International Journal of Innovative Research in Advanced Engineering (IJIRAE) ISSN: 2349-2163
Volume 1 Issue 7 (August 2014) http://ijirae.com

A Framework for Color Image Retrieval Using Full Range Gaussian Morkov Random Field Model and Multi-Class SVM Learning Approach

K.Seetharaman[1] S.Sathiamoorthy[2]*
Department of Computer Science and Engineering, Annamalai University

Abstract— A content based image retrieval (CBIR) system for diverse collection of color images is proposed. The proposed image retrieval framework consists of Full Range Gaussian Markov Random Field (FRGMRF) model with Bayesian Approach (BA) for image feature extraction and multi-class Support Vector Machine (SVM) learning mechanism for the categorization of image feature vectors in the feature vector database. The Minkowski distance based similarity measure is performed in the final level on the pre-filtered images. In order to incorporate a better perception subjectivity, relevance feedback (RF) technique is added to update the query image dynamically. Experiments are conducted on various image databases. The experimental results based on precision and recall method are reported. Experimental result demonstrates the progress, effectiveness, and efficiency achieved by the proposed framework.

Keywords— Content based image retrieval, Full Range Gaussian Markov Random Field model, Support vector machine, Relevance feedback, Bayesian approach.

I. INTRODUCTION

The concurrent increase of image repositories and the extensive use of images in various fields namely medicine, engineering, entertainment, commerce, earth science, forensic science, agriculture, law enforcement, etc. have broadened the scope of image retrieval. Though numerous approaches have been proposed by many researchers for image retrieval, still the utilization of images in various fields was limited due to the lack of effective and efficient image retrieval approaches. Thus, a demand for effective and efficient image retrieval system has been created and the attention of researchers has been paid to the new approaches of image retrieval.

Since 1970’s, image retrieval has been an active research area and two different approaches are used by the researchers for retrieving images: 1) text-based image retrieval and 2) content based image retrieval (CBIR). Since image data contains very rich information, it is very difficult to capture the content of an image using text-based keywords and it is also practically impossible to annotate all the images on huge image repositories. Apart from these aspects, manual annotation on images is being subjective, very time consuming, laborious, and ambiguous [1]. To resolve the aforementioned problem, numerous CBIR approaches was proposed by many researchers and CBIR is considered as one of the most effective approach for retrieving the images from huge repositories. The CBIR deals with the retrieval of images based on low-level visual features like color, shape, spatial and temporal constructs, texture, etc., and can be generated automatically with or without human assistance. Despite many research efforts to CBIR [2-11], the existing are still not powerful enough to retrieve images from huge and heterogeneous image repositories. This motivated us to propose a CBIR system using a framework based on Full Range Gaussian Markov Random Field (FRGMRF) model with Bayesian approach (BA).

Color is an important and most extensively used attribute of an image. Thus, several approaches have been proposed in the literature for describing the color attribute. For instance, color moments, color histograms, binary color set, color coherence vector (CCV), color correlogram, color co-occurrence histogram, color anglogram, Motion Picture Expert Group-7’s(MPEG-7) scalable color descriptor (SCD), dominant color descriptor (DCD), color layout descriptor (CLD) and color structure descriptor (CSD), chromaticity moments descriptor (CM), color-based clustering descriptor (CBC) and border/interior pixel classification descriptor (BIC), color bitmap descriptor, wavelet coefficients of color histogram, color autocorrelogram etc. [1, 12-14] have been reported in the literature. Subsequently, Penatti et al. [14] performs a comparative study of various color descriptors in terms of efficiency, effectiveness, scalability and diversity, and reported that the color autocorrelogram is promising in heterogeneous image collections and web scenario. Thus, the proposed CBIR system computes the color autocorrelogram using a framework based on FRGMRF model with Bayesian approach (BA).

Since human can recognize objects solely from their shapes, shape features provide important information for image retrieval [15]. The shape feature techniques generally fall into two categories: region based and boundary based techniques. In the literature, several approaches have been proposed for region based shape representation and description [13, 16, 17] for image retrieval. However, the region based shape representation may not be easy and reliable, since there is no generalized accurate automatic scheme for region based approach [14, 18]. Since human beings recognize shapes mainly by their boundary features and in many shape applications, the shape contour is the only interest, boundary based methods are more familiar than the region based methods [19]. Thus, a number of research efforts using boundary based methods [9, 20] have been taken by various researchers. However, Zhang and Lu [21] reported that some of them are not suitable to be a standalone shape descriptors, complex in implementation and matching, failure to capture global shape features and high computation cost. As a result, the researchers used spectral domain based approaches such as Fourier and wavelet descriptors. Though the wavelet descriptor outperforms the Fourier descriptor, the increase of spatial resolution will certainly sacrifice frequency resolution and matching of wavelet representation is more complex, which makes it impractical for online shape retrieval. Since edge histogram descriptor (EHD) can also be viewed as shape descriptor, it represents shapes based on boundary primitives [3, 13]. Though the histogram based feature representation increases robustness to noise and compactness [21] and EHD captures rich shape, texture and spatial information [13, 19, 22-25], MPEG-7's EHD is constructed using the edges extracted by the Sobel edge detector, which is sensitive to noise and failed to detect very minute and fine edges. Recently, a new version of EHD is proposed in [11] and is computed by extracting the fine and minute edges using a framework based on Full Range Autoregressive model (FRAR) model [26] in the HSV color space and it outperforms the existing EHD's. Since the FRAR model [11, 26] can be seen to satisfy the properties of FRGMRF and Gaussian Morkov random field can be used to model a broader class of distributions, we have adopted a new version of EHD [11] in the proposed CBIR system.

