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Content Based Image Retrieval Methods Using Self Supporting Retrieval Map Algorithm

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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 searchfunction for the user to update the input query for image similarity characterization. The revolutionary internet and digital technologies haveimposed a need to have a system to organize abundantlyavailable digital images for easy categorization andretrieval. These techniques encompass diversifiedareas, viz. image segmentation, image feature extraction,representation, mapping of features to semantics, storage and indexing, image similarity distance measurementand retrieval making CBIR system development achallenging task. The state of the art techniques are reviewedand future scope is cited.Theexperimental evaluations based on coverage ratio measure show that our scheme significantly improves the retrievalperformance 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 requiredquerysimilar images fromabundantly 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 metadataassociated with digital images. The paper addresses and analyseschallenges & issues of CBIR techniques/systems, evolvedduring recent years covering various methods forsegmentation; edge, boundary, region, color, texture, andshape based feature extraction; object detection andidentification. For better precision of theretrieved resultant images, this type of search requiresassociating meaningful image descriptive text labels asmetadata with all images of the database.

Manual imagelabeling, known as manual image annotation, is practicallydifficult for exponentially increasing image database. Theimage 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 semanticmatching with the query, showing vast scope of researchleading to improvements in the state-of-art-techniques. The need evolved two solutions automatic imageannotation 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 databaseimages 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 applyingappropriate similarity measures for retrieving query similar Images.In the area of CBIR, it overcomes thedifficulties of manual annotations by using visualfeature based representations, such as color, texture,shape, etc.However, after over a decade of intensified.The major bottleneck of this approach is the gapbetween visual feature representations and semanticconcepts of images. Low-level contents often don't describe the high level.

Semantic concepts in users minds. Some researcher considered to improve thisburden, one promising direction towards semanticretrieval is the adoption of relevance feedbackmechanism [8]. Many researchers focus on theserelevance techniques because they are important inachieving a better precision rate [9]. Thetechnique is a variation of "query by example" thatinvolves multiple interactions with a user at search time[6]. It refers to the feedback from a user on specificitems regarding their

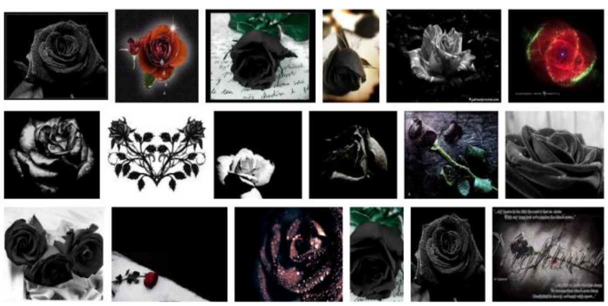

Fig 1. Image search results for query – rose black

relevance to a target image, in eachiteration, the refined query is re-evaluated.

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 andshapes have been reported in the literature.Histogram is one of the simplest image features.Despite being invariant to translation and rotation aboutviewing axis, lack of inclusion of spatial information is itsmajor drawback. Many totally dissimilar images mayhave similar histograms as spatial information of pixels isnot reflected in the histograms. Consequently, manyhistogram refinement techniques have been reported in theliterature. Histogram intersection based method forcomparing 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 classifiespixels of histogram buckets as coherent if they belong to asmall region and incoherent otherwise. Though beingcomputationally expensive, the technique improvesperformance of histogram based matching. Colorcorrelogram feature for images was proposed in [2] whichtake into account local color spatial correlation as well asglobal distribution of this spatial correlation. Thecorrelogram gives the change of spatial correlation ofpairs of colors with distance and hence performs well overclassical histogram based techniques. A modifiedhistogram based technique to incorporate spatial layoutinformation of each color with annular, angular and hybridhistograms has been proposed in [4]. In [5], cumulativehistogram and respective distances for image similaritymeasures, overcoming quantization problem of thehistogram bins was proposed.

The representation of colordistribution features for each color channel based onaverage, variance and skewness, described as moments,for image similarity was also presented.Various segmentation techniques based on edgedetection, contour detection and region formation havebeen reported in the literature. These techniques, ingeneral, process low level cues for deriving image featuresby following bottom-up approach. Automatic imagesegmentation 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, possessingdiversified characteristics. Hence, for required scale ofsegmentation, parameter tuning or threshold adjustmentbecomes unavoidable for versatile image segmentationalgorithms.Directional changes in color and texture have beenidentified in [10], using predictive color model to detectboundaries by iteratively propagating edge flow.

