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A voluminous survey on Content based image retrieval

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Abstract:

The amount of images or the pictorial data is growing day by day with the expansion of internet services. As the network and development of multimedia technologies are becoming more popular, users are not satisfied with the traditional information retrieval techniques. So nowadays the content based image retrieval is becoming a source of exact and fast retrieval. . It is very difficult for the users to retrieve the required images using a operative and efficient mechanism. There are many techniques which are used to retrieve the images depending upon the requirement of different applications. This paper provides an extensive review of various latest research work and methodologies applied in the field of CBIR. Images are retrieved on the basis of automatically derived features such as, texture, shape and color which is generally referred to as Content-Based Image Retrieval (CBIR). Content based image retrieval is an important research area in image processing, with a vast domain of applications like recognition systems i.e. finger, face, biometrics, medical sciences etc. However, the technology still lacks maturity, and is not yet being used on a significant scale. In the absence of hard evidence on the effectiveness of CBIR techniques in practice, opinion is still sharply divided about their usefulness in handling real-life queries in large and diverse image collections.

Keywords — **Region Based Image Retrieval (RBIR), Subspace learning based Techniques, CBIR**

I. INTRODUCTION

During the last decade there has been a rapid increase in volume of image and video collections. A huge amount of information is available, and daily gigabytes of new visual information is generated, stored, and transmitted. However, it is difficult to access this visual information unless it is organized in a way that allows efficient browsing, searching, and retrieval. Data bases rely on a number of descriptive keywords, associated with each image. However, this manual annotation approach is subjective and recently, due to the rapidly growing database sizes, it is becoming outdated. To overcome these difficulties in the early 1990s, Content-Based Image Retrieval (CBIR) emerged as a promising means for describing and retrieving images. According to its objective, instead of being manually annotated by text-based keywords, images are indexed by their visual

Information Retrieval

In the past decade, more and more information has been published in computer readable formats. In the meanwhile, much of the information in older books, journals and newspapers has been digitized and made computer readable. Big archives of films, music, images, satellite pictures, books, newspapers, and magazines have been made accessible for computer users. Internet makes it possible for the human to access this huge amount of information. The greatest challenge of the World Wide Web is that the more information available about a given topic, the more difficult it is to locate accurate and relevant information. Most users know what information they need, but are unsure where to find it. Search engines can facilitate the ability of users to locate such relevant information.

In this computer age, virtually all spheres of human life including commerce,, academics, hospitals, crime prevention, surveillance, engineering, architecture, journalism, fashion and graphic design, and historical research use images for efficient services. A large collection of images is referred to as image database. An image database is a system where image data are integrated and stored [1]. Image data include the raw images and information extracted from images by automated or computer assisted image analysis.

The police maintain image database of criminals, crime scenes, and stolen items. In the medical profession, X-rays and scanned image database are kept for diagnosis, monitoring, and research purposes. In architectural and engineering design, image database exists for design projects, finished projects, and machine parts. In publishing and advertising, journalists create image databases for various events and activities such as sports, buildings, personalities, national and international events, and product advertisements. In historical research, image databases are created for archives in areas that include arts, sociology, and medicine. In a small collection of images, simple browsing can identify an image. This is not the case for large and varied collection of images, where the user encounters the image retrieval problem. An image is the problem encountered when searching and retrieving images that are relevant to a user's request from a database. To solve this problem, text-based and content-based are the two techniques adopted for search and retrieval in an image database.

Text-Based and Content-Based Image Retrieval

In text-based retrieval, images are indexed using keywords, subject headings, or classification codes, which in turn are used as retrieval keys during search and retrieval [2]. Text-based retrieval is non-standardized because different users employ different keywords for annotation. Text descriptions are sometimes subjective and incomplete because they cannot depict complicated image features very well. Examples are texture images that cannot be described by text. Textual information about images can be easily searched using existing technology, but requires humans to personally describe every image in the database. This is impractical for very large databases, or for images that are generated automatically, e.g. from surveillance cameras. It is also possible to miss images that use different synonyms in their descriptions. Systems based on categorizing images in semantic classes like "cat" as a subclass of "animal" avoid this problem, but still face the same scaling issues [3].

