Content Based Image Retrieval Methods Using Self Supporting Retrieval Map Algorithm

P.Jayaprabha
Vidyaa Vikas College of Engineering Thiruchengode, Tamilnadu, India

Rm.Somasundaram
SNS College of Engineering Coimbatore, Tamilnadu, India

Abstract
The need to have a versatile and general purpose content based image retrieval (CBIR) system for a very large image database has attracted focus of many researchers of information technology-giants and leading academic institutions for development of CBIR techniques. In a high-level semantic retrieval process, we utilize the search engine to retrieve a large number of imagesusing a given text-based query. In a low level image retrieval process, the system provides a similar image search function for the user to update the input query for image similarity characterization. The revolutionary internet and digital technologies have imposed a need to have a system to organize abundantly available digital images for easy categorization andretrieval. These techniques encompass diversified areas, viz. image segmentation, image feature extraction, representation, mapping of features to semantics, storage and indexing, image similarity distance measurement and retrieval making CBIR system development a challenging task. The state of the art techniques are reviewedand future scope is cited. The experimental evaluations based on coverage ratio measure show that our scheme significantly improves the retrieval performance of existing image search engine.

Key Words:
CBIR, Image feature extraction, Imageanalysis, Image retrieval, Image search, Image similarity

1. Introduction

Content Based Image Retrieval (CBIR) has been anongoing area of research for decades but is still notappearing in the mainstream. Many applications like Qbic [1], Visual Seek [2], Blob world [3], and Meta SEEk[4] are attracting attention, but they are still not verycommon. Retrieval of required query similar images from abundantly available accessible digital images is achallenging need of today. The image retrieval techniques based on visual image content has been in-focus for morethan a decade. Many web search engines retrieve similar images by searching and matching textual metadata associated with digital images. The paper addresses and analyses challenges & issues of CBIR techniques/systems, evolved during recent years covering various methods forsegmentation; edge, boundary, region, color, texture, andshape based feature extraction; object detection and identification. For better precision of the retrieved resultant images, this type of search requires associating meaningful image descriptive text labels as metadata with all images of the database.

Manual image labeling, known as manual image annotation, is practicallydifficult for exponentially increasing image database. The image search results, appearing on the first page for firedtext query rose black for leadingweb search engines Google, Yahoo and AltaVista. Many resultant images have lack semantic matching with the query, showing vast scope of researchleading to improvements in the state-of-art-techniques. The need evolved two solutions automatic image annotation and content based image retrieval. The contentbased image retrieval techniques aim to respond to aquery image (or sketch) with query similar resultantimages obtained from the image database.

The database images are preprocessed for extracting and then storing indexing corresponding image features. The query imagealso gets processed for extracting features which arecompared with features of database images by applying appropriate similarity measures for retrieving query similar Images.In the area of CBIR, it overcomes thedifficulties of manual annotations by using visual feature based representations, such as color, texture, shape, etc. However, after over a decade of intensified.The major bottleneck of this approach is the gap between visual feature representations and semantic concepts of images. Low-level contents often don't describe the high level.

Semantic concepts in users minds. Some researcher considered to improve this burden, one promising direction towards semantic retrieval is the adoption of relevance feedback mechanism [8]. Many researchers focus on theserelevance techniques because they are important inachieving a better precision rate [9]. The technique is a variation of "query by example" that involves multiple interactions with a user at search time[6]. It refers to the feedback from a user on specific items regarding their relevance to a target image, in eachiteration, the refined query is re-evaluated.

