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PRECISION FACE IMAGE RETRIEVAL BY EXTRACTING THE FACE FEATURES AND COMPARING THE FEATURES WITH DATABASE IMAGES

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ABSTRACT

An image retrieval system is a computer system for browsing, searching and retrieving images from a large database of digital images. Most traditional and common methods of image retrieval utilize some method of adding metadata such as captioning keywords, or descriptions to the images so that retrieval can be performed over the annotation words. Content-based face image retrieval is an existing technology for retrieving of images from large data base. Often, the retrieval results are not very satisfactory.The proposed method reduces the error and achieves better gain in face retrieval. By combining two orthogonal methods, results in improving of content-based face image retrieval.The proposed scheme uses two orthogonal methods named attribute-enhanced sparse coding and attribute embedded inverted indexing in order to reduce errors and achieve better extraction of images. These methods are used to improve the face retrieval in the offline stage such that the features of the image is extracted and then compared with the images present in the database.

INDEX TERMS: Face feature, Content-based image retrieval

I. INTRODUCTION

The multimedia and social networking sites are rapidly increasing, these sites make use of large amount of images. As a consequence, new techniques need to be discovered for efficient image retrieval. The existing Content-based image retrieval (CBIR) system enables the user to find and retrieve those images that he/she wants from a database. CBIR operates on a totally different principle; i.e., to retrieve the stored images from a collection of images by comparing the features that were automatically extracted from the images themselves. CBIR involves matching a query image with the images stored in a database. Firstly it involves the extracting of feature vector to represent the unique characteristics of each image but not efficiently .While the mannual image annotation is time-consuming, laborious and expensive. There have been several systems and techniques developed such as the IBM's query by image content (QBIC) system [1], Virage's VIR engine [2], Visual Seek [3], and Photo Book [4]. A significant problem in CBIR is the gap between semantic concepts and low-level image features. The subjectivity of human perception of visual content plays an important role in the CBIR systems. Often, the retrieval results are not very satisfactory especially when the level of satisfaction is closely related to user subjectivity. For example, given a query image with a tiger lying on the grass, one user may want to retrieve those images with the tiger objects in them, while another user may find the green grass background more interesting. Since textual annotations are not available for most images, searching for particular pictures becomes an inherently difficult task. Content-based image retrieval (CBIR) does not rely on textual attributes but allows search based on features that are directly extracted from the images [5]. This however is, not surprisingly, rather challenging and often relies on the notion of visual similarity between images or image regions. While humans are capable of effortlessly matching similar images or objects, machine vision research still has a long way to go before it will reach a similar performance for computers. Currently, many retrieval approaches are based on low-level features such as color, texture, and shape features, leaving a 'semantic gap' to the high-level understanding of users [5]. Several approaches for bridging this gap have been introduced, such as relevance feedback [6] or automatic image annotation [7], but much work still remains to be done for CBIR to become truly useful. To address this problem the proposed method mainly aims to utilize the face features that contain semantic cues of the face photos to improve content-based face retrieval by constructing semantic codeword's for efficient large-scale face retrieval. The two orthogonal methods named attribute-enhanced sparse coding and attribute embedded inverted indexing are used to improve the face retrieval in the offline stage. This investigates the effectiveness of different attributes and vital factors essential for face retrieval. The commonly used face features include color, shape, and Texture. Queries are issued through query by image example (QBE), which can either be provided or constructed by the users, or randomly selected from the image database. A new perspective on content-based image retrieval is provided by extraction of face features and comparing it with the images present in the database. By combining low- level features with high-level human features, it enables to find better feature representations and achieve better retrieval results .The two orthogonal methods named ie Attribute-enhanced sparse coding exploits the global structure of feature space and uses several important extracted features combined with low-level features to construct semantic codeword in the offline stage. On the other hand, attribute-embedded inverted indexing locally considers extracted features of the designated query image in a binary signature and provides efficient retrieval of images. By incorporating these two methods, the large-scale content-based face image retrieval system can be built by taking advantages of both low-level features and high-level semantics.

