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Content Based Image Retrieval Systems

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Abstract: **The introduction of network and development of multimedia technologies are becoming more popular and so the users are not satisfied with the traditional information retrieval techniques. So nowadays the content based image retrieval are becoming a source of exact and fast retrieval. In this paper the techniques of content based image retrieval are discussed, analysed and compared. It also introduces the feature like neuro fuzzy technique, color histogram, texture and edge density for accurate and effective Content Based Image Retrieval System.**

Keywords: **Image retrival system, Multimedia Technology.**

1. INTRODUCTION

Everyday, both military and civilian equipments have been generating giga-bytes of images. Huge amounts of information are out there. However, we cannot access or make use of the information unless it is organized so as to allow efficient browsing, searching, and retrieval. Image retrieval has been a very active research area since the 1970s.Content Based Image Retrieval (CBIR) is a technology and it is a principle that helps to organize digital image archives by visual content. Anything that ranges from an image similarity function to a robust image annotation falls under CBIR. The most common form of CBIR is an image search based on visual. The amounts of increased digital images have led to the arrival of new methods to archive and access the data. Content Based Image Retrieval (CBIR) is a technique and it uses visual contents, normally represented as features, to search the images from large scale image databases according to the request given by the user in the form of a query image. Leaving the usual features aside, like color and texture, a new feature extraction algorithm called edge histogram is being introduced. Edges convey the essential information that are required in a picture and therefore it can be applied to image retrieval. The edge histogram captures the spatial distribution of edges. This model expects the input in the form of a Query for Example (QBE) and any combination of features can be selected for retrieval. The main focus is to build a universal CBIR system using low level features. They are mean, median, and standard deviation of Red, Green, and Blue channels of color histograms. Then the texture features such as contrast, energy, correlation, and homogeneity can be retrieved. Finally the edge features include five categories vertical, horizontal, 45 degree diagonal, 135 degree diagonal, and isotropic are added . Human being get images, sound and any other information by seeing, hearing or by perception and analysis. Humans usually judge similarity of images and sounds according to their semantic contents, for instance the searching for a star’s picture is based on his facial characters or other contents. So the retrieval methods based on the text or keywords for the digital multimedia apparently can’t meet the demand that human being can get the multimedia information exactly. With more and more multimedia information that appears on the Internet and other digital multimedia , as well as human beings need for exact and fast retrieval, based on this criteria’s multimedia information retrieval has become the focus of the academe research , as well as images retrieval of contents is one of the important study aspect of multimedia information retrieval. Existing color-based general-purpose image retrieval systems roughly fall into three categories depending on the approach used:

Histogram, color layout, and region-based search. The search methods based on the Histogram are investigated in two different color spaces. A color space is defined as a model for representing color in terms of their intensity values. Color spaces are related to each other by mathematical formulas. The two three-dimensional color spaces, RGB (Red ,Green

,Blue)and HSV, are investigated. CBIR involves the following four parts in system realization: data collection, build up the feature database, search in the database, arrange in order and deal with the results of the retrieval.

Data collection: This can be done by using the Internet spider program that can collect webs automatically in order to interview Internet and to do the collection of the images on the web site, and then it will go through all the other webs through the URL, repeating this process and collecting all the images it has reviewed into the server.

Build up feature database: By using the index system program we can proceed by doing an analysis for the collected images and extract the feature information. Currently, the features that are used widely involve low level features such as color, texture and so on, the middle level features such as shape etc.

Search the Database: The system can extract the feature of image that waits for the search when user gives the input image sample that needs to be search, then the search engine will search the suited feature from the database and calculate the similar distance, then will continue to find several related webs and images with the minimum similar distance.

Process and index the results: After researching , the image that is obtained from searching due to the similarity of features, are to be returned to the retrieval images , that is to the user and let the user select. If the user is not satisfied with the searching result, he can re-retrieval the image again, and searches database again.