Texture features becomes predominantly important in image classification and retrieval as they potentially reflect the fine details contained within an image. Hence, many researchers have conducted a number of studies on texture features in the past. For instance, Tamura et al. describes six visual texture properties: coarseness, line-likeness, contrast, directionality, regularity, and roughness, the gray-level co-occurrence matrix (GLCM), Markov random field (MRF) model, Gibbs random field (GRF) model such as Derin–Elliot model and auto-binomial model, fractal dimension, the local binary pattern (LBP), Scale Invariant Feature Transform (SIFT) descriptor, color edge co-occurrence histogram (CECH), multi-texton histogram (MTH), local ternary co-occurrence patterns (LTCoP), etc. [14, 27-29] have been reported in the literature. In contrast with the aforesaid spatial domain based techniques, several approaches for texture analysis have been proposed in the frequency domain. Initially, researchers used Fourier domain for texture analysis [18]. Since the progress of multi-channel filtering methods, a number of researchers [5, 30-32] have turned their attention on analysing textures in the frequency domain by using the wavelet transforms like orthogonal, bi-orthogonal, tree-structured, pyramid, Gabor wavelet transform, etc. The review of literature reveals that most of the wavelet-based approaches uses energy based distribution, which characterizes the texture properties in the images, and it might lead to wrong results. Because, different types of textures may have same energy values [31]. Since most relevant texture information has been removed by iterative low-pass filtering, the energy of the lowest resolution is generally not considered as a texture feature [31]. Furthermore, the high computational complexity of the existing wavelet based texture analysis methods affects the performance of image retrieval [33], which is also valid for the texture analysis method proposed in [33]. Mojsilovi´c et al. [34] reported that some of the wavelet based techniques for texture analysis provide good results for some kind of applications and many of them produce very low classification rate when texture samples are of small dimensions. Recently, the FRGMRF model [35] and the autocorrelation coefficients derived from the FRGMRF model is used to perform texture characterization and discrimination at local as well as global level in RGB color space and it outperforms the conventional methods on texture analysis. The literature [35] reveals that the aforesaid combination is sufficient to capture everything about a texture. Quite Recently, Seetharaman and Sathiamorthy [11] proposed a compact micro-textures (MT's), which is extracted using a framework based on FRAR model [36] and outperforms the existing micro-textures [36] in terms of time and storage cost [11]. Since the FRAR model [11, 26] can be seen to satisfy the properties of FRGMRF and Gaussian Morkov random field can be used to model a broader class of distributions, we have employed the compact MTs [11] in the proposed image retrieval system based on FRGMRF with BA.

Since diversity of images contributes to the high level of complexity and difficulty in the context of image retrieval, classification of images are important for a large scale heterogeneous image databases. Over the last decades, artificial neural networks (ANN) have been used broadly in various domains for classification problems. Many researchers have found that ANN has more flexibility in modeling and reasonable accuracy in classification problems [11, 37]. In the literature, the support vector machine (SVM) developed by Vapnik (1995) based on statistical learning theory has been used extensively for non linear and non separable problems in various domains like medicine, engineering, etc. due to its high generalization ability, robustness to high-dimensional data and a well-defined learning theory [38], and it shown better accuracy and achieves a fast classification than the radial basis function neural network (RBFNN) when the datasets are more unbalanced. Thus, in order to consider an efficient multi-class categorization of images in feature vector space, we adopted multi-class SVM [38] for the proposed CBIR system.

In the context of image retrieval, fully automated system does not lead to success, as the computer vision technique is not there yet. Hence, recent research draws its attention to interactive systems and human in the loop. Thus, the relevance feedback (RF) technique in short-term learning [39, 40] is adopted to reduce the semantic gap between the low-level visual features and high-level semantic concepts perceived by the users and it considerably improves the retrieval performance of the proposed CBIR system. The Minkowski distance measure [5] of metric order 3 is used to measure the similarity between the query and target images in the classified and indexed [41] feature vector space.

Since Precision and Recall [33, 40] is the most common performance evaluation measure used in the CBIR system, it is employed in the proposed CBIR system. Precision is defined as the fraction of retrieved images which is relevant to a query. In contrast, recall measures the fraction of the relevant images which has been retrieved.

II. FRGMRF MODEL

Recent literature reports that an image retrieval system based on FRGMRF model [35] outperforms the existing systems for color images. Thus, the proposed CBIR system is designed so as to use the effectiveness of a framework based on FRGMRF model with the BA for extracting color and its spatial information, texture information, shape and its spatial information at local and global level respectively.

Let X be a random variable that represents the intensity value of a pixel at location (k, l) in an image of size L×L. It is also assumed that X may have noise and is considered as independently and identically distributed Gaussian random variable with discrete time space and continuous state space with mean zero and variance σ^2 and is denoted as $\varepsilon(k, l)$ i.e. $\varepsilon(k, l) \sim N(0, \sigma^2)$.

Since $\{X(t); t \in S\}$ is a stochastic process, where $S=\{t:(k,l);\ 1 \le k, l \le N\}$, $\{X(t)\}$ can be considered as a Markov process and we have the conditional probability

$$P\{X(t_n) = i_n \mid X(t_k) = i_k ;\ k=0,1,2, \ldots, n-1\}$$
$$= P\{X(t_n) = i_k \mid X(t_n\text{-}1) = i_n\text{-}1\}$$

$\forall\, i_k$, k=0,1,2, . . . , n-1 and t_k belonging to the state space S and $t_0 < t_1 < \ldots < t_n$. Thus, the FRGMRF model [35] is given by the difference equation (1) and represents the pixel $X(k,l)$ as a linear combination of nearest neighbourhood values.

$$X(k,l) = \sum_{\substack{p=-M \\ p=q\neq 0}}^{M} \sum_{q=-M}^{M} \Gamma_r X(k+p,\ l+q) + \varepsilon(k,l) \tag{1}$$

where $\Gamma_r = \dfrac{K \sin(r\theta)\cos(r\phi)}{\alpha^r}$, and $r = |p| + |q| + M(M-1)/2$.