Manuscript received January 5, 2013
Manuscript revised January 20, 2013

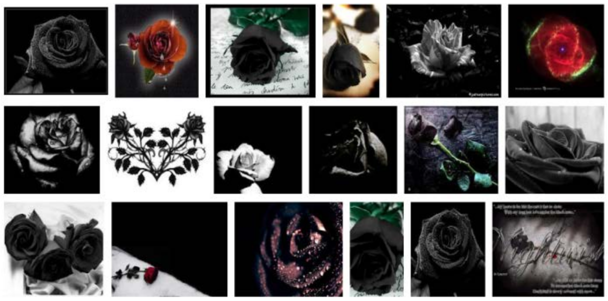
Fig 1. Image search results for query – rose black

2. Image features

Various techniques for extraction and representation of image features like histograms local (corresponding toregions or sub-image) or global, color layouts, gradients,edges, contours, boundaries & regions, textures and shapes have been reported in the literature.Histogram is one of the simplest image features. Despite being invariant to translation and rotation about viewing axis, lack of inclusion of spatial information is its major drawback. Many totally dissimilar images mayhave similar histograms as spatial information of pixels isnot reflected in the histograms. Consequently, many histogram refinement techniques have been reported in theliterature. Histogram intersection based method for comparing model and image histograms was proposed in[1] for object identification.

Histogram refinement based on color coherence vectors was proposed in [3]. Thetechnique considers spatial information and classifies pixels of histogram buckets as coherent if they belong to asmall region and incoherent otherwise. Though being computationally expensive, the technique improves performance of histogram based matching. Color correlogram feature for images was proposed in [2] whichtake into account local color spatial correlation as well as global distribution of this spatial correlation. The correlogram gives the change of spatial correlation ofpairs of colors with distance and hence performs well overclassical histogram based techniques. A modified histogram based technique to incorporate spatial layout information of each color with annular, angular and hybrid histograms has been proposed in [4]. In [5], cumulative histogram and respective distances for image similaritymeasures, overcoming quantization problem of the histogram bins was proposed.

The representation of color distribution features for each color channel based onaverage, variance and skewness, described as moments, for image similarity was also presented. Various segmentation techniques based on edge detection, contour detection and region formation have been reported in the literature. These techniques, in general, process low level cues for deriving image featuresby following bottom-up approach. Automatic image segmentation is a very crucial phase as the overallperformance of retrieval results significantly depends onthe precision of the segmentation. The most difficult taskfor any automatic image segmentation algorithm is toavoid under and over segmentation of images, possessing diversified characteristics. Hence, for required scale of segmentation, parameter tuning or threshold adjustment becomes unavoidable for versatile image segmentation algorithms. Directional changes in color and texture have beenidentified in [10], using predictive color model to detect boundaries by iteratively propagating edge flow.

This iterative method is computationally expensive because ofprocessing of low level cues at all pixels for given scale. A novel hierarchical classification frame work basedapproach for boundary extraction with Ulrtametric Contour Maps UCM - representing geometric structure ofan image has been proposed in [7]. A generic grouping algorithm based on Oriented Watershed Transform and UCM [7] has been proposed in [6] to form a hierarchical region tree, finally leading to segmentation. The method enforces bounding contour closures, avoiding leaks a root cause of under segmentation. Exhaustive precisionrecallevaluation of OWT-UCM technique for differentscales also has been presented. Region based imageretrieval, incorporating graphs, multiple low level labelsand their propagation, multilevel semantic representation and support vector machine has been proposed in [14], implying effectiveness of the method.In [14], the models and techniques were used to merge textual and image features to classifyimages. Lu [15] proposed the framework of relevance feedback technique to take advantage of the semantic network on top of the keyword association on the images in addition to the low-level features.

Chang [6] further improved this framework using the probabilisticoutput of SVM to perform annotation propagation inorder to updating unlabeled images in addition to labeled images. [7] Proposed a unified image retrieval framework based on both keyword annotations andimage visual feature. For each keyword, a statistical model is trained by using visual feature of labeled images. Moreover, an effective update keyword models using newly labeled images periodically approach isproposed. However, the common limitation of this framework is the keyword models built from visual feature of a set of images are labeled with semantickeywords.In this paper, we utilize the search engine to retrievea large number of images using a given text-based query. In the low-level image retrieval process, thesystem provides a similar image search function for theuser to update the input query for image similaritycharacterization.