The rest of the paper is organized as follows. Section II discusses related work. Section III introduces the proposed methods including system overview, content-based image search, Attribute based search and Face Image Retrieval.Section IV describes the performance discussion, and Section V concludes this paper.

II. RELATED WORK

This work is closely related to several different research topics, including content-based image retrieval (CBIR), scalable face image retrieval and content-based face image retrieval. A Dynamic User Concept Pattern Learning Framework for CBIR [8] provides two learning techniques. First, user relevance feedback is supported during the retrieval process, which means that users interact with the system by choosing the positive and negative examples from the retrieved images based on their own concepts. Then, the user's feedback is fed into the retrieval system and triggers the modification of the query criteria, which best matches the user's concepts .Second, multiple instances learning (MIL) and neural network techniques are integrated into the query-refining process. The content-based retrieval [9] focuses on the issues of colour (or more precise colour variance), image compression, and image database browsing. While colour features are the most widely used image descriptors for CBIR, colour is not necessarily a stable cue as it also depends on various image capture conditions. Colour invariants are features designed to be robust with respect to these confounding factors. Image compression, which is typically applied to most images in use, leads to both processing overheads but also to a small but noticeable drop in retrieval performance. To address these problems, they have developed image retrieval techniques that operate directly in the compressed domain, yet provide better retrieval performance than many standard CBIR techniques finally, they look at browsing systems as an alternative approach to dealing with large image databases**.** The scalable face image retrieval with identity-based and multi-references [10] overcome the problem of inverted indexing as they are high-dimensional and global and thus not scalable in either computational or storage cost. They aim to build a scalable face image retrieval system. For this purpose, they develop a new scalable face representation using both local and global features. In the indexing stage, it exploits special properties of faces to design new component-based local features, which are subsequently quantized into visual words using a novel identity-based quantization scheme. They also use a very small Hamming signature (40 bytes) to encode the discriminative global feature for each face. In the retrieval stage, candidate images are first retrieved from the inverted index of visual words. They then use a new multi-reference distance to re-rank the candidate images using the Hamming signature**.** The detecting and aligning faces by image retrieval [11] gives the solution to overcome the problem of traditional face detection methods due to the large variation in facial appearances, as well as occlusion and clutter. In order to overcome these challenges, it presents a novel and robust exemplar-based face detector that integrates image retrieval and discriminative learning. A large database of faces with bounding rectangles and facial landmark locations is collected, and simple discriminative classifiers are learned from each of them. A voting-based method is then proposed to let these classifiers cast votes on the test image through an efficient image retrieval technique. By using this method, faces can be very efficiently detected by selecting the modes from the voting maps, without resorting to exhaustive sliding window-style scanning.

III. PROPOSED METHOD

The proposed method achieves the better extraction of images and reduces the errors while extracting the images. The two orthogonal methods are used in order to achieve strong detection, i.e. Attribute-enhanced sparse coding and attribute-embedded inverted indexing. The

Attribute-enhanced sparse coding exploits the global structure of feature space and uses several important query features combined with low-level features to construct semantic code words in the offline stage. On the other hand, attribute-embedded inverted indexing locally considers features of the designated query image in a binary signature and provides efficient retrieval of images. Using these it reduces the quantization error and achieve salient gains in face retrieval. The following are the functions performed in the proposed method:

1. Combining high-level extracted features and low-level features.
2. To balance global representations in image collections and locally embedded facial characteristics.
3. Two orthogonal methods are used ie Attribute-enhanced sparse coding and attribute-embedded inverted indexing to utilize human attributes to improve content-based face image retrieval under a scalable framework.

A) System Overview

System architecture is a generic discipline to handle objects called "systems" in a way that supports reasoning about the structural properties of these objects.

