

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

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.

IV. Support Vector Machines

Support Vector Machines (SVMs) are supervised learning strategies used for image classification. It views the given image info as 2 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 several pattern matching and machine learning tools and techniques for cluster and classification of linearly separable and non separable data. Support vector machine (SVM) is a comparatively new classifier and it's based on robust foundations from the broad area of statistical learning theory.

It is being employed in several application areas like character recognition, image classification, bioinformatics, face detection, financial time series prediction etc. SVM offers several benefits over alternative classification strategies like neural networks. Support vector machines have several benefits as compared with alternative classifiers:

- They're computationally very efficient as compared with different classifiers, particularly neural networks.
- They work well, even with high dimensional data and with less range of training data.
- They attempt to minimize test error instead of training error.
- They're very strong against noisy data.
- The curse of dimensionality and over fitting issues will not occur throughout classification.

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

SVM typically incorporates kernel functions for mapping of non-linearly separable input space to a higher dimension linearly separable area. several kernel functions exist like radial bases functions (RBF), Gaussian, linear, sigmoid etc. The basic principle of SVMs may be a maximum margin classifier.

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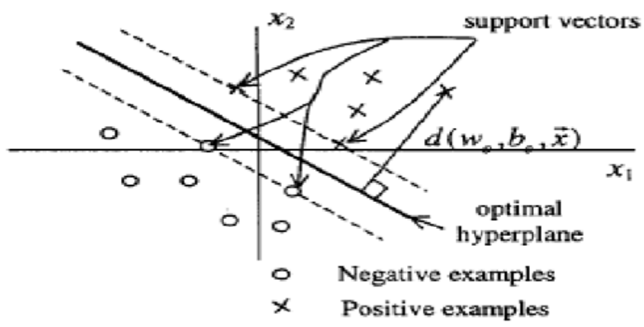

Fig 2. Hyperplane through two linearly separable classes

Using the kernel methods, the data is 1st implicitly mapped to a high dimensional kernel space. the maximum margin classifier is set within the kernel space and also the corresponding decision function within the original space is non-linear. The non-linear data within the feature space is classed into linear data in kernel space by the SVMs.

The aim of SVM classification technique is to search out an optimum hyper-plane separating relevant and irrelevant vectors by maximising the dimensions of the margin (between both classes). Image classification or categorization is a machine learning approach and might be treated as a step for speeding-up image retrieval in giant databases and to boost retrieval accuracy. Similarly, within the absence of labeled data, unsupervised cluster is additionally found helpful for increasing the retrieval speed as well as to improve retrieval accuracy. Image clustering inherently depends on a similarity measure, whereas image classification has been performed by completely different ways that neither need nor create use of similarity measures.

In our experiment, we tend to used svmsmoset function . The practicality of the svmsmoset function is incorporated into the svmtrain and statset functions. svmsmoset has the subsequent properties:

MaxIter: Maximum number of iterations of main loop. If this number is exceeded before the algorithm converges then the algorithm stops and offers an error. Default value is 15000.
Display: Controls the extent of information about the optimization iterations that's displayed because the algorithm runs. The value is 'off', that displays nothing, 'iter', that reports every 500 iterations.
Final: It that reports when the algorithm finishes to run. Default value is 'off'.
KernelCacheLimit: This range specifies the size of the kernel matrix cache. The algorithm keeps a matrix with up to KernelCacheLimit * KernelCacheLimit double numbers in memory. Default value is 5000.

V. SELF ORGANIZING MAPS

The Self-Organizing Map was developed by Kohonen within the early Nineteen Eighties. Based on the synthetic neural networks, the weights of the neurons in the SOM are adjusted to suit the varied input categories of patterns within the training data. In follow, the SOM can construct a topology map, conserving mapping from the high dimensional space onto map units with one or two dimensions. It's a great tool for visualizing high dimensional data in one or two dimensional space.
Moreover, the topology map are often simply adjusted to fit the particular patterns consistent with several external parameters of the SOM. The various components of Self Organization process involves four major components:

Initialization: All the connection weights are initialized with small random values.

Competition: For each input pattern, the neurons compute their respective values of a discriminant function which provides the basis for competition. The particular neuron with the smallest value of the discriminant function is declared the winner.

Cooperation: The winning neuron determines the spatial location of a topological neighbourhood of excited neurons, thereby providing the basis for cooperation among neighbouring neurons.