The proposed scheme is not the sameas the existing framework of unifying keywords andvisual content systems. The key word models built from visual feature of a set of images are labeled withkeywords. It incorporates an image analysis algorithm into the text-based image search engines. Moreover, it is implemented on real-world image database. A high-level semantic retrieval can be done by using relevance images from Yahoo image search engine. For low-level feature, we introduce a fast and robust color feature extraction technique namely auto color correlogram and correlation (ACCC) based on color correlogram (CC)[7] and autocorrelogram (AC) [7] algorithms, for extracting and indexing low-level features of images.The retrieval performance is satisfactory and higher thanthe average precision of the retrieved images using autocorrelogram (AC). Moreover, It can reduce computational time from O(m2d) to O(md) [8]. Theframework of multi-threaded processing is proposed toincorporate an image analysis algorithm into the text basedimage search engines. It enhances the capabilityof an application when downloading images, indexing and comparing the similarity of retrieved images fromdiverse sources.

3. CBIR Systems

A brief summary of some of the CBIR systems hasbeen presented in this section. QBIC - Query By ImageContent system, developed by IBM, makes visual content similarity comparisons of images based on properties such as color percentages, color layout, and textures occurring in the images. The query can either be example images,user-constructed sketches and drawings or selected colorand texture patterns [6] [7]. The IBM developed QBIC technology based Ultimedia Manager Product for retrievalof visually similar images [8]. Virage 35] and Excaliburare other developers of commercial CBIR systems.Visual Seek- a joint spatial-feature image searchengine developed at Columbia university performs image similarity comparison by matching salient color regionsfor their colors, sizes and absolute & relative spatiallocations[9][3]. Photo book developed at MediaLaboratory, Massachusetts Institute of Technology – MITfor image retrieval based on image contents where in color, shape and texture features are matched for euclidean, mahalanobis, divergence, vector space angle, histogram, Fourier peak, and wavelet tree distances. Theincorporation of interactive learning agent, named Four Eyes for selecting & combining feature-based models has been a unique feature of Photo book [11]. MARS -Multimedia Analysis and Retrieval Systems [12] and FIRE- Flexible Image Retrieval Engine [13] incorporate relevance feedback from the user for subsequent result refinements. Similar images are retrieved based on color features, Gabor filter bank based texture features, Fourier descriptor based shape features and spatial location information of segmented image regions in NeTra [14].For efficient indexing, color features of image regions has been represented as subsets of color code book containing total of 256 colors.

The frame work proposed in [10] has been incorporated for image segmentation in NeTra. PicSOM (Picture & Self-organizing Map) was implemented using tree structured SOM, where SOM was used for image similarity scoring method [3]. Visual content descriptors of MPEG-7 (Moving Pictures Expert Group Multimedia Content Description Interface) were used in PicSOM [6] for CBIR techniques and performance comparison with Vector Quantization basedsystem was proposed in [3]. Incorporation of relevance feedback in it caused improvements in the precision ofresults of Picsom. SIMPLIcity Semantics sensitive Integrated Matching for Picture Libraries incorporates integrated region matching methodology for overcomingissues related to improper image segmentation. The segmented images are represented as sets of regions.These regions, roughly corresponding to objects are characterized by their colors, shapes, textures and locations. The way of distance computation was inspired by the paper[5], where the detailed description of the method can befound. To measure the distance on the basis of the part **v**CLD the method was modified to deal with the three values referring to the three components of a color.

The distance is transformed into the range (0-100). In particular 0 means the same image. The example of visual distance calculation betweena query image and each of images in the database. For thequery image the similarity vector to each image in the base is obtained. In the performed experiments weights wFCTH and wCEDD were set to 2, because these descriptors have the best individual retrieval scores. Remaining weights were equal to 1.The second component in evaluation of images similaritytakes into account emotional aspect and is based on the vecto**re**. For every matching label, 1 is added to a temporal resultand then the final number is casted on the range 0-100, with 0 denoting maximal similarity. The query image is describedby a vector of emotional similarities to each database image. Finally, both results (visual and emotional) are added and divided by 2. This is the final answer of the system. In a case with multiple query images, an average from all rankings is taken. Twelve images from the database with thesmallest values are presented to the user.