Figure 1 shows the Architectural design which combines both query and database images which will go through the same procedures including face detection, facial landmark detection, face alignment, attribute detection, and LBP feature extraction. Attribute-enhanced sparse coding is used to find sparse code words of database images globally in the offline stage. Code words of the query image are combined locally with binary attribute signature to traverse the attribute-embedded inverted index and derive real-time ranking results over database images. This method reduces the quantization error and achieves salient gains in face retrieval. Hence by using these methods, it not only reduces the errors and achieve better extraction of images but also improves content-based face image retrieval in which the retrieval results are not very satisfactory.

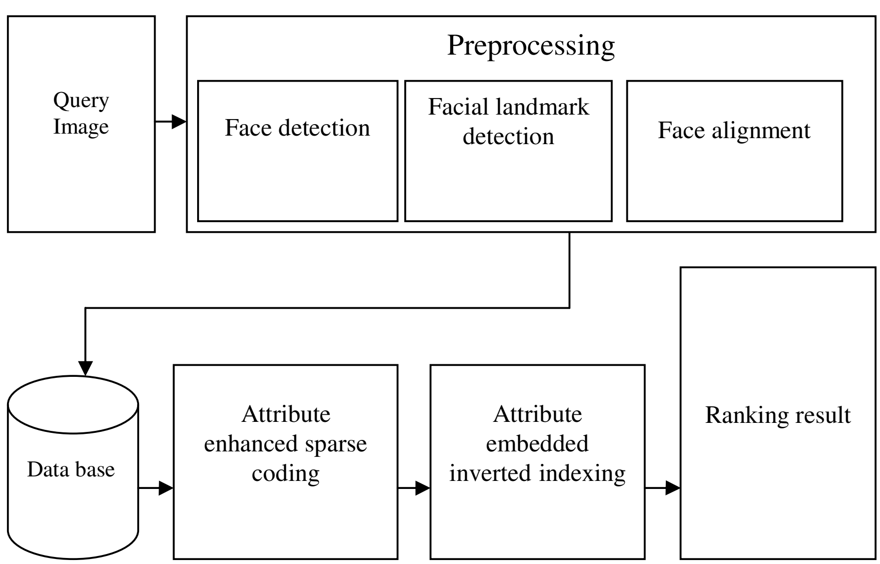

Fig 1. System Architecture

B) Content-based image search

Content-based image retrieval (CBIR), also known as query by image content (QBIC) and CBVIR is the application of computer vision techniques the image retrieval problem that is, the problem of searching for digital images in large databases. Traditional content-based face image retrieval techniques use image contents like color, texture and gradient to represent images. To deal with large-scale data, mainly two kinds of Indexing systems are used, mainly inverted indexing or hash-based indexing combined with bag-of-word model and many local features, to achieve efficient similarity search. Although these methods can achieve high precision on rigid object retrieval, they suffer from low recall problem due to the semantic gap. The semantic gap can be bridged by finding semantic image representations to improve the CBIR performance. The idea of this work is simple, instead of using extra information that might require intensive human annotations (and tagging), the face features can be used to construct semantic code words for the face image retrieval task can be used

C) Attribute based search:

Attribute detection has adequate quality on many different face features. Using these face features, promising results can be achieved in different applications such as face verification, face identification, keyword-based face image retrieval, and similar attribute search. The Attribute based search includes two techniques i.e. Attribute-enhanced sparse coding and attribute-embedded inverted indexing. Attribute-enhanced sparse coding exploits the global structure of feature space and uses several important extracted features combined with low-level features to construct semantic codeword in the offline stage. On the other hand, attribute-embedded inverted indexing locally considers extracted features of the designated query image in a binary signature and provides efficient retrieval of images.

D) Face Image Retrieval

The facial image retrieval gives the solution for the problem of similar facial images searching and retrieval in the search space of the facial images by integrating content-based image retrieval (CBIR) techniques and face recognition techniques, with the semantic description of the facial image. The aim is to reduce the semantic gap between high level query requirement and low level facial features of the human face image such that the system can be ready to meet human nature way and needs in description and retrieval of facial image.