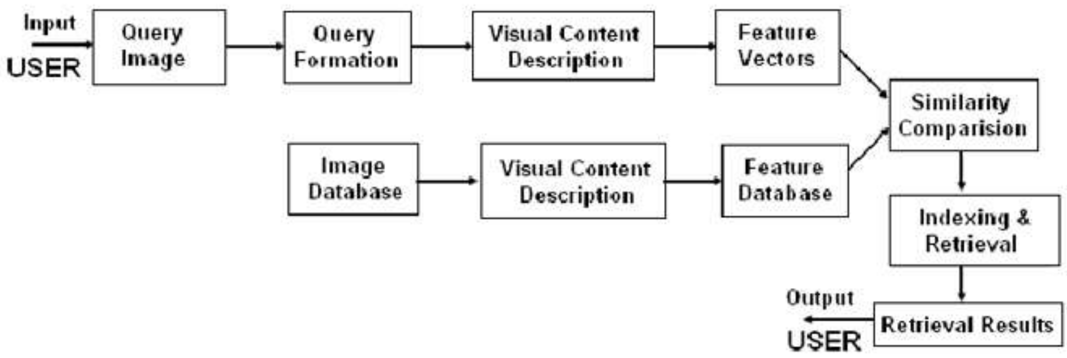

Figure 1. Flow Chart of Content Based Image Retrieval

The retrieval of content based image involves the following systems:

Color-based retrieval

Color feature is the most essential and obvious feature of the image, and generally they adopt histograms to describe it. Color histograms method has the advantages of speediness, low demand of memory space and not sensitive with the images changes of the size and rotation, it wins extensive attention consequently.

The retrieval based on texture feature

When it comes to the description of the images texture, we usually use texture's statistic feature and structure feature as well as the features that are based on special domain are changed into frequency domain.

The retrieval based on shape feature

There are three problems that need to be solved during the image retrieval that is based on the shape feature. First the shape is usually related to the specific object in the image so the semantic feature is stronger than texture.

The retrieval based on Neuro Fuzzy

The technique of neuro fuzzy content is based on the image retrieval system in two stages. Stage 1: the query to retrieve the images from database is prepared in terms of natural language such as mostly content, many content and few content of some specific color. Fuzzy logic is used to define the query.

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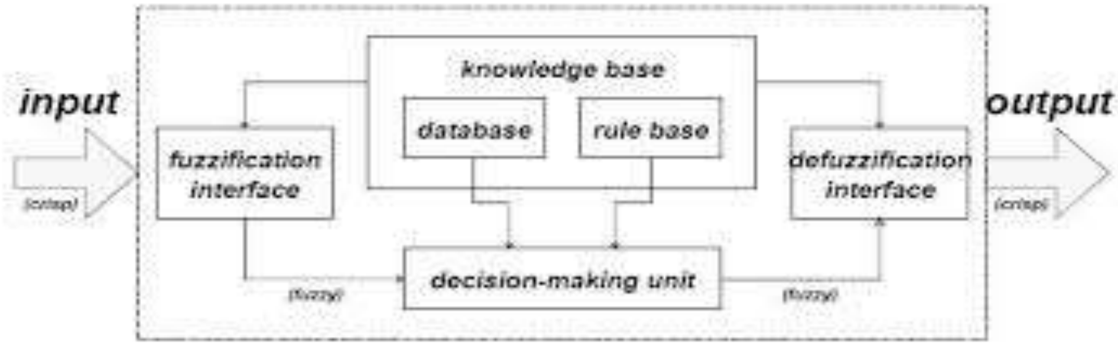

2. EVOLUTION

Content based image retrieval is also known as query by image content(QBIC) and content-based visual information retrieval (CBVIR) is the application computer vision techniques to the image retrieval problem, that is, the problem of searching for digital images in large databases (see this survey for a recent scientific overview of the CBIR field). Content-based image retrieval is opposed to traditional concept based approach. "Content-based" means that the search analyzes the contents of the image rather than the metadata such as keywords, tags, or descriptions associated with the image. The term "content" in this context might refer to colors, shapes, textures, or any other information that can be derived from the image itself. CBIR is desirable because searches that rely purely on metadata are dependent on annotation quality and completeness. Having humans manually annotate images by entering keywords or metadata in a large database can be time consuming and may not capture the keywords desired to describe the image. The evaluation of the effectiveness of keyword image search is subjective and has not been well-defined. In the same regard, CBIR systems have similar challenges in defining success.