4. Image Browsing Example

Query based on texture properties will have many applications inimage and multimedia databases. Here, we describe with an example our current work on incorporating these features forbrowsing large satellite images and air photos. This work relates tothe UCSB Alexandria digital library project [11] whose goal is tocreate a digital library of spatially indexed data such as maps andsatellite images. Typical images in such a database range from few megabytes to hundreds of megabytes, posing challenging problems in image analysis and visualization of data. Content based retrieval will be very useful in this context in answering queriessuch as "Retrieve all LANDSAT images of Santa Barbara whichhave less than 20% cloud cover," or "Find a vegetation patch thatlooks like this region."We are currently investigating the use of texture primitives to accomplish rapid content based browsing within an image or across similar images.

$$E = \frac{\frac{N_{pr}}{N_{sr}}}{1 + 0.05 \cdot (N_{Runs} - 1)} \cdot 100\% \quad (1)$$

The example of browsing 5,248 x 5,248air photos. The original image is analyzed in blocks 128 x 128 pixels and the texture features are computed and stored as image"meta-data." The user can select any position and use that pattern tosearch for similar looking regions. Our current work is on incorporating simple texture based segmentation schemes into this browsingthus allowing arbitrarily shapeoi regions into the analysis. Percentage of correctly assigned labels is used as measurementof system’s efficiency because more common measures like recall and precision can not be used here. The system hasto return 12 pictures in every run, so there is no possibility todefine a set of false positives (even if some pictures score lessthan others, they are still present in results as complementto true positives). Moreover, if more than 12 images in thedatabase are similar to the query image, the system has no possibility to show them all as a result.As it can be seen in Table II, the network trained on a moregeneral learning set (LS3) performs better than the one trained on less general one (LS1).

The most problematic categories are basic emotions and positive-negative. It proves that emotional content of pictures cannot be fully expressed only with chosenby us visual descriptors.The network was trained two times on learning set LS3(starting from random values of weights) and answers of thenetwork from both trials were compared. Only in 17% of casesboth networks were wrong and most of these mistakes wereconnected to basic emotions, which were not possible to be discovered without semantic knowledge about the picture. In20% of cases one of the networks was wrong.

4.1 Emotions’ filter

Emotion filter is a tool which uses vector **e** to producefinal similarity score between two pictures. Without it, only vector **v** is used. To evaluate an input ofan emotion filter to the final result, the same tests as in thesubsection IV-B were run, but without calculating the vector of emotional distance between pictures. It is clear that emotions are important in the image retrieval process and improve results of traditional CBIR systems. Inthe EBIR system, more adequate pictures are found and itis done faster. Moreover, it can be noticed that the numberof not relevant images (for example green building returned for tropical forest query) decreases when emotions’ filter wasused. Quality of results is higher for the system with the filter,what supports our theory.

5. The Proposed Framework

Self Supporting Retrieval Map Algorithm Before introducing our framework of multi-threading for a joint querying image search scheme, we will briefly examine the properties of the queries to be answered.The query modalities require different processing methods and support for user interaction. We can characterize query processing from a system perspective including text-based, content-based, composite, interactive-simple, and interactive-composite [9].Our retrieval model is interactive-composite because itintegrates multi-model information (associated text,visual similarity, and user’s feedbacks) for providing search results. We have developed a novel framework ofreal-time processing for an on-line CBIR system, using relevance images from Yahoo images search. Thismethod uses the following major steps: (a) YahooImages is first used to obtain a large number of images that are returned for a given text-based query; (b) The users can select any certain images to perform an update the input query for image similarity characterization; (c) A multi-threaded processing method is used to manage and perform data parallelism or loop-level parallelism such as downloading images, extraction of visualfeatures and computation of visual similarity measures.