Adaptation: The excited neurons decrease their individual values of the discriminant function in relation to the input pattern through suitable adjustment of the associated connection weights, such that the response of the winning neuron to the subsequent application of a similar input pattern is enhanced.

In our experiments, we tend to use initsompc function to initialize SOM weights with principal components ; initsompc initializes the weights of an N-dimensional self-organizing map so that the initial weights are distributed across the space spanned by the most significant N principal components of the inputs. Distributing the weight significantly speeds up SOM learning, as the map starts out with a reasonable ordering of the input space.

VI. ACTIVE CONTOURS WITHOUT EDGES

Active contours accustomed find objects in a given image u0 exploiting techniques of curve evolution. The fundamental plan is beginning with an initial curve C, to deform the curve to the boundary of the object, under some constraints from the image u0. The classical approaches use the gradient of the image u0 to find the edges.

The active contour model supported Mumford–Shah segmentation techniques and therefore the level set technique is taken for consideration. Active contours without edges model isn't based on an edge-function to prevent the evolving curve on the specified boundary. Also, we have a tendency to don't need to smooth the initial image, though it's very noisy and during this approach, the locations of boundaries are very well detected and preserved. By our model, we are able to discover objects whose boundaries don't seem to be essentially defined by gradient or with very smooth boundaries, that the classical active contour models don't seem to be applicable.

Finally, we will automatically observe interior contours beginning with just one initial curve. The position of the initial curve will be anywhere within the image, and it doesn't essentially surround the objects to be detected. we have a tendency to valid our model by numerous numerical results

VII. PROBLEM IDENTIFICATION

Shape illustration compared to different features, like texture and color, is far more effective in semantically characterizing the content of an image. However, the difficult task of shape descriptors is that the accurate extraction and illustration of shape information. The development of shape descriptors is even more sophisticated once invariance, with reference to variety of possible transformations, like scaling, shifting and rotation, is needed. The performance of shape descriptors is divided into qualitative and quantitative performances. The qualitative characteristics involve their retrieval performance based on the captured shape details for illustration. Their quantitative performance includes the amount of data required to be indexed in terms of number of descriptors, so as to fulfill certain qualitative standards also as their retrieval computational cost. Numerous shape descriptors exist within the literature, primarily categorized into 2 groups: contour-based shape descriptors and region-based shape descriptors.

Contour-based methods want extraction of boundary information that in some cases might not available. Region-based methods, however, don't rely on shape boundary info, however they take into consideration all the pixels within the shape region. So for generic functions, each types of shape representations are necessary. Content based Image Retrieval (CBIR) systems based on shape exploits invariant image moments, viz., Moment Invariants (MI) and Zernike Moments (ZM) are available within the literature. MI and ZM are smart at representing the shape features of an image. However, non-orthogonality of MI and poor reconstruction of ZM limit their application in CBIR. Therefore, an efficient and orthogonal moment based CBIR system is required. Legendre Moments (LM) are orthogonal, therefore, an efficient and orthogonal moment based CBIR system is required. Legendre Moments (LM) are orthogonal, computationally quicker, and may represent image shape compactly.

CBIR system using Accurate Legendre Moments (ALM) for grey scale images and color images is projected during this work. Superiority of the projected CBIR system is ascertained in terms of average retrieval efficiency and average retrieval time. Further, the classification efficiency is improved by employing Support Vector Machine (SVM) and Self-Organizing Map (SOM) as classifiers.

VIII. PROPOSED METHODOLOGY

Faster and accurate CBIR algorithms are needed for real time applications. This could be achieved by using classifiers like Support Vector Machine (SVM) and Self Organizing Maps (SOM). The fundamental procedure concerned within the projected CBIR system is as follows:

- Input the image from the image data set.
- Applying median filter to denoise the image.
- Setting the parameters for calculating Accurate Legendre Moments (ALM) considering Active Contours Without Edges algorithm for the input image to calculate shape attributes such as Curvature, Contour Lines, Level Set ,Area.
- Use svmsmoset function and initsomp function to classify the images in the database and obtain the Receiver Operating Characteristic Curve plot for the input image under consideration.
- Calculate average retrieval time and average retrieval efficiency.
- Calculate various error metrics values for the image such as Mean Square Error, Peak Signal to Noise Ratio, Entropy in order to find similar images from the image dataset.
- Increase the number of training samples to improve the classification efficiency**.**

Accurate Legendre moments for the database images are computed by via equations (10) - (12) to form the feature database.
A query image could also be anyone of the database images. This query image is then processed to compute the feature vector .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.