In 1979, a conference on Database Techniques for Pictorial Applications was held in Florence. Since then, the application potential of image database management techniques has attracted the attention of researchers. In the early 1990s, as a result of advances in the Internet and new digital image sensor technologies, the volume of digital images produced by scientific, educational, medical, industrial, and other applications available to users increased dramatically. The difficulties faced by text based retrieval became more and more severe. The efficient management of the rapidly expanding visual information became an urgent problem. In 1996, Greg Pass Ramin Zabih described for comparing images called histogram refinement, which imposes additional constraints on histogram based matching. Histogram refinement splits the pixels in a given bucket into several classes, based upon some local property. Within a given bucket, only pixels in the same class are compared. Here describe a split histogram called a color coherence vector (CCV), which partitions each histogram bucket based on spatial coherence. After that Chad Carson, Serge Belongie, Hay it Greenspan, and Jitendra Malik Retrieved images from large and varied collections using image content as a key is a challenging and important problem.

In 1997 they present a new image representation which provides a transformation from the raw pixel data to a small set of localized coherent regions in color and texture space. This so-called “blobworld” representation is based on segmentation using the Expectation Maximization algorithm on combined color and texture features. The texture features we use for the segmentation arise from a new approach to texture description and scale selection. Then Yong Rui, Thomas S. Huang and Sharad Mehrotra in 1998 research many visual feature representations have been explored and many system built. While these research efforts establish the basis of CBIR, the usefulness of the proposed approaches is limited. Specifically, these efforts have relatively ignored two distinct characteristics of CBIR systems: the gap between high level concepts and low level features; subjectivity of human perception of visual content. This research proposes a relevance feedback based interactive retrieval approach, which effectively takes into account the above two characteristics in CBIR. During the retrieval process, the user’s high level query and perception subjectivity are captured by dynamically updated weights based on the user’s relevant feedback. This approach greatly reduces the user’s effort of composing a query and captures the user's information need more precisely. In 1999 Mircea Ionescu, Anca Ralescu analysed the performance of Content-Based Image Retrieval (CBIR) systems is mainly depending on the image similarity measure it use , the feature space of each image is real valued the Fuzzy Hamming Distance which can be successfully used as image similarity measure.

The study reports in 1999, shows the results of applying Fuzzy Hamming Distance as a similarity measure between the color histograms of two images. The Fuzzy Hamming Distance is suitable for this application because it can take into account not only the number of different colors but also the magnitude of this difference. Constantin Vertan , Nozha Boujemaa propose to revisit the use of color image content as an image descriptor through the introduction of fuzziness, which naturally arises due to the imprecision of the pixel color values and human perception. In 2000 they proposed the use of both fuzzy color histograms and their corresponding fuzzy distances for the retrieval of color images within various databases. Again in 2000 Stefano Berretti, Alberto Del Bimbo, and PietroPala, proposes retrieval by shape similarity using local descriptors and effective indexing. Shapes are partitioned into tokens in correspondence with their protrusions, and each token is modelled according to a set of perceptually salient attributes. Shape indexing is obtained by arranging shape tokens into a suitably modified M-tree index structure. Two distinct distance functions model respectively, token and shape perceptual similarity Arnold W.M. Smeulders, Marcel Worring, Simone Santini, Amarnath Gupta, and Ramesh Jain, [6] starts discussing In 2000 the working conditions of content-based retrieval: patterns of use, types of pictures, the role of semantics, and the sensory gap. Subsequent sections discuss computational steps for image retrieval systems. Step one of the review is image processing for retrieval sorted by color, texture, and local geometry. Features for retrieval are discussed next, sorted by: accumulative and global features, salient points, object and shape features, signs, and structural combinations thereof. Similarity of pictures and objects in pictures is reviewed for each of the feature types, in close connection to the types and means of feedback the user of the systems is capable of giving by interaction.