With the Markovian assumption, the conditional probability of $X(s)$ given all other values only depends upon the nearest neighbour-hood values. The fact that $X(s)$ has regression on its neighborhood pixels gives rise to the terminology of Markov process. However, in this case the dependence of $X(s)$ on neighborhood values may be true to some extent. The initial assumption about the parameters is $K \in R; \alpha > 1$; θ and $\phi \in [0,2\pi]$. In equation (1), $X(k+p, l+q)$ is the spatial variation due to image properties and $\varepsilon(k,l)$ is the spatial variation due to additive noise and FRGMRF model coefficients Γ_r, (r = 1, 2) are the variation among the low-level primitives in the sub-image region of size M x M, (M<L). The model coefficients are interrelated. The interrelationship is established through the model parameters K, α, θ, and ϕ, which are estimated using the BA [35].

III. PROPOSED IMAGE RETRIEVAL SYSTEM

Since the HSV (hue, saturation, value) color space is commonly used in the literature and is more intuitive to human visual system [42] and the classification performance of HSV is higher than the RGB color space [43], the proposed image retrieval system employs HSV color space. In the proposed CBIR system, the color images in RGB color space are converted into HSV color space [42], then the images are segregated into H (Hue), S (Saturation) and V (Intensity) component images, where H and S component images have chromatic information and V component image contains achromatic information. The FRGMRF model based framework is applied on H and S component image, then the color autocorrelogram is computed from the uniformly quantized H and S component images respectively, and is formed as color feature vector; the compact MTs feature vector is formed by extracting the MTs from the V component image. The proposed system next extracts the edges from the V component image and the detected edges are used to compute the orientation of edges, which are used to construct an improved EHD.

The extracted feature vectors are combined and normalized to form a query feature vector and it is categorized using the SVM to reduce the search space. The categorized feature vector space is indexed [41] in order to increase the image retrieval speed. Then, the proposed system computes the distance between the query and each target feature vectors using Minkowski distance measure. The computed distances between the query and each target feature vectors are ordered in ascending manner. The target image with the lowest distance value has higher similarity. Subsequently, the proposed image retrieval system displays a list of similar images based on the distance criteria specified by the user. Suppose, If the user is not satisfied with the results of the proposed system due to the gap between the low-level features and high-level semantic concepts perceived by the user then the proposed system permits the users to employ query refinement approach of short-term learning based RF technique to reduce the semantic gap, which forms a new query image by combing the query image used in the last search session and the images that are marked by the users as positive examples in the last retrieved results, and a newly formed query image is fed into the proposed CBIR system. This process continuous until the results is closer to the user perception.

A. Feature Extraction Method

1) Color Feature: In the proposed CBIR system, color autocorrelogram is extracted from the uniformly quantized [5, 11] H and S components of an image. The number of quantization level (L) is fixed to 8 in accoradance with the results of [5]. The autocorrelation coefficients (α_c^k) are derived from the FRGMRF model coefficients Γ_r as follows:

$$(\alpha_c^1) = \frac{\Gamma_1}{1-\Gamma_2};$$

$$(\alpha_c^2) = \frac{\Gamma_1^2 + \Gamma_1 - \Gamma_2^2}{1-\Gamma_2} \text{ and}$$

$$(\alpha_c^3) = \frac{\Gamma_1\left(\Gamma_1^2 + 2\Gamma_1 - \Gamma_2^2\right)}{1-\Gamma_2}$$

Similarly, the k^{th} order autocorrelation coefficient can be obtained by solving the following equation using recurrence relation.

$$\alpha_c^k = \Gamma_1\, \alpha_c^{k-1} + \Gamma_2\, \alpha_c^{k-2}; 1 \le k \le m;\ c \in (1,2,\ldots,L) \tag{2}$$

where m is the lag variable, k is the order of autocorrelation coefficient and c represents the color. In the proposed CBIR system, the color autocorrlogram, which captures the spatial correlation between the identical colors at a distance 1 is computed for H and S components of an image. Since, the smallest distance gave the most detailed local properties of the image, the proposed system fix the distance to 1.

2) Texture Feature: The V component of an image is divided into number of overlapping sub-image regions of size 3 x 3 to locally characterize the nature of the image. The FRGMRF model coefficients Γ_r, (r = 1, 2) are computed for each sub-image region by using the FRGMRF model parameters K, α, θ and ϕ, which are estimated using the BA. The autocorrelation coefficient is computed for each sub-image region from its model coefficients Γ_r.

The MTs [11, 35] that are below or above the threshold for humans to understand are identified in each sub-image regions by measuring the homogeneity of variances among the computed autocorrelation coefficients using a statistical test of hypotheses and it is given in equation (3).

$$\tilde{D}_m = n\left[1 - \left|\tilde{R}_m\right|^{1/m}\right] \tag{3}$$

where, $\tilde{R}_m$ is the autocorrelation matrix built by using the standardized autocorrelation coefficients, n is the number of samples and m is the lag variable. The statistical test of hypotheses is based on the measure $\pm\alpha\left(\sigma/\sqrt{n}\right)$, where α is level of significance and σ is standard deviation. The autocorrelation coefficient is compared with the measure $\pm\alpha\left(\sigma/\sqrt{n}\right)$ to find the outcome of the test. If the autocorrelation is highly significant, then it is considered that there exist micro-textures in the sub-image region, or else (autocorrelation coefficients that fall inside the confidence limit, at 80% level of significance), it is identified as untexturedness. The identified MTs are clustered into 32 categories using k-means clustering algorithm and the centre of each cluster is used to represent the MTs of that cluster. A number of clusters is determined empirically for the image database considered in the experiments without affecting the performance of the proposed CBIR system. Subsequently, the representatives of all the clusters are ordered in ascending manner and numbered from 0 to 31. These numbers represent the MTs and called *texnum*. Then, the number of MTs in each cluster is computed and called *texspectrum*. The histogram of *texnum* Vs *texspectrum* is formed to represent an image.