Thisiterative 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 groupingalgorithm based on Oriented Watershed Transform andUCM [7] has been proposed in [6] to form a hierarchicalregion tree, finally leading to segmentation. The methodenforces bounding contour closures, avoiding leaks aroot 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 representationand support vector machine has been proposed in [14],implying effectiveness of the method.In [14], the models and techniques wereused to merge textual and image features to classifyimages. Lu [15] proposed the framework of relevancefeedback technique to take advantage of the semanticnetwork on top of the keyword association on theimages 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 labeledimages. [7] Proposed a unified image retrievalframework based on both keyword annotations andimage visual feature. For each keyword, a statisticalmodel is trained by using visual feature of labeledimages. Moreover, an effective update keyword modelsusing newly labeled images periodically approach isproposed. However, the common limitation of thisframework is the keyword models built from visualfeature 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-basedquery. 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 fromvisual feature of a set of images are labeled withkeywords. It incorporates an image analysis algorithminto the text-based image search engines. Moreover, it isimplemented on real-world image database. A high-levelsemantic retrieval can be done by using relevanceimages from Yahoo image search engine. For low-levelfeature, we introduce a fast and robust color featureextraction technique namely auto color correlogram andcorrelation (ACCC) based on color correlogram (CC)[7] and autocorrelogram (AC) [7] algorithms, forextracting and indexing low-level features of images.The retrieval performance is satisfactory and higher thanthe average precision of the retrieved images usingautocorrelogram (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 contentsimilarity comparisons of images based on properties suchas color percentages, color layout, and textures occurringin the images. The query can either be example images,user-constructed sketches and drawings or selected colorand texture patterns [6] [7]. The IBM developed QBICtechnology 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 imagesimilarity 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 incolor, shape and texture features are matched foreuclidean, mahalanobis, divergence, vector space angle,histogram, Fourier peak, and wavelet tree distances. Theincorporation of interactive learning agent, namedFour Eyesfor selecting & combining feature-based modelshas been a unique feature of Photo book [11]. MARS - Multimedia Analysis and Retrieval Systems [12] andFIRE-Flexible Image Retrieval Engine [13] incorporaterelevance feedback from the user for subsequent resultrefinements. Similar images are retrieved based on colorfeatures, Gabor filter bank based texture features, Fourierdescriptor based shape features and spatial locationinformation of segmented image regions in NeTra [14].For efficient indexing, color features of image regions hasbeen represented as subsets of color code book containingtotal of 256 colors.

The frame work proposed in [10] hasbeen incorporated for image segmentation in NeTra. PicSOM (Picture & Self-organizing Map) wasimplemented using tree structured SOM, where SOM wasused for image similarity scoring method [3]. Visualcontent descriptors of MPEG-7 (Moving Pictures ExpertGroup Multimedia Content Description Interface) wereused in PicSOM [6] for CBIR techniques andperformance comparison with Vector Quantization basedsystem was proposed in [3]. Incorporation of relevancefeedback in it caused improvements in the precision ofresults of Picsom. SIMPLIcity SemanticssensitiveIntegrated Matching for Picture Libraries incorporatesintegrated 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 arecharacterized by their colors, shapes, textures andlocations.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**CLDthe method was modified to deal with the three values referringto the three components of a color.

The distance is transformedinto 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 isobtained.In the performed experiments weights wFCTH and wCEDDwere set to 2, because these descriptors have the best individualretrieval scores. Remaining weights were equal to 1.The second component in evaluation of images similaritytakes into account emotional aspect and is based on the vector**e**. For every matching label, 1 is added to a temporal resultand then the final number is casted on the range 0-100, with0 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 anddivided by 2. This is the final answer of the system. In a case with multiple query images, an average from allrankings 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 exampleour 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 fewmegabytes to hundreds of megabytes, posing challenging problems in image analysis and visualization of data. Content basedretrieval 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 accomplishrapid content based browsing within an image or acrosssimilar images.

The example of browsing 5,248 x 5,248air photos. The original image is analyzed in blocks 128 x 128 pixelsand 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 incorporatingsimple 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 measureslike 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 nopossibility 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 trainedon less general one (LS1).

The most problematic categories arebasic emotions and positive-negative. It proves that emotionalcontent 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

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

emotions, which were not possible to bediscovered 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

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

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 retrievalprocess 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 returnedfor 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 AlgorithmBefore introducing our framework of multi-threading fora joint querying image search scheme, we will brieflyexamine the properties of the queries to be answered.The query modalities require different processingmethods and support for user interaction. We cancharacterize query processing from a system perspectiveincluding text-based, content-based, composite,interactive-simple, and interactive-composite [9].Ourretrieval model is interactive-composite

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

because itintegrates multi-model information (associated text,visual similarity, and user's feedbacks) for providingsearch results. We have developed a novel framework ofreal-time processing for an on-line CBIR system, usingrelevance images from Yahoo images search.

Thismethod uses the following major steps: (a) YahooImages is first used to obtain a large number of imagesthat are returned for a given text-based query; (b) Theusers can select any certain images to perform an updatethe input query for image similarity characterization; (c)A multi-threaded processing method is used to manageand perform data parallelism or loop-level parallelismsuch as downloading images, extraction of visualfeatures and computation of visual similarity measures.
(d) If necessary, users can also change a keyword beforeselecting a relevance image for the query; (e) Theupdated queries are further used to adaptively create anew answer for the next set of returned imagesaccording to the users' preferences.