In the concluding section, presenting the view on : the driving force of the field, the heritage from computer vision, the influence on computer vision, the role of similarity and of interaction, the need for databases, the problem of evaluation, and the role of the semantic gap. ConstantinVertan, NozhaBoujemaa in 2001 focuses on the possible embedding of the uncertainty regarding the colors of an image into histogram type descriptors. The uncertainty naturally arises from both the quantization of the color components and the human perception of colors. Fuzzy histograms measure the typicality of each color within the image. And also define various fuzzy color histograms following a taxonomy that classifies fuzzy techniques as crude fuzzy, fuzzy paradigm based, fuzzy aggregational and fuzzy inferential. For these fuzzy sets, must develop appropriate similarity measures and distances. For a region-based image retrieval system, performance depends critically on the accuracy of object segmentation. Yixin Chen James Z Wang proposed a soft computing approach, unified feature matching (UFM), which greatly increases the robustness of the retrieval system against segmentation related uncertainties. In the retrieval system, an image is represented by a set of segmented regions each of which is characterized by a fuzzy feature (fuzzy set) reflecting color, texture, and shape properties. Ju Han and KaiKuang Ma, in 2002 presents a new color histogram representation, called fuzzy color histogram (FCH), by considering the color similarity of each pixel's color associated to all the histogram bins through fuzzy-set membership function. A novel and fast approach for computing the membership values based on fuzzy c-means algorithm is introduced. The proposed FCH is further exploited in the application of image indexing and retrieval. Experimental results clearly show that FCH yields better retrieval results than CCH. Minakshi Banerjee, Malay K. Kundu in 2003 discussed the common problem in content based image retrieval (CBIR) is selection of features. Image characterization with lesser number of features involving lower computational cost is always desirable. Edge is a strong feature for characterizing an image so a robust technique is presented for extracting edge map of an image which is followed by computation of global feature (like fuzzy compactness) using gray level as well as shape information of the edge map. Unlike other existing techniques it does not require pre segmentation for the computation of features. This algorithm is also computationally attractive as it computes different features with limited number of selected pixels. DeokHwanKim ,ChinWanChung in 2003 propose a new content-based image retrieval method using adaptive classification and cluster merging to find multiple clusters of a complex image query. When the measures of a retrieval method are invariant under linear transformations, the method can achieve the same retrieval quality regardless of the shapes of clusters of a query. Yuhang Wang, FilliaMakedon, James Ford, Li Shen Dina Goldin in 2004 propose a novel framework for automatic metadata generation based on fuzzy kNN classification that generates fuzzy semantic metadata describing spatial relations between objects in an image. For each pair of objects of interest, the corresponding R-Histogram is computed and used as input for a set of fuzzy k-NN classifiers. Typical content-based image retrieval (CBIR) system would need to handle the vagueness in the user queries as well as the inherent uncertainty in image representation, similarity measure, and relevance feedback. Raghu Krishnapuram, Swarup Medasani, Sung Hwan Jung, Young-Sik Choi, and Rajesh Balasubramaniam in 2004 discuss how fuzzy set theory can be effectively used for this purpose and describe an image retrieval system called FIRST (Fuzzy Image Retrieval SysTem) which incorporates many of these ideas. S. Kulkarni, B. Verma1, P. Sharma and H. Selvaraj proposed a neuro-fuzzy technique for content based image retrieval in 2005. The technique is based on fuzzy interpretation of natural language, neural network learning and searching algorithms. Firstly, fuzzy logic is developed to interpret natural expressions such as mostly, many and few. Secondly, a neural network is designed to learn the meaning of mostly red, many red and few red RouhollahRahmani, Sally A. Goldman, HuiZhang, John Krettek, and Jason E. Fritts [20] in 2005 presents a localized CBIR system , that uses labeled images in conjunction with a multiple instance learning algorithm to first identify the desired object and reweight the features, and then to rank images in the database using a similarity measure that is based upon individual regions within the image.