The Content Based Image Retrieval (CBIR) technique uses image content to search and retrieve digital images. Content-based image retrieval systems were introduced to address the problems associated with text-based image retrieval. Content based image retrieval is a set of techniques for retrieving semantically-relevant images from an image database based on automatically-derived image features [4]. The main goal of CBIR is efficiency during image indexing and retrieval, thereby reducing the need for human intervention in the indexing process. The computer must be able to retrieve images from a database without any human assumption on specific domain (such as texture vs. non-texture, or indoor vs. outdoor).One of the main tasks for CBIR systems is similarity comparison; extracting feature signatures of every image based on its pixel values and defining rules for comparing images. These features become the image representation for measuring similarity with other images in the database. An image is compared to other images by calculating the difference between their corresponding features.

Principle of CBIR

Content-based retrieval uses the contents of images to represent and access the images. Atypical content-based retrieval system is divided into off-line feature extraction and online image retrieval. In off-line stage, the system automatically extracts visual attributes (color, shape, texture, and spatial information) of each image in the database based on its pixel values and stores them in a different database within the system called a feature database. The feature data (also known as image signature) for each of the visual attributes of each image is very much smaller in size compared to the image data ,thus the feature database contains an abstraction (compact form) of the images in the image database. One advantage of a signature over

the original pixel values is the significant compression of image representation. However, a more important reason for using the signature is to gain an improved correlation between image representation and visual semantics [4].
In on-line image retrieval, the user can submit a query example to the retrieval system in search of desired images. The system represents this example with a feature vector. The distances (i.e., similarities) between the feature vectors of the query example and those of the media in the feature database are then computed and ranked. Retrieval is conducted by applying an indexing scheme to provide an efficient way of searching the image database. Finally, the system ranks the search results and then returns the results that are most similar to the query examples. If the user is not satisfied with the search results, he can provide relevance feedback to the retrieval system, which contains a mechanism to learn the user's information needs.

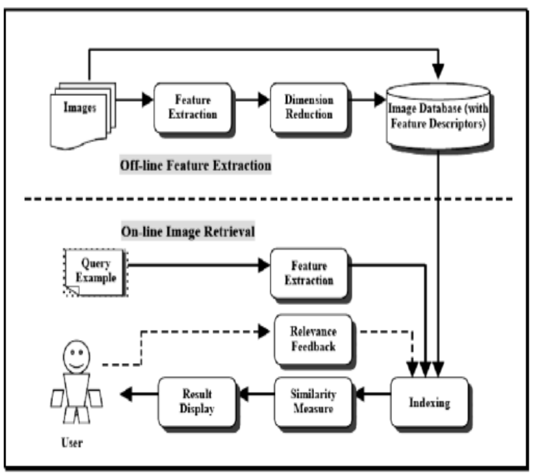

Figure 1: A Conceptual Framework for Content-Based Image Retrieval

Region Based Image Retrieval (RBIR)