3) Shape Feature: The FRGMRF model in equation (1) is applied on V component image to estimate its image surface. Then, the difference between the V component image and estimated surface are computed and the resultant image is called residual images. The global confidence limit is measured for each sub-image region (3 x 3) of residual image with a desired significance level. The global confidence limit is calculated with the use of global mean and standard deviation. If the pixel value is greater than or equal to the global confidence limit then it is squared; otherwise the pixel value is replaced with zero. The value other than 0 represents the edges and 0 represents non-edge part in the image.

This extracts thick edges. To suppress the pixels around the edge pixel and to obtain thin edges, the non-maxima suppression algorithm is applied with the use of local confidence limit. The local confidence limit is calculated with the use of local mean and standard deviation of thick edge map. Each value in the thick edge map is compared with the confidence limit. If the value in the thick edge map is greater than the confidence limit then it is identified as edge pixel and is represented with the actual pixel value. Otherwise it is identified as non-edge pixel and is represented as 0. After extracting the edge pixels for the entire image, the orientation of each edge pixel is computed. Then, the orientations of edge pixels are quantized into 72 bins of 5 degree each, which is used to form an improved EHD.

B. Classification and Indexing

1) Support Vector Machine:

Given a training dataset $T = \{(x_i, y_i)\}_{i=1}^{n}$, where each input feature vector $x_i \in \Re^d$, *d* is the dimension of training dataset and y_i corresponds to x_i's class label and it has only two values, -1 or +1. If the training data set is linearly separable, the hyperplane is defined as $w^T x_i + b = 0$, which satisfies that $y_i(w^T x_i + b) \geq 0$, where *w* is the weight vector orthogonal to the hyperplane, b is an offset term and x_i is the data. Thus, the problem for the linearly separable case could be formulated as (4).

$$\min_{w,b} \frac{1}{2} w^T w \tag{4}$$

Subject to $y_i(w^T x_i + b) \geq 0$

In case the data are non-linearly separable in the input space, the previous analysis can be generalized by introducing a slack variable ξ_i to x_i, which transfers the optimal hyperplane problem into (5)

$$\min \frac{1}{2} w^T w + C \sum_{i=1}^{n} \xi_i \tag{5}$$

Subject to $y_i(w^T x_i + b) \geq 1 - \xi_i$ and

$\xi_i \geq 0, i = 1, \ldots n$

where the parameter *C* can be regarded as a regulation parameter that imposes a balance between the minimization of the error function and the maximization of the margin of the optimal hyperplane. Slack variable is used to measure the error in the SVM classifier. The optimization problem (6) can be solved by introducing a Lagrange multiplier α_i to x_i and then based on the Karush–Kuhn–Tucker (KKT) theorem, and the dual form of (6) could be formulated as

$$\max_{\alpha} w(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} y_i y_j \alpha_i \alpha_j k(x_i, x_j)$$

$$\text{Subject to } \sum_{i=1}^{n} y_i \alpha_i = 0, 0 \leq \alpha_i \leq C, i = 1, \ldots, n \tag{6}$$

Finally, the decision function *h(x)* of SVM classifier can be expressed as

$$f(x) = \text{sign}(h(x)) = \text{sign}\left(\sum_{i=1}^{n} \alpha_i y_i k(x, x_i) + b\right)$$

The shape of the decision function is depends on the employed kernel function *k*, which determines the success of SVM learning process. In SVMs different kernel functions are used such as linear, polynomial and Gaussian RBF, which automatically maps the data from the input space into a higher dimensional feature space nonlinearly. But, choosing an appropriate kernel function for a problem is depends on the data and still there is no method for choosing a suitable kernel function. In this thesis, the choice of the kernel functions was studied empirically and optimal results were achieved using the most widely used RBF kernel function and it is defined as

$$k(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right)$$

The hyper parameters of kernel function control the trade off between the complexity of SVM and the number of non separable points. The parameters of the multi-class SVM classifier has been tuned by using the grid search algorithm. The best combinations of parameters are used to build the final multi-class SVM training model.

In the proposed CBIR system, the extracted feature vectors are combined and normalized then the multi-class SVM classifies the feature vectors in the feature vector space into classes viz, birds, bus, car, sea, forest, flowers, cannel, boat, ships, people, etc. Thus, the search space is reduced significantly by filtering the irrelevant classes of images and it improves the retrieval speed.

In order to attain the best generalization and to reduce the over-fitting problem, ten-fold cross-validation is used in the proposed system. In each execution of ten-fold cross-validation, nine sub-sets are considered for training and one for testing. So that every sub-set is used in both training and testing phase of multi-class SVM classifier.

The classified feature vectors are indexed using the kD-tree [41] indexing method and it increases the retrieval speed of the proposed CBIR system.