(d) If necessary, users can also change a keyword before selecting a relevance image for the query; (e) The updated queries are further used to adaptively create anew answer for the next set of returned imagesaccording to the users’ preferences.

$$ACCC(i,j,k) = \left\{ \gamma_{C_i}^{(k)}(I),\ MC_j\, \gamma_{C_i,VC_j}^{(k)}(I) \right\} \quad (2)$$

5.1 A Framework Design for Multi-ThreadProcessing

The image indexation and similarity measure computation of images are complex processes and theyare an obstacle for the development of a practical CBIRsystem. Especially, when it is developed based on areal-time process optimization approach.There are anumber of papers concerning parallel computing forimage processing [10] [11] [12] , For instance,Yongquan Lu, et al [3] presented a paralleltechnique to perform feature extraction and asimilarity comparison of visual features, developed on cluster architecture. The experiments conducted show that a parallel computing technique can be applied that will

$$d(I,I') = \lambda_1 \sum_{\forall i} \frac{|\alpha_i - \alpha_i'|}{1+\alpha_i+\alpha_i'} + \lambda_2 \sum_{\forall i} \frac{|\beta_i - \beta_i'|}{1+\beta_i+\beta_i'} \quad (3)$$

significantly improve the performance of a retrieval system. Kao, et al [4] proposed a clusterplatform, which supports the implementation of retrieval approaches used in CBIR systems. Their paperintroduces the basic principles of image retrieval with dynamic feature extraction using cluster platform architecture. The main focus is workload balancingacross the cluster with a scheduling heuristic and execution performance measurements of the implemented prototype. Although, cluster computing is popularly used in images retrieval approaches, it only attacks this problem at the macro level. Fortunately,with the increasing computational power of moderncomputers, some of the most time-consuming tasks inimage indexing and retrieval are easily parallelized, sothat the multi-core architecture in modern CPU and multi-threaded processing may be exploited to speed upimage processing tasks. It is possible to incorporate animage analysis algorithm into the text-based imagesearch engines such as Google, Yahoo, and Bing withoutdegrading their response time. Multi-threading is not thesame as distributed processing.

6. Feature Extraction

There are various visual descriptors used to extract alow-level feature vector of an image[3]. However, in this paper, we usedcolor descriptors for retrieving images. The color the texture database used in the experiments consists of 116 different texture classes. Each of the 512 x 512 images is divided into16 128 x 128 no overlapping sub images, thus creating a database of 1,856 texture images. A query pattern in the following is anyone of the 1,856 patterns in the database. This pattern is then processed to compute the feature vector as in (7). The distance d(i, j),where i is the query pattern and j is a pattern from the database, iscomputed. The distances are then sorted in increasing order and the closest set of patterns are then retrieved. correlogram is an efficient feature extraction techniques used in content-based image retrieval (CBIR) systems. The technique, namely color correlogram, is widely used for finding the spatial correlation of each color in animage. It was introduced by Huang J. et al [7]. The technique was implemented and it was found that the retrieval performance of a color correlogram was betterthan the standard color histogram and the color coherence vector methods. However, the color correlogram is expensive to compute and the computation time of the correlogram is O(m2d). The authors also present a technique that captures the spatial correlation between identical colors called an autocorrelogram with a computation time of O(md).However, an autocorrelogram only captures thedistribution of each color in the image. The disadvantages are: 1) the color correlogram hascomputation complexity, and 2) the auto correlogram mainly captures the distribution of each color in theimages. They mainly capture spatial information of thecolors. In this section, we present an efficient colorfeature extraction algorithm for low-level feature similarity in query process, namely Auto ColorCorrelogram and Correlation (ACCC) [8], The retrieval performance is satisfactory and higher than the averageprecision of the retrieved images using autocorrelogram(AC). The ACCC is the integration of Autocorrelogram and Auto Color Correlation techniques [6]. It is a fastand robust algorithm for spatial color feature extractionfor image indexing.

7. Experimental Result

We have implemented a joint querying image search scheme using the Yahoo image database based on the Evaluation of retrieval performance is a crucial problem in Content-Based Image Retrieval (CBIR).Many different methods for measuring the performance of a system have been created and used by researchers. We have used the most common evaluation methods namely, Precision and RecallYahoo BOSS' API.