Early CBIR methods used global feature extraction to obtain the image descriptors. For example, QBIC [5] developed at the IBM Almaden Research Center extracts several features from each image, namely color, texture, and shape features. These descriptors are obtained globally by extracting information by means of color histograms for color features; global texture information on coarseness, contrast, and direction; and shape features about the curvature, moments invariants, circularity, and eccentricity. Similarly, the Photo book system [6] , Visual seek [7], and VIR [8], use global features to represent image semantics.
These global approaches are not adequate to support queries looking for images where specific objects in an image with particular colors and/or texture are present, and shift/scale invariant queries, where the position and/or the dimension of the query objects may not be relevant. For example, suppose in one image there are two flowers with different colors: red and yellow. The global features describe the image as the average of the global average color which is orange. This description is certainly not there presentation of the semantic meaning of the image. Therefore, the weakness of global features is observable.
Region-based retrieval systems attempt to overcome previous method limitations of global based retrieval systems by representing images as collections of regions that may correspond to objects such as flowers, trees, skies and mountains [9].
A key prerequisite for a good region based image retrieval system is a robust segmentation algorithm [10]. A segmentation algorithm takes an input image and clusters pixels of this image that seem to be similar with respect to some feature (e.g. color, texture, or shape). The result of this clustering phase is to decompose an image into regions, which correspond to physical objects (trees, people, cars, flowers) if the decomposition is ideal. The feature descriptors are then extracted from each object instead of global image. Color, texture, and shape features are extracted on each pixel that belongs to the object, and each object is described by the average value of these pixel features.
For efficient image retrieval we have discussed feature based challenges in the previous section, in this section we discuss the major challenges in terms of classifiers.
SVM RF approaches ignore the basic difference between the two distinct groups of feedbacks i.e., all positive feedbacks share a similar concept while each negative feedback usually varies. This has been found to drastically degrade the effectiveness of this method. This can be overcome by

implementing CBIR both on-line and off-line [23]. Also choosing proper kernel functions and parameters for a real specific database remains challenging. The number of support vectors that compose the decision function increase dramatically when the decision procedure becomes complicated. Moreover the over fitting problem can become more severe i.e., training samples may be few to train a good classifier in a high dimensional space [24].

Subspace learning based Techniques

Based on the user's relevant feedback, learning based approaches are typically used in modifying the feature set or similarity measure [25]. The subspace learning based methods define a class problem and find a subspace within which to separate the one positive class from the unknown number of negative classes. Few of the methods come under this category are: Biased Discriminant Analysis or BDA, the Direct Kernel Biased Discriminant Analysis (DKBDA) and Marginal Biased Analysis (MBA). To prevent the problem of learning from small training sets, discriminant algorithms have been used for unlabeled images in the database. Recently, BDA has been used as a feature selection method to improve RF, because BDA models the RF better than many other methods. However, BDA assumes all positive samples from a single Gaussian distribution, which means all positive samples, should be similar with similar view angle, similar illumination, etc. Clearly, this is not the case for CBIR. The kernel based learning is used in BDA to overcome the problem. However, kernel-based learning has to rely on parameter tuning, which makes the online learning unfeasible [26].

The performance of image retrieval task can be significantly improved in low-dimensional subspace by making the system learn a semantic concept subspace from the RF log data with contextual information without using any class label information. This method which is called the Semantic Subspace Learning (SSL) [27] exploits the RF log data to improve its performance.

II. LITERATURE SURVEY

1. *J. Han and S. J. Mckenna, "Query-dependent metric learning for adaptive, content-based image browsing and retrieval," in IET Image Processing, vol. 8, no. 10, pp. 610-618, Oct. 2014[13]*

Content-based image retrieval (CBIR) systems often incorporate a relevance feedback mechanism in which retrieval is adapted based on users identifying images as relevant or irrelevant. Such relevance decisions are often assumed to be category-based. However, forcing a user to decide upon category membership of an image, even when unfamiliar with a database and irrespective of context, is restrictive. An alternative is to obtain user feedback in the form of relative similarity judgments. The ability of a user to provide meaningful feedback depends on the interface that displays retrieved images and facilitates the feedback. Similarity-based 2D layouts provide context and can enable more efficient visual search. Motivated by these observations, this study describes and evaluates an interactive image browsing and retrieval approach based on relative similarity feedback obtained from 2D image layouts. It incorporates online maximal-margin learning to adapt the image similarity metric used to perform retrieval. A user starts a session by browsing a collection of images displayed in a 2D layout. He/she may choose a query image perceived to be similar to the envisioned target image. A set of images similar to the query are then returned. The user can then provide relational feedback and/or update the query image to obtain a new set of images. Algorithms for CBIR are often characterised empirically by simulating usage based on pre-defined, fixed category labels, deeming retrieved results as relevant if they share a category label with the query. In contrast, the purpose of the system in this study is to enable browsing and retrieval without predefined categories. Therefore evaluation is performed in a target-based setting by quantifying the efficiency with which target images are retrieved given initial queries.