C. *Similarity and Performance Measure*

In the proposed CBIR system, the similarity between the query and target images is measured using the Minkowski distance measure, which is used extensively in the literature due to its efficiency. The Minkowski distance [5] between the query and target images is computed as follows:

$$\Delta d = \left[\sum_{i=1}^{n} (Q_i - T_i)^m \right]^{\frac{1}{m}} \tag{7}$$

where, Q_i is a query image feature vector, T_i is a target image feature vector in the feature vector database, *n* is the size of the combined feature vector and m denotes the metric order. In the proposed CBIR system the metric order is 3.

The retrieval accuracy of the proposed CBIR system is measured using the most widely used precision (percentage of retrieved images that are also relevant) and recall (percentage of relevant images that are retrieved) methods and is defined as follows:

$$\text{Precision} = \frac{R_i}{T_i} \tag{8}$$

$$\text{Recall} = \frac{R_i}{T} \tag{9}$$

where Ri is the number of relevant retrieved images, T is the total number of relevant images in the image database, and Ti is the number of all retrieved images.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed CBIR system is experimented on Wang's database [http://wang.ist.psu.edu/docs/related.shtml], VisTex DB [http://vismod.media.mit.edu/pub], UCID database [http: // vision.cs.aston.ac.uk/ datasets/ UCID/ ucid.html], Freefoto database [http://Freefoto.com] and self-photographed image database. For sample, due to space constraint, some of the images from the experimental databases are presented in Fig.1.

The experimental image databases consists of images like birds, mountain, bus, car, sea, buildings, forest, flowers, cannel, waterfall, cloud, iceberg, boat, people, etc. and the images are in JPEG and TIFF format, and vary in size-wise. Some of the images in each experimental database are replicated, and few of them are rotated through different angles and the remaining replicated images are either scaled up or scaled down. The images taken in different viewing positions and lighting conditions are also considered in our experiments.

The proposed CBIR system is implemented with the system configuration: Pentium® Dual core personal computer with 2.20 GHz processor; 2 GB RAM; Java, MATLAB, Oracle and Windows 7.

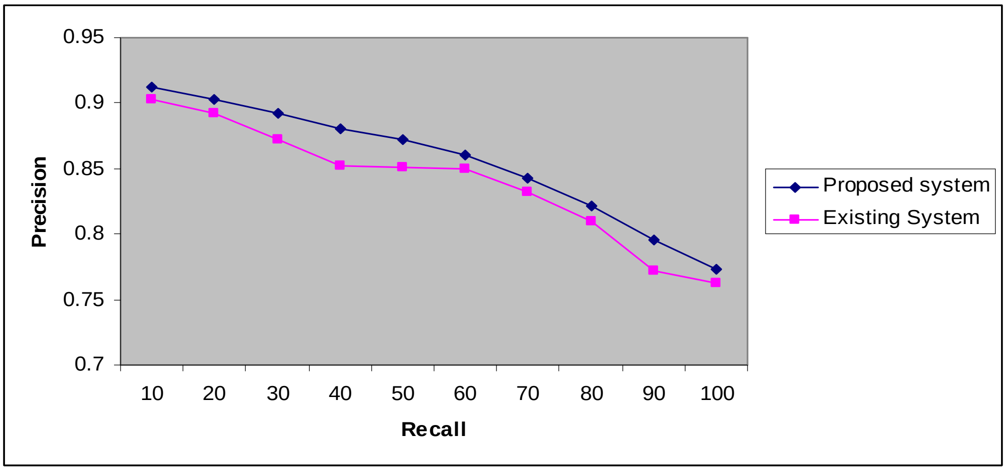
In order to evaluate the retrieval performance of the proposed CBIR system, we have chosen different sub-sets of query images from each experimental database and a number of query images in each sub-set varies i.e. 10, 20, 30, . . . , 100. The proposed CBIR system is tested by 50 users with queries. As described in section III, the color autocorrelogram, improved EHD and MTs features are extracted from the images of experimental databases using the FRGMRF model with BA and the extracted feature vectors are combined and normalised then classified using the multi-class SVM and then indexed using kD-tree indexing method. Finally, Minkowski distance measure of order 3 is used to find the similarity between the query and target images. Whereas in the existing system [11], color autocorrelogram, improved EHD and compact MTs features are extracted using the FRAR model with BA, RBFNN is used to perform classification and Manhatten distance measure of order 1 is used to measure the similarity between the query and target images.

In the experiment, as described in section III, we have implemented the proposed CBIR system and the system described in [11] then the retrieval results are compared for various image databases considered in the experiments. The average precision and recall of the proposed and existing systems for the experimental databases are presented in Fig. 2. The average retrieval rates attained by the proposed and existing system for the experimental databases are tabulated in table 1. The experimental results clearly reveal that the retrieval performance of the proposed system is superior to existing system.

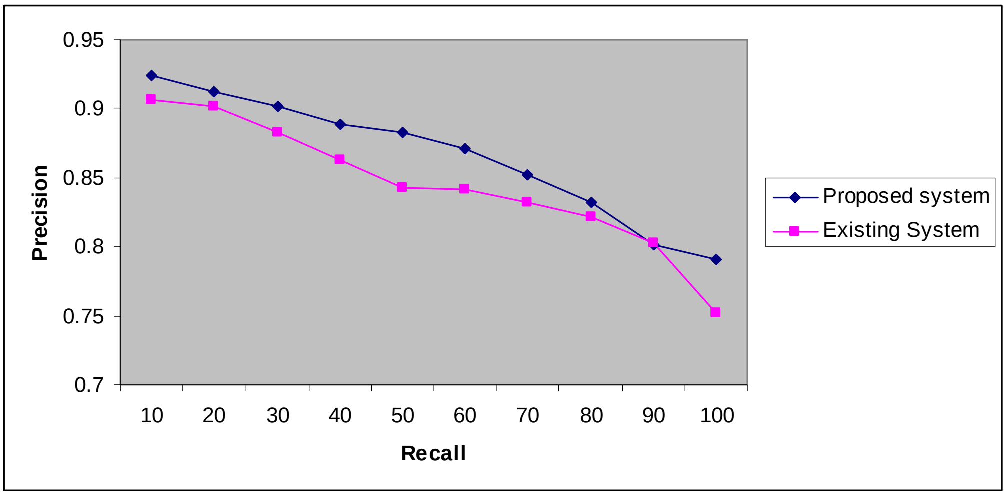
***Fig 1**. Sample images taken from the experimental databases.*