The application are developed by using Microsoft .NET and implemented on Quad Intel Xeon processor E5310 1.60 GHz, 1066 MHz FSB 1 GB (2 x 512 MB) PC2-5300 DDR2, and tested on the Windows NT environment.The goal of this experimentis to show that relevant images can be found after asmall number of iterations, the first round was used inthis experiment. From the viewpoint of User design, precision and recall measures are less appropriate for assessing an interactive system evaluate the performance of the system in terms of user feedback user-

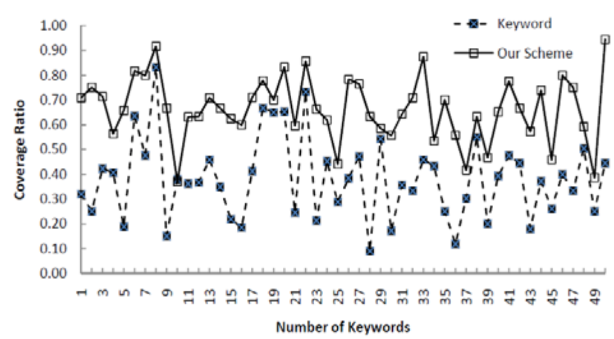

Fig 2. Comparison of the traditional Yahoo text-based search and our scheme with the SSRM algorithm

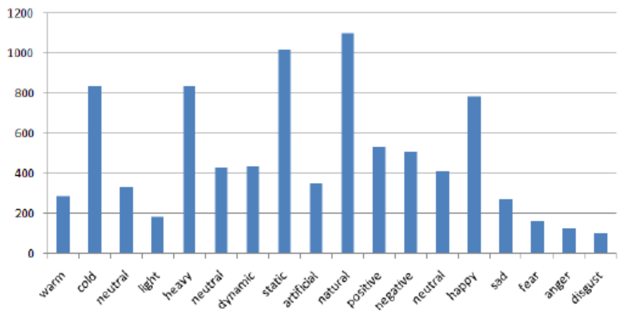

Fig 3. Number of representatives of emotions in SSRM

It alsodecreases the opportunity of the images in othercategories to be retrieved. In the experiment, we usedtwo sample images obtained from the keyword search totest querying images for evaluating the performance ofthe system.

8. Conclusions

This paper proposed an on-line content-based image retrieval system using joint querying and relevance feedback scheme. The proposed framework can beefficiently merged textual and image features for image retrieval systems. To incorporate an image analysis algorithm into the text-based image search engines without degrading their response time, the framework ofmulti-threaded processing is developed. In a high-level semantic retrieval system, we utilized the search engine to retrieve a large number of images using a given text based query. In low-level image retrieval process, the system provides a similar image search function.

References

[1] M. Swain and D. Ballard, “Color indexing”, InternationalJournal of Computer Vision, 7(1), 1991, pp. 11–32.

[2] J. Huang, S. R. Kumar, M. Mitra, W. Zhu and R. Zabih,“Image Indexing Using Color Correlograms”, IEEEComputer Society Conference on Computer Vision andPattern Recognition, 1997, pp. 762 – 768.

[3] G. Pass and R. Zabih, “Histogram Refinement for ContentBased Image Retrieval”, 3rd IEEE Workshop onApplications of Computer Vision, WACV , 1996 , pp. 96-102.

[4] A. Rao, R. K. Srihari and Z. Zhang, “Spatial ColorHistograms for Content-Based Image Retrieval”, 11thIEEE International Conference on Tools with ArtificialIntelligence, 1999, pp. 183 – 186.

[5] M. A. Stricker and M. Orengo, “Similarity of colorimages”, Proc. of the SPIE conference on the Storage andRetrieval for Image and Video Databases III, 1995, pp.381–392.

[6] P. Arbel´aez, M. Maire, C. Fowlkes, and J. Malik, “FromContours to Regions: An Empirical Evaluation”, CVPR2009, pp. 2294-2301.

[7] P. Arbel´aez, “Boundary Extraction in Natural ImagesUsing Ultrametric Contour Maps”, Proceedings of the2006 Conference on Computer Vision and PatternRecognition Workshop (CVPRW’06), 2006, pp. 182-182.