The figure 2 shows the system flow diagram which describes how the control flow is drawn from one operation to another or the flow of control from one step to the other. Firstly it starts with the user input ie image entered by the user. Next the pre-processing step is done for the query image this stage includes three operations i.e. generating of sparse code, generating of local binary pattern and comparing the images present in the data base. Once the pre-processing stage is done it just have to compare the features of the image extracted, with the images present in the data base, as indicated in the figure this result in the accurate extraction of the similar images present in the database. As shown in the below figure. Finally the ranking result is displayed to the user. It is basically a flow chart to represent the flow from one activity to another activity i.e. how the process is carried out in system. The activity can be described as an operation of the system so this flow can be sequential, branched or concurrent.

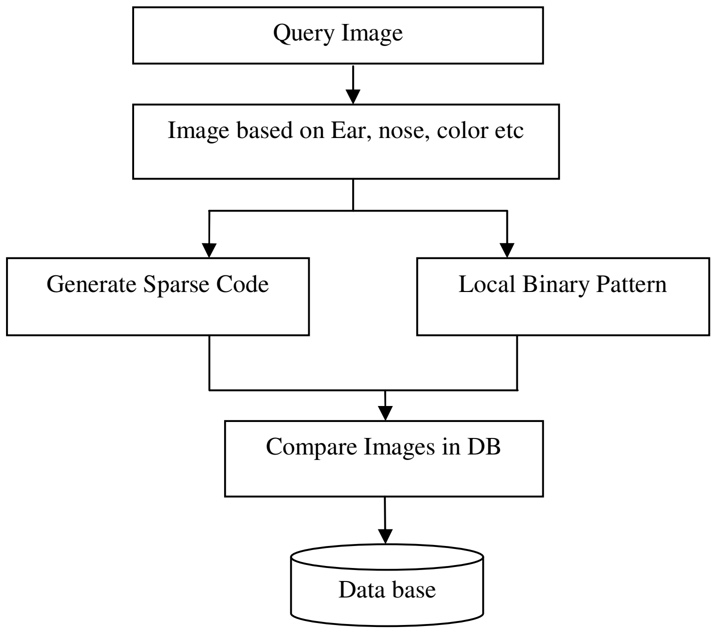

Fig 2. System Flow Diagram

IV. IMPLEMENTATION

In order to set the database, the images are browsed from the drives consisting of different image formats. Next the face features of the browsed image such as eyes, nose, mouth and face should be extracted. Once the features is extracted the attributes of the face such as colour of the hair, age, races, region and other identifiable details are marked for the better identification of images and finally local binary pattern (lbp) is applied for the face features in which it labels the pixels of an image by thresholding the 3-by-3 neighbourhood of each pixel with the centre pixel value and considering the result as a binary number. Finally the data base is set. Next for the extraction process the query image is loaded by the user and the attributes of the image is entered by the user for the better extraction. This process can be done for the number of images stored in the database. The matched query image features and the database images are finally extracted and displayed as the ranking result.

V. PERFORMANCE DISCUSSION

The performance of the proposed method is more efficient than the existing systems because in the proposed method the images are extracted based on the face features and the attributes of the image entered by the user, which results in accurate extraction of the images and also the two orthogonal methods are combined which results in improving of content-based face image retrieval. Hence the efficient extraction of images can be achieved using the proposed method. Firstly the pre-processing step extracts the features of the query image which is entered by the user; once the pre-processing step is done it just matches the extracted image features with the images present in the database. Hence the proposed method reduces the quantization error and achieves salient gains in face retrieval.

VI. CONCLUSION

The proposed method provides an efficient retrieval of images and also reduces the quantization error and achieves better extraction of the images. Attribute-enhanced sparse coding exploits the global structure and uses several face features to construct semantic-aware code words in the offline stage. Attribute-embedded inverted indexing further considers the local attribute signature of the query image and still ensures efficient retrieval of images.

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