Table 1. The average retrieval attained by the proposed and existing for the experimental databases

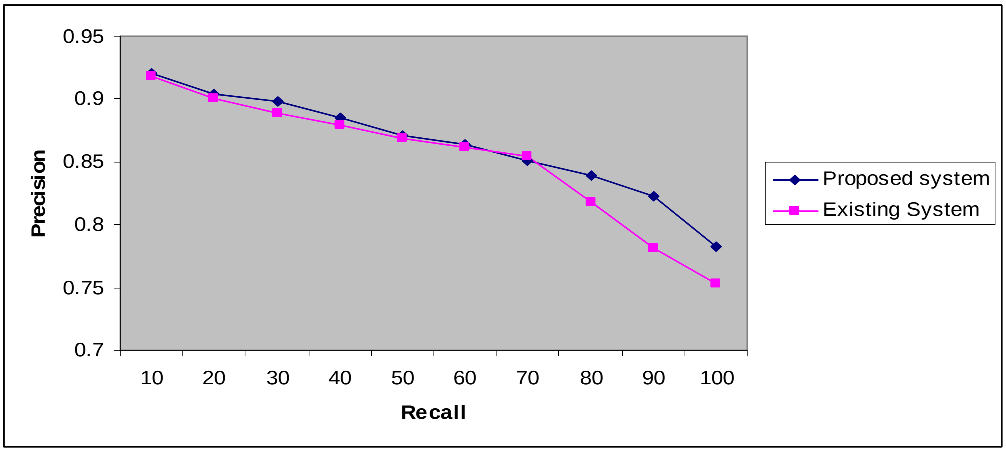
	Wang's database	VisTeX database	Freefoto database	Self-Photographed Database
Proposed System	85.46%	86.32%	86.12%	84.29%
Existing System	84.08%	84.67%	85.02%	83.42%



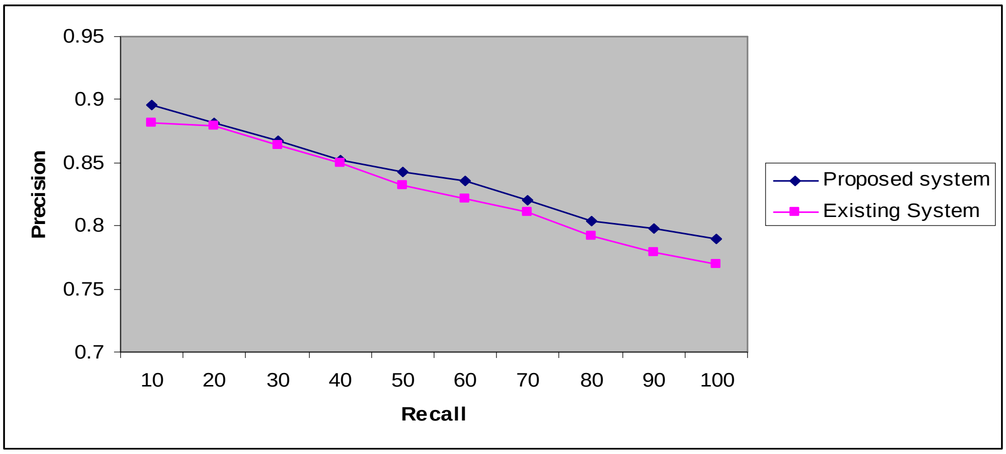
(a)



(b)



(c)



(d)

Fig 2*. a) Average precision verses recall of the proposed and existing CBIR system for a) Wang's database b) VisTex database c) Freefoto database d) Self-photographed image database*

The retrieval result of the proposed system is shown in Fig.3. Fig.3(a) show a test query image and Fig.3 (b)-(f) is the top five retrieval results (ascending order of obtained distances between the query image and the target images) of the proposed CBIR system. The distance between the query image (Fig.3(a)) and target image (Fig.3(g)) in the proposed and existing systems are 0.69 and 0.94 and the query image (Fig.3(a)) and target image (Fig.3. (f)) in the proposed and existing systems are 0.87 and 1.32 respectively.

The experimental result confirms that the classification performance of SVM and the efficiency of Minkowski distance measure improve the performance of the proposed CBIR system. The computational efficiency of the proposed and existing systems is 2.07s and 1.94s respectively and is measured with respect to CPU utilization time for extracting the feature vector and search time of the image database for a given query image. Though the computational complexity of the proposed system is significantly higher than the existing system, the proposed system significantly outperforms the existing system and the storage cost of proposed and existing systems are same.