[8] J. Malik, S Belongie, T LeungAnd J Shi, “Contour andTexture Analysis for Image Segmentation”, InternationalJournal of Computer Vision, Vol. 43, Issue 1, 2001, pp. 7-27.

[9] D. Comaniciu and P. Meer, “Mean shift: A robust approachtoward feature space analysis”, IEEE transaction on PAMI,Vol. 24, No 5, May 2002, pp. 603-619.

[10] W. Ma and B. S. Manjunath, “EdgeFlow: A Technique forBoundary Detection and Image Segmentation”, IEEEtransaction on, Image Processing, Vol. 9, Issue 8, August2000, pp. 1375-1388.

[11] R. C. Veltkamp and M. Hagendoorn, “State-of-the-Art inShape Matching”, Multimedia Search: State of the Art,Springer-Verlag, 2000.

[12] M. Kass, A. Witkin and D. Terzopoulos, “Snakes: ActiveContour Models”, IJCV, 1988, pp. 321-331.

[13] V. Ferrari, L. Fevrier, F. Jurie, and C. Schmid, “Groups ofAdjacent Contour Segments for Object Detection”, IEEEtransaction on PAMI, Volume 30 , Issue 1, Jan. 2008, pp.36-51.

[14] F. Li, Q. Dai, W. Xu and G. Er, “Multilabel NeighborhoodPropagation for Region-Based Image Retrieval”, IEEETransactions On Multimedia, Vol. 10, No. 8, December2008, pp. 1592-1604.

[15] P.S.Hiremath, S.Shivashankar, ” WAVELET BASED FEATURES FOR TEXTURE CLASSIFICATION”, GVIP Journal, Volume 6, Issue 3, December, 2006

[16] Subrahmanyam Murala, Anil Balaji Gonde, R. P. Maheshwari,” Color and Texture Features for Image Indexing and Retrieval”, 2009 IEEE International Advance Computing Conference (IACC 2009) Patiala, India, 6-7 March 2009.

[17] L. Kotoulas and I. Andreadis, “Colour histogram content-based image retrieval and hardware implementation”, IEE Proc.-Circuits Devices Syst., Vol. 150, No. 5, October 2003.

[18] T F. Ang , 2 Y K. Cheong, 3 L Y. Por, 4 K K. Phang, “Colour-Based Image Retrieval Using Global Colour Histogram and Harbin”, Multimedia Cyberscape Journal, Volume 5, Number 1, Year 2007.

[19] Igor Marinovi and Igor Fürstner Manufaktura d.o.o., Subotica, Serbia “Content-based Image Retrieval ”, 1-4244-2407-8/08/$20.00 ©2008 IEEE.

[20] Dengsheng Zhang and Guojun Lu , “EVALUATION OF SIMILARITY MEASUREMENT FOR IMAGE RETRIEVAL”, 1-4240-2407-8/08/$25.00 ©2004 IEEE

[21] Greg Pass Ramin Zabih*, “Histogram Refinement for Content-Based Image Retrieval”, 0-8186-7620-5/96 $5.00 0 1996 IEEE.

P.Jayaprabha received the MCA. degree in 2002 from Bharathidasan University, Trichy, Tamilnadu, India. She is pursuing the Ph.D degree in Anna University of Technology, Coimbatore, and going to submit her thesis in image processing. Currently working as Professor in the Department of MCA, in Vidyaa Vikas College of Engineering & Technology, Tamil Nadu, India. Her current research interest includes document analysis, optical character recognition, pattern recognition and network security. She is a life member of ISTE..

Rm. Somasundaram received a Ph.D in Computer Science in 2000, from the University of Periyar, Tamilnadu, India. He is working as a Professor at SNS College of Engineering, Coimbatore, Tamilnadu, India, specialised in the field of Computer Science. He published many papers on computer vision applied to automation, motion analysis, image matching, image classification and view-based object recognition and management oriented empirical and conceptual papers in leading journals and magazines. His present research focuses on statistical learning and its application to computer vision and image understanding and problem recognition.