5.1 A Framework Design for Multi-ThreadProcessing

The image indexation and similarity measurecomputation 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, developedon cluster architecture. The experiments conductedshow that a parallel computing technique can be appliedthat will significantly improve the performance of aretrieval system. Kao, et al [4] proposed a clusterplatform, which supports the implementation of retrievalapproaches used in CBIR systems. Their paperintroduces the basic principles of image retrieval withdynamic feature extraction using cluster platformarchitecture. The main focus is workload balancingacross the cluster with a scheduling heuristic andexecution performance measurements of theimplemented prototype. Although, cluster computing ispopularly used in images retrieval approaches, it onlyattacks 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 andmulti-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 colorthe texture database used in the experiments consists of 116 differenttexture classes. Each of the 512 x 512 images is divided into16 128 x 128 no overlappingsub images, thus creating a databaseof 1,856 texture images. A query pattern in the following is anyone of the 1,856 patterns in the database. This pattern is then processedto 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 andthe closest set of patterns are then retrieved.correlogram is an efficient feature extraction techniquesused in content-based image retrieval (CBIR) systems.The technique, namely color correlogram, is widely usedfor finding the spatial correlation of each color in animage. It was introduced by Huang J. et al [7]. Thetechnique was implemented and it was found that theretrieval performance of a color correlogram was betterthan the standard color histogram and the colorcoherence vector methods. However, the colorcorrelogram is expensive to compute and thecomputation time of the correlogram is O(m2d). Theauthors also present a technique that captures the spatialcorrelation between identical colors called anautocorrelogram with a computation time of O(md).However, an autocorrelogram only captures thedistribution of each color in the image. Thedisadvantages are: 1) the color correlogram hascomputation complexity, and 2) the auto correlogrammainly 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 featuresimilarity in query process, namely Auto ColorCorrelogram and Correlation (ACCC) [8], The retrievalperformance is satisfactory and higher than the averageprecision of the retrieved images using autocorrelogram(AC). The ACCC is the integration of Autocorrelogramand 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 searchscheme using the Yahoo image database based on theEvaluation of retrieval performance is a crucialproblem in Content-Based Image Retrieval (CBIR).Many different methods for measuring theperformance of a system have been created and usedby researchers. We have used the most commonevaluation 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 userdesign, precision and recall measures are lessappropriate for assessing an interactive system evaluate the performance of the system in terms of userfeedback user-

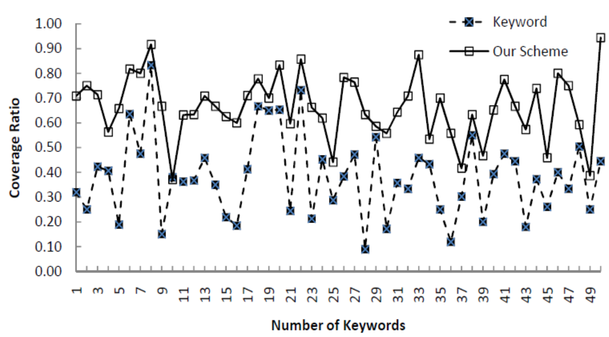

Fig 2. Comparison of the traditional Yahoo text-based search and our scheme with the SSRM algorithm

orientation measures are used. Therehave been other design factors proposed such as relativerecall, recall effort, coverage ratio, and novelty ratio [4]. In this experiment the coverage ratio measure isselected. Let R be the set of relevant images of query qand A be the answer set retrieved.

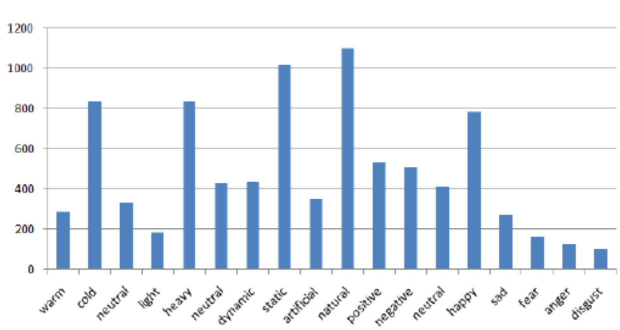

Fig 3. Number of representatives of emotions in SSRM

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 imageretrieval system using joint querying and relevancefeedback scheme. The proposed framework can beefficiently merged textual and image features for imageretrieval systems. To incorporate an image analysis algorithm into the text-based image search engineswithout degrading their response time, the framework ofmulti-threaded processing is developed. In a high-levelsemantic retrieval system, we utilized the search engineto retrieve a large number of images using a given text basedquery. In low-level image retrieval process, thesystem provides a similar image search function.

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