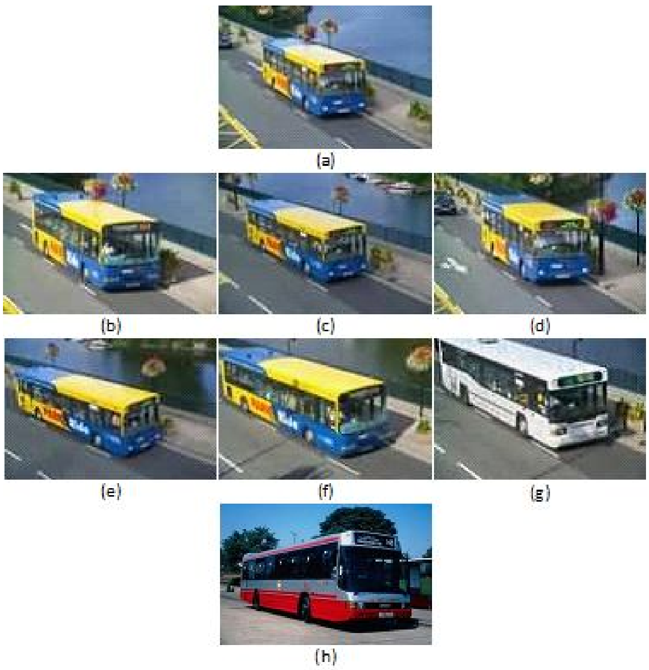


Fig 3*. a) Query image; (b) – (h) retrieval results obtained with the proposed CBIR system.*

V. CONCLUSIONS

In this paper, we proposed an image retrieval system using Full Range Gaussian Markov Random Field model with Bayesian approach and multi-class SVM machine learning based image pre-filtering approach with the combination of Minkowski similarity matching technique and relevance feedback mechanism in color image databases. The proposed image retrieval technique is very effective, and showed improvement in retrieval results than that of existing method. The proposed CBIR system can be used as a front-end tool for the image databases of various fields like medicine, engineering, agriculture, earth science, law enforcement, etc., where the search can be directed to the right place and images can be accessed at the right time.

REFERENCES

[1] M. Stricker, M. Orengo, Similarity of color images, in: Proc. SPIE Storage and Retrieval for Image and Video Databases, San Jose, pp. 381–392, 1995.
[2] M. Flickner, H. Sawhney, W. Niblack, J. Ashley, Q. Huang, B. Dom, M. Gorkani, J. Hafine, D. Lee, D. Petkovic, D. Steele, and P.Yanker, “Query by image and video content: The QBIC system,” IEEE Computer, vol. 28, no. 9, pp. 23-32, 1995.
[3] A. K. Jain and A. Vailaya, “Image retrieval using color and shape,” Pattern Recognit., vol. 29, no. 8, pp. 1233–1244, 1996.
[4] M. M. Rahman, P. Bhattacharya, B. C. Desai, “A Framework for Medical Image Retrieval Using Machine Learning and Statistical Similarity Matching Techniques with Relevance Feedback,” IEEE transactions on information technology in biomedicine, vol. 11, no. 1, pp.59-69, 2007.
[5] Y.D. Chun, N.C. Kim, and I.H. Jang, “Content-Based Image Retrieval using Multiresolution Color and Texture Features,” IEEE Transactions on Multimedia, vol. 10, no.6, pp. 1073-1084, 2008.
[6] H. Chen, Z. Gao, G. Lu, S. Li, "A Novel Support Vector Machine Fuzzy Network for Image Classification Using MPEG-7 Visual Descriptors," International Conference on MultiMedia and Information Technology, pp.365-368, 2008.
[7] C.H. Lin, R.T. Chen, Y.K. Chan, “A smart content-based image retrieval system based on color and texture feature,” Image and Vision Computing, vol. 27, no. 6, pp. 658–665, 2009.
[8] K. Iqbal, M. O. Odetayo, A. James, “Content-based image retrieval approach for biometric security using colour, texture and shape features controlled by fuzzy heuristics,” Journal of Computer and System Sciences, vol. 78, no. 4, pp. 1258-1277, 2012.
[9] X.Y. Wang, Y.J. Yu, H.Y. Yang, “An effective image retrieval scheme using color, texture and shape features,” Computer Standards & Interfaces, vol. 33, pp. 59–68, 2011.
[10] W.X.Yuan, C.Feng, Y.Jiao, “An effective method for color image retrieval based on texture,” Computer Standards & Interfaces, vol.34, pp. 31–35, 2012.
[11] K.Seetharaman, S.Sathiamoorthy. Color image retrieval using statistical model and radial basis function neural network. Egyptian Informatics Journal, 15, 59-68, 2014.
[12] Huang, J., Kumar, S. R., Mitra, M., Zhu, W. J. and Zabih, R., 1997. Image indexing using color correlogram, in Proc. 16th IEEE Conf. on Computer Vision and Pattern Recognition, pp. 762–768.
[13] Cieplinski, L., Kim, M., Ohm, J.-R., Pickering, M., Yamada, A. (Editors), 2001. Text of ISO/IEC 15938-3/FCD Information Technology -Multimedia Content Description Interface-Part 3: Visual. Final Committee Draft, ISO/IEC/JTC1/SC29/WG11 (MPEG), document no. N4062.
[14] Penatti, O. A. B., Valle, E., Torres, R. D. S., 2012. Comparative study of global color and texture descriptors for web image retrieval, J. Vis. Commun. Image R., vol. 23, pp. 359–380.
[15] Gonzalez, R.C., Woods, R.E., 1993. Digital Image Processing. Prentice Hall.
[16] Andalo′. F.A., Miranda, P.A.V., Torres, R.S., Falcao, A.X., 2010. Shape feature extraction and description based on tensor scale, Pattern Recognition 43(1):26-36.
[17] Michel, D., Oikonomidis, I., Argyros, A., 2011. Scale invariant and deformation tolerant partial shape matching, Image Vision. Comput. 29(7): 459-469.
[18] Müller H., N. Michoux, D. Bandon, A. Geissbuhler. 2004. A review of content-based image retrieval systems in medical applications-clinical benefits and future directions. International Journal of Medical Informatics 73(1): 1-23.
[19] Liu, Y., Zhang, D., Lu, G., Ma, W.Y., 2007. A survey of content-based image retrieval with high-level semantics, Pattern Recognition 40 (11) : 262–282.
[20] Collins, M., Xu, J., Grady, L., Singh, V., 2012. Random walks based multi-image segmentation: quasiconvexity results and GPU-based solutions. In: IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 1656–1663.
[21] Zhang, D., Lu, G., 2004, Review of shape representation and description, Pattern Recognition 37(1): 1-19.
[22] Liu G.H., Li, Z.Y., Zhang, L., Xu. Y., 2011. Image retrieval based on micro-structure descriptor. Pattern Recognition 44(9) : 2123-2133.
[23] Mahmudur Rahman, Md., Daekeun You, Matthew S. Simpson, Dina Demner-Fushman, Sameer K. Antani, and George R. Thoma, 2013. Multimodal biomedical image retrieval using hierarchical classification and modality fusion. Int J Multimed Info Retr. 2, 159-173.
[24] Alefs, B., Eschemann, G., Ramoser, H., et al, 2007. Road sign detection from edge orientation histogramms. In: Proceedings of the 2007 IEEE Intelligent Vehicles Symposium, Istanbul, Turkey, pp. 993-998.
[25] Chatzichristofis S.A., Zagoris, K., Boutalis Y. S., and Papamarkos. N., 2010. Accurate image retrieval based on compact composite descriptors and relevance feedback information. International Journal of Pattern Recognition and Artificial Intelligence 24(2): 207-244.