2. *E. Aptoula, "Remote Sensing Image Retrieval With Global Morphological Texture Descriptors," in IEEE Transactions on Geoscience and Remote Sensing, vol. 52, no. 5, pp. 3023-3034, May 2014.[14]*

This work presents the results of applying global morphological texture descriptors to the problem of content-based remote sensing image retrieval. Specifically, multiscale texture descriptors, namely, the circular covariance histogram and the rotation-invariant point triplets are explored. Moreover, a couple of new descriptors, exploiting the Fourier power spectrum of the quasi-flat-zone-based scale space of their input are introduced

3. *L. Zheng, S. Wang and Q. Tian, "Coupled Binary Embedding for Large-Scale Image Retrieval," in IEEE Transactions on Image Processing, vol. 23, no. 8, pp. 3368-3380, Aug. 2014.[15]*

Visual matching is a crucial step in image retrieval based on the bag-of-words (BoW) model. In the baseline method, two keypoints are considered as a matching pair if their SIFT descriptors are quantized to the same visual word. However, the SIFT visual word has two limitations. First, it loses most of its discriminative power during quantization. Second, SIFT only describes the local texture feature. Both drawbacks impair the discriminative power of the BoW model and lead to false positive matches. To tackle this problem, this paper proposes to embed multiple binary features at indexing level. To model correlation between features, a multi-IDF scheme is introduced, through which different binary features are coupled into the inverted file.

4. *L. Zhu, J. Shen, H. Jin, R. Zheng and L. Xie, "Content-Based Visual Landmark Search via Multimodal Hypergraph Learning," in IEEE Transactions on Cybernetics, vol. 45, no. 12, pp. 2756-2769, Dec. 2015.*[16]

While content-based landmark image search has recently received a lot of attention and became a very active domain, it still remains a challenging problem. Among the various reasons, high diverse visual content is the most significant one. It is common that for the same landmark, images with a wide range of visual appearances can be found from different sources and different landmarks may share very similar sets of images. As a consequence, it is very hard to accurately estimate the similarities between the landmarks purely based on single type of visual feature. Moreover, the relationships between landmark images can be very complex and how to develop an effective modeling scheme to characterize the associations still remains an open question. Motivated by these concerns, multimodal hyper graph (MMHG) to characterize the complex associations between landmark images is proposed. In MMHG, images are modeled as independent vertices and hyper edges contain several vertices corresponding to particular views. Multiple hyper graphs are firstly constructed independently based on different visual modalities to describe the hidden high-order relations from different aspects. Then, they are integrated together to involve discriminative information from heterogeneous sources. A novel content-based visual landmark search system based on MMHG to facilitate effective search is also proposed.

5. *J. Luo, Z. Jiang and J. Li, "Multi-scale orderless cross-regions-pooling of deep attributes for image retrieval," in Electronics Letters, vol. 52, no. 4, pp. 276-277, 2 18 2016.*[17]

To build a powerful image representation, a novel method named cross-regions-pooling (CRP) combining two key ingredients is proposed: (i) region proposals detected by objectness detection technique; (ii) deep attributes (DA), i.e. the outputs of the softmax layer of off-the-shelf convolutional neural network pre-trained on a large-scale dataset. The ultimate representation of an image is the aggregation (e.g. max-pooling) of DA extracted from all the regions. In addition, a multi-scale orderless pooling strategy considering layout of contexts of an image is proposed to integrate with CRP to improve the image representation.