IX. EXPERIMENTAL RESULTS

Retrieval performance of the proposed CBIR system is tested by conducting experiments on Corel shape database, COIL-20 and Georgia Tech Face database, GT face database(128 MB). COIL-20 consists of twenty classes of images with every class consisting of seventy two completely different orientations leading to a total of 1440 pictures. All these grey scale images within the database are of the dimensions 128×128. But for homogeneity we will set the dimension 255x255. 23 images of the COIL-20 are used for experimentation. Georgia tech face database (128MB) contains images of fifty individuals taken in 2 or 3 sessions between 06/01/99 and 11/5/99 at the middle for Signal and Image processing at Georgia Institute of Technology.

All people in the GT Face database are represented by 15 color JPEG images with cluttered background taken at resolution 640x480 pixels. The average size of the faces in these images is 150x150 pixels. The pictures show frontal and/or tilted faces with different facial expressions, lighting conditions and scale. Each image is manually labeled to determine the position of the face in the image. But for homogeneity we will set the dimension 255x255. 27 images of the GT Face database are used for experimentation. Experiments would be conducted using MATLAB 7.12.0 with INTEL C-I3, 2.40 GHz computer.

As SVM is a kernel technique, the kernel function utilized in SVM is incredibly crucial in deciding the performance. A kernel function has to be chosen with appropriate parameters. The kernel is tuned with a pre-defined ideal kernel matrix. As a kernel methodology, SVMs will efficiently handle nonlinear patterns. However, the selection of kernel and standardization of appropriate parameters, adapting SVMs

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for specific needs of CBIR like learning with small sample is a difficult problem.

	Image	Curvature	Contour Lines	Level Set	Area	Average Retrieval Time	Average Retrieval Efficiency	MSE (Mean Squre Error)	PSNR (Peak Signal To Noise Ratio)	Entropy	Match Found
		Shape Attributes						Image Properties			
GT Face DB	1	-1.38	44.00	28.45	0.51	1.32	94.17	252.56	24.11	7.54	12.00
	2	1.22	59.21	25.14	0.47	1.32	94.98	251.85	24.12	7.58	10.00
	3	0.90	53.46	28.03	0.50	1.32	94.10	252.53	24.11	7.54	12.00
	4	0.67	57.00	-24.37	0.52	1.22	94.73	254.16	24.08	7.49	5.00
	5	1.35	55.76	27.77	0.49	1.35	94.45	252.42	24.11	7.53	12.00
	6	0.67	56.46	30.00	0.51	1.33	94.10	252.24	24.11	7.54	12.00
	7	-0.49	53.22	28.67	0.48	1.37	94.45	252.44	24.11	7.53	12.00
	8	1.41	47.00	29.70	0.51	1.32	94.23	251.64	24.12	7.51	12.00
	9	0.79	51.00	-20.11	0.50	1.22	94.15	254.17	24.08	7.50	5.00
	10	-1.29	55.64	31.75	0.49	1.31	94.06	252.49	24.11	7.54	12.00
COIL - 20 DB	28	0.00	163.59	41.22	0.50	1.13	94.22	37.39	32.40	1.75	4.00
	30	0.00	137.00	-63.38	0.53	1.11	94.53	11.99	37.34	0.68	2.00
	31	0.00	62.00	-91.54	0.51	1.14	94.76	10.62	37.87	0.61	3.00
	32	0.00	132.00	40.95	0.51	1.15	94.54	4.09	42.01	0.28	3.00
	33	0.00	128.58	47.93	0.52	1.15	94.69	30.77	33.25	1.46	5.00
	45	0.00	183.00	56.42	0.50	1.22	94.65	47.69	31.35	2.20	No Match
	46	0.00	152.00	39.64	0.50	1.16	94.63	24.62	34.22	1.27	No Match
	47	0.00	63.00	26.98	0.50	1.56	94.22	48.35	31.29	2.20	No Match
	48	0.00	191.00	92.94	0.51	1.11	94.59	79.63	29.12	3.39	No Match
	50	0.00	35.54	35.29	0.49	1.15	94.43	34.32	32.78	1.78	No Match