3. APPROCHES TO RETRIEVAL

Once a decision on the visual feature set choice has been made, how to steer them towards accurate image retrieval is the next concern. There has been a large number of fundamentally different frameworks proposed in the last few years. Leaving out those discussed in, here we briefly talk about some of the more recent approaches .A semantics-sensitive approach to content-based image retrieval has been proposed in. A semantic categorization (e.g., graph - photograph, textured, non-textured) for appropriate feature extraction followed by a region based overall similarity measure, allows robust image matching. An important aspect of this system is its retrieval speed. The matching measure, termed integrated region matching (IRM), has been constructed for faster retrieval using region feature clustering and the most similar highest priority (MSHP) principle . Region based image retrieval has also been extended to incorporate spatial similarity using the Hausdorff distance on finite sized point sets , and to employ fuzziness to characterize segmented regions for the purpose of feature matching . A framework for region-based image retrieval using region codebooks and learned region weights has been proposed in a new representation for object retrieval in cluttered images without relying on accurate segmentation has been proposed in another perspective in image retrieval has been region-based querying using homogeneous color texture segments called blobs, instead of image to image matching . For example, if one or more segmented blobs are identified by the user as roughly corresponding to the concept “tiger”, then her search can comprise of looking for a tiger within other images, possibly with varying backgrounds. While this can lead to a semantically more precise representation of the user’s query objects in general, it also requires greater involvement from and dependence on her. For finding images containing scaled or translated versions of query objects, retrieval can also be performed without the user’s explicit region labeling.

Instead of using image segmentation, one approach to retrieval has been the use of hierarchical perceptual grouping of primitive image features and their inter-relationships to characterize structure. Another proposition has been the use of vector quantization (VQ) on image blocks to generate codebooks for representation and retrieval, taking inspiration from data compression and text-based strategies. A windowed search over location and scale has been shown more effective in object-based image retrieval than methods based on inaccurate segmentation . A hybrid approach involves the use of rectangular blocks for coarse foreground/background segmentation on the user’s query region-of-interest (ROI), followed by the database search using only the foreground regions . For textured images, segmentation is not critical. A method for texture retrieval by a joint modeling of feature extraction and similarity measurement using the Kullback-Leibler distance for statistical model comparison has been proposed.Another wavelet-based retrieval method involving salientpoints has been proposed . Fractal block code based image histograms have been shown effective in retrieval on textured image databases . The use of the MPEG-7 content descriptors to train self-organizing maps (SOM) for the purpose of image retrieval has been explored .Among other new approaches, anchoring-based image retrieval system has been proposed.

Anchoring is based on the fairly intuitive idea of finding a set of representative "anchor" images and deciding semantic proximity between an arbitrary image pair in terms of their similarity to these anchors. Despite the reduced computational complexity, the relative image distance function is not guaranteed to be a metric. For similar reasons, a number of approaches have relied on the assumption that the image feature space is a manifold embedded in Euclidean space [38, 101, 39]. Clustering has been applied to image retrieval to help improve interface design, visualization, and result pre-processing [19, 61, 116]. A statistical approach involving the Wald-Wolfowitz test for comparing non-parametric multivariate distributions has been used for color image retrieval [92], representing images as sets of vectors in the RGB-space. Multiple-instance learning was introduced to the CBIR community in [114]. A number of probabilistic frameworks for image retrieval have been proposed in the last few years [48, 102]. The idea in [102] is to integrate feature selection, feature representation, and similarity measure into a combined Bayesian formulation, with the objective of minimizing the probability of retrieval error. One problem with this approach is the computational complexity involved in estimating probabilistic similarity measures. Using VQ to approximately model the probability distribution of the image features, the complexity is reduced [99], making the measures more practical for real-world systems.