6. *L. Jiao, X. Tang, B. Hou and S. Wang, "SAR Images Retrieval Based on Semantic Classification and Region-Based Similarity Measure for Earth Observation," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 8, no. 8, pp. 3876-3891, Aug. 2015.[18]*

Based on the semantic categorization and region-based similarity measure, a novel synthetic aperture radar (SAR) image retrieval method is proposed in this paper, which is inspired by the existing content-based image retrieval (CBIR) techniques and is oriented toward the Earth observation (EO). First, due to the large sizes of SAR images, new method semantically classifies the land covers in the patch level rather than the pixel level by the classic semi supervised learning (SSL), which could reduce the workload of selecting the representative image patch and decrease the searching space in the similarity calculation component. Furthermore, to overcome the inevitable classification error, our method provides an error recovery scheme, preventing the errors produced in categorization to contaminate the retrieval results. Third, the similarity between two patches is calculated by the improved integrated region matching (IIRM) measure based on the region-based similarity measure, which fails to meet the expectation in SAR images.

7. *S. R. Dubey, S. K. Singh and R. Kumar Singh, "Local neighbourhood-based robust colour occurrence descriptor for colour image retrieval," in IET Image Processing, vol. 9, no. 7, pp. 578-586, 7 2015[19]*

This study introduces a novel local neighbourhood-based robust colour occurrence descriptor (LCOD) to encode the colour information present in the local structure of the image. The colour information is processed in two steps: first, the number of colours is reduced into a less number of shades by quantising the red-green-blue colour space; second, the reduced colour shade information of the local neighbourhood is used to compute the descriptor. A local colour occurrence binary pattern is generated for each pixel of the image by representing each reduced colour shade occurrence in its local neighbourhood using a binary pattern.

8. *J. Luo, Z. Jiang and J. Li, "Multi-scale orderless cross-regions-pooling of deep attributes for image retrieval," in Electronics Letters, vol. 52, no. 4, pp. 276-277, 2 18 2016.[17]*

This paper presents a new approach to index color images using the features extracted from the error diffusion block truncation coding (EDBTC). The EDBTC produces two color quantizer and bitmap images, which are further processed using vector quantization (VQ) to generate the image feature descriptor. Herein two features are introduced, namely, color histogram feature (CHF) and bit pattern histogram feature (BHF), to measure the similarity between a query image and the target image in database. The CHF and BHF are computed from the VQ-indexed color quantizer and VQ-indexed bitmap image, respectively. The distance computed from CHF and BHF can be utilized to measure the similarity between two images.

9. *B. Xu, J. Bu, C. Chen, C. Wang, D. Cai and X. He, "EMR: A Scalable Graph-Based Ranking Model for Content-Based Image Retrieval," in IEEE Transactions on Knowledge and Data Engineering, vol. 27, no. 1, pp. 102-114, Jan. 2015.*

Graph-based ranking models have been widely applied in information retrieval area. In this paper, we focus on a well-known graph-based model - the Ranking on Data Manifold model, or Manifold Ranking (MR). Particularly, it has been successfully applied to content-based image retrieval, because of its outstanding ability to discover underlying geometrical structure of the given image database. However, manifold ranking is computationally very expensive, which significantly limits its applicability to large databases especially for the cases that the queries are out of the database (new samples). A novel scalable graph-based ranking model called Efficient Manifold Ranking (EMR) is proposed, trying to address the shortcomings of MR from two main perspectives: scalable graph construction and efficient ranking computation.

10. J. K. Dash, S. Mukhopadhyay and R. D. Gupta, "Content-based image retrieval using fuzzy class membership and rules based on classifier confidence," in IET Image Processing, vol. 9, no. 9, pp. 836-848, 9 2015[22]

This study proposes a novel image retrieval scheme. In this scheme, effort is taken to reduce the overall search time of the recently proposed approach called `class membership-based retrieval' (CMR). The proposed method identifies the confidence in the classification and limits the search to single output class and therefore, reduces the overall search time by 21.76% as compared to CMR. Quantitative methods are proposed to select various parameters used in the algorithm which were computed empirically in the case of earlier approach CMR.

III. CONCLUSION

This paper provides 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. This paper discusses about various feature extraction methods, similarity measurement techniques and the various applications. It has been found that variation in feature extraction methodologies can ensure the better and more accurate retrieval of relevant images from the large database. The CBIR system also depends on the size of the database.

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