Table 1: Computed Values for different images

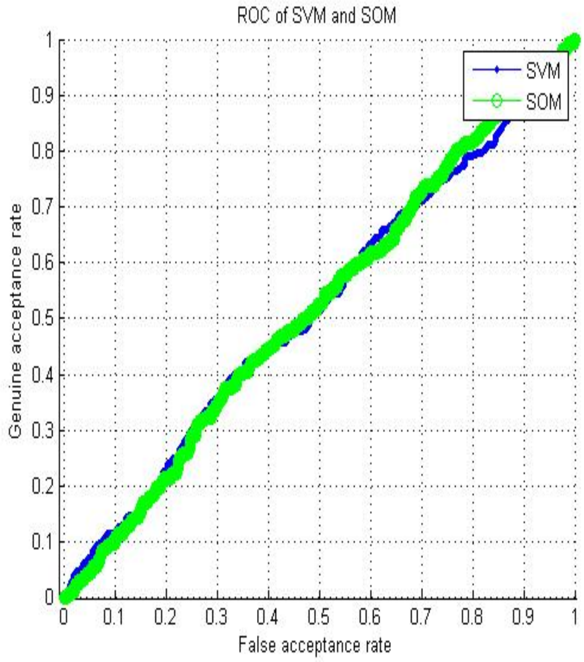

Fig 4. Receiver Operating Characteristic Curve for Image-2

Fig 5. Match Found for Image-2

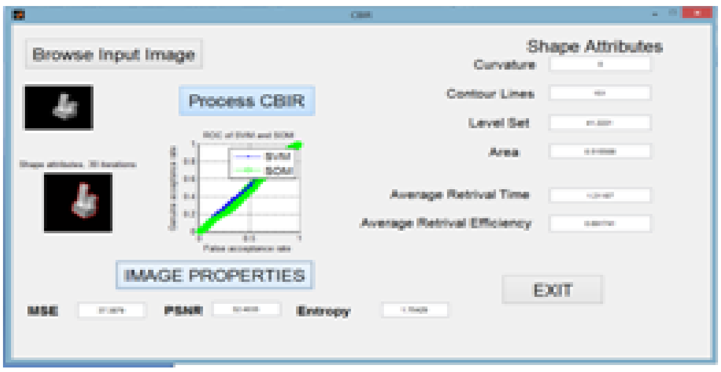

Fig 6 .GUI showing CBIR processing for image - 28

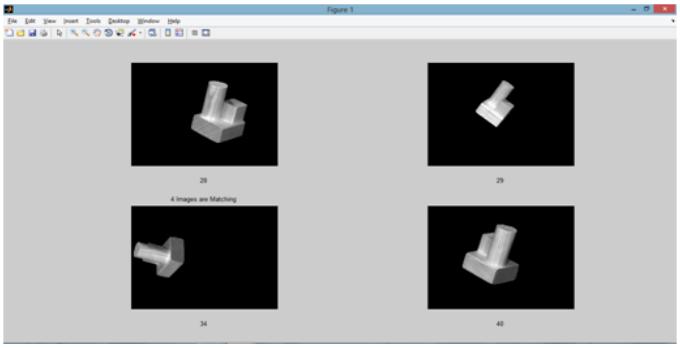

Fig 7. Match found for image - 28

Improved image classification efficiency is desired to be obtained by using active contour without edges technique in conjunction with SVM and SOM classifiers. The image classification efficiency of the proposed CBIR system ought to increase with the increase in the number of training samples.

X. CONCLUSION AND SCOPE FOR FUTURE WORK

A CBIR system using Accurate Legendre Moments (ALM) is proposed during this work. Performance of the proposed CBIR system is predicted to be superior once practiced on COIL- 20 database and GT Face database in terms of average retrieval efficiency and average retrieval time. Further, improved classification efficiency would even be obtained by using SVM and SOM classifiers. It's also assumed that the classification efficiency of the proposed CBIR system will increase with the increase in the number of training samples.

In future for image classification we will emphasize on the analysis and usage of various advanced classification techniques like Artificial Neural Networks, Fuzzy Measures, Genetic algorithms and their combos for digital image classification .

In digital image classification the conventional statistical approaches for image classification use solely the gray values. completely 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 is developed for image classification for higher and efficient retrieval results.

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