4. ANNOTATION AND CONCEPT DETECTION

While image retrieval has been active over the years, an emerging new and possibly more challenging field is automatic concept recognition from visual features of images. The challenge is primarily due to the semantic gap [90] that exists between low level visual features and high level concepts. A note on the topic of concept and annotation: The primary purpose of a practical content based image retrieval system is to discover images pertaining to a given concept in the absence of reliable meta-data. All attempts at automated concept discovery, annotation, or linguistic indexing essentially adhere to that objective more closely than do systems which return an ordered set of similar images. Of course, ranked results have their own role to play, e.g. visualization of search results, retrieval of specific instances within a semantic class of images etc. Annotation, on the other hand, allows for image search through the use of text. For this purpose, automated annotation tends to be more practical for large data sets than a manual process. If the resultant automated mapping between images and words can be trusted, then text-based image searching can be semantically more meaningful than CBIR. Image understanding has been attempted through automated concept detection. The annotation process can be thought of as a subset of concept detection, i.e., images pertaining to the same concept can be described linguistically in different ways based on the specific instance of the concept. The question is whether visual features of images convey anything about their concept or not. Concept detection through supervised classification, involving simple concepts such as city, landscape, sunset, and forest, have been achieved with high accuracy in [98]. An extension of multiple-instance learning has been shown effective for categorization of images into semantic classes [18]. Learning concepts from user's feedback and within a dynamically changing image database using Gaussian mixture models is discussed in [27]. An approach to soft annotation, using Bayes Point machines, to give images a confidence level for each trained semantic label has been explored in [14]. This vector of confidence labels can then be exploited to rank relevant images in case of a keyword search. Automated annotation of pictures with a few hundreds of words using two-dimensional multi-resolution hidden Markov models has been explored in [65]. While the classification process chooses a set of categories an image may belong to, the annotation set is chosen in a way that favors statistically salient words for a given image. A confidence based dynamic ensemble of SVM classifiers has been used for the purpose of annotation in [62]. Many of the approaches to image annotation have been inspired by research in the text domain. In [29], the problem of annotation is treated as a translation from a set of image segments to a set of words, in a way analogous to linguistic translation. Hierarchical statistical methods for modeling the association between image segments and words, for the purpose of automated annotation, have been proposed in [5, 8]. Generative language models have been used for the task of image annotation in [45, 60]. Closely related is an approach, involving coherent language models, which exploits word-to-word correlations to strengthen annotation decisions [47]. All the annotation strategies discussed so far model visual and textual features separately prior to association. A departure from this trend is seen in [73], where latent semantic analysis (LSA) is used on uniform vectored data consisting of both visual features and textual annotations. The LSA model, previously used in document analysis, helps to identify semantically meaningful subspaces in the visual-textual feature space. Automated image annotation is a difficult question. We humans segment objects better than machines, having learned to associate over a long period of time, through multiple viewpoints, and literally through a "streaming video" at all times, which partly accounts for our natural segmentation. The association of words and blobs become truly meaningful only when blobs isolate objects well. Moreover, how exactly our brain does this association is still unclear. While Biology tries to answer this fundamental question, researchers in information retrieval tend to take a pragmatic stand in that they aim to build retrieval and annotation systems that have practical significance.

5. OPEN AREAS

There are various areas to work with for the improvement of the content based image retrieval system. It is already been discussed that the existing techniques may be used to improve the quality of image retrieval and the understanding of user intentions. An approach that combines two different approaches to image retrieval, together with active use of context information and interaction has been proposed. An important aspect of the research work outlined here is to design and evaluate a system that, in addition to combine the use of TBIR with CBIR [37]. Use of the hybrid feature including color, texture and shape as feature vector of the regions to match images can give better results. Results on a database of 1000 general-purposed images demonstrate the efficiency and effectiveness of the image representation for region based image retrieval. [33]. The technique called self taught multiple-instance learning (STMIL) that deals with learning from a limited number of ambiguously labeled examples is also a effective area to work with for efficient results. STMIL uses a sparse representation forexamples belonging to different classes in terms of a shared dictionary derived from the unlabeled data. This representation can be optimized under the multiple instances setting to both construct high level features and unite the data distribution [34].The problem of bridging the semantic gap between high level query which is normally in terms of an example image and low level features of an image such as colour, texture, shape and object forced to apply techniques to reduce the semantic gap. Existing techniques for image retrieval based on fuzzy logic and natural language query is a novel approach based on natural language fuzzy logic queries, fuzzy mapping of image database and fuzzy similarity distance for retrieving the images based on their contents. Fuzzy logic for the interpretation of the texture queries for content-based image retrieval is latest and effective technique [36].

6. CONCLUSION

The purpose of this survey is to provide an overview of the functionality of content based image retrieval systems. Most systems use color and texture features, few systems use shape feature, and still less use layout features. Fuzzy logic has been used extensively in various areas to improve the performance of the system and to achieve better results in different applications. The fuzzy inference integrates various features perfectly in content based image retrieval system and reflects the user's subjective requirements, the experiments achieve good performance and demonstrate the efficiency and robustness of system.

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