[26] K. Seetharaman and R. Krishnamoorthi, "A statistical framework based on a family of full range autoregressive models for edge extraction," Pattern Recognition Letters, vol. 28, no. 7, pp. 759–770, 2007.
[27] Liu G, Zhang L, Hou Y, Li Z, Yang J., 2010. Image retrieval based on multi-texton histogram. Elsevier J Pattern Recognit. 43: 2380–2389.
[28] Lowe, D.G., 2004. Distinctive image features from scale-invariant keypoints, International Journal of Computer Vision 60 (2): 91–110.
[29] Subrahmanyam Murala, Q.M. Jonathan Wu, 2013. Local ternary co-occurrence patterns: A new feature descriptor for MRI and CT image retrieval, Neurocomputing, 119: 399–412.
[30] Vogel, J., Schiele, B., 2006. Performance evaluation and optimization for content-based image retrieval, Pattern Recognition 39 (5): 897–909.
[31] He, Z., You, X., Yuan, Y., 2009. Texture image retrieval based on non-tensor product wavelet filter banks, Signal Processing 89:1501–1510.
[32] Subrahmanyam M, Maheshwari R.P, 2011. A correlogram algorithm for image indexing and retrieval using wavelet and rotated wavelet filters. Int J Signal Imaging Syst Eng 4:27–34.
[33] Krishnamoorthi, R., Sathiya devi, S., 2012. A multiresolution approach for rotation invariant texture image retrieval with orthogonal polynomials model, J. Vis. Commun. Image R. 23: 18–30.
[34] A. Mojsilovi´c, M. V. Popovi´c, A. N. Ne˘skovi´c, and A. D. Popovi´c, "Wavelet Image Extension for Analysis and Classification of Infarcted Myocardial Tissue," IEEE transactions on biomedical engineering, vol. 44, no. 9, pp.856-866, 1997.
[35] A. Annamalai Giri, K. Seetharaman, Statistical Model Based Color Image Retrieval Using Low-level Features, International Conference on Emerging Trends in Engineering and Technology (ICETET'2013) Dec. 7-8, 2013 Patong Beach, Phuket (Thailand).
[36] Seetharaman, K., and Palanivel. N, 2013. Texture characterization, representation, description, and classification based on full range Gaussian markov random field model with Bayesian approach. International journal of image and data fusion. pp. 1-24.
[37] Zhang, G.P., 2000. Neural network for classification: A survey, IEEE transactions on systems, man, and cybernetics—part c: applications and reviews, 30(4): 451-462.
[38] JuiHsi Fu, SingLing Lee, A multi-class SVM classification system based on learning methods from indistinguishable chinese official documents, Expert Systems with Applications 39 (2012) 3127–3134.
[39] Su, Z., Zhang, H., Li, S., and Ma, S., 2003. Relevance feedback in content-based image retrieval: Bayesian framework, feature subspaces, and progressive learning, IEEE Transactions on Image Processing, vol. 12, no. 8, pp. 924–937.
[40] Hossein Nezamabadi-pour, Ehsanollah Kabir, 2009. Concept learning by fuzzy k-NN classification and relevance feedback for efficient image retrieval, Expert Systems with Applications 36: 5948–5954.
[41] White, D.A., Jain, R., 1996. Algorithms and strategies for similarity retrieval, Tech. Rep. VCL-96-101, Visual Computing Laboratory, University of California, San Diego, 9500 Gilman Drive, Mail Code 0407, La Jolla, CA 92093-0407.
[42] Karkanis, S. A., Iakovidis, D. K., Maroulis, D. E., Karras, D. A., Tzivras, M, 2003. Computer-aided tumor detection in endoscopic video using color wavelet features. IEEE transactions on information technology in biomedicine, 7(3), 141-152.
[43] Chen, W., Shi, Y.Q., Xuan, G., July 2, 2007. Identifying computer graphics using HSV color model and statistical moments of characteristic functions, IEEE International Conference on Multimedia and Expo (ICME07), Beijing, China.