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AESC Technique for Scalable Face Image Retrieval

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ABSTRACT*:* Photos with people (for example, family, friends, celebrities, etc.) are the main interests of users. Therefore, with photos of exponential growth, the recovery of large-scale images of faces based on content is an enabling technology for many emerging applications. In this work, our goal is to use automatically detected human attributes that contain semantic facial photo signals to improve the recovery of face-based content by constructing semantic code words for efficient large-scale facial recovery. Taking advantage of human attributes in a scalable and systematic structure, we propose two orthogonal methods called dispersed coding enhanced by attributes and embedded inverted indexed attribute to improve facial recovery in offline and online phases. We examined the effectiveness of different vital attributes and vital factors for facial recovery.

KEYWORDS: Face image, human attributes, Content-based image retrieval, LBP (Local binary Pattern).

I. INTRODUCTION

Due to the popularity of digital devices and the rise of social network/photo sharing services (e.g., Face book, Flicker), there are largely growing consumer photos available in our life. Among all those photos, a big percentage of them are photos with human faces (estimated more than 60%).

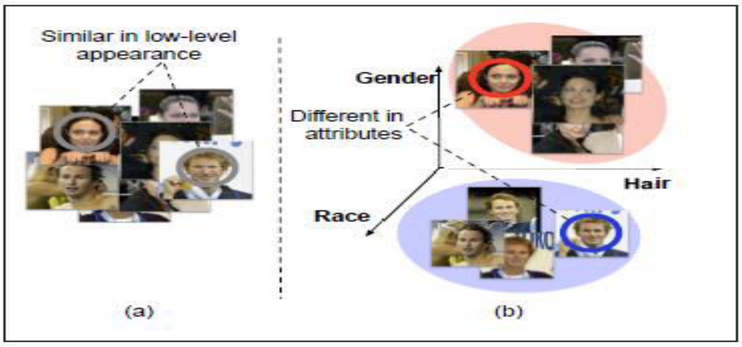

Fig. 1 (a) Because low-level features are lack of semantic meanings, face images of two different people might be close in the traditional low-level feature space. (b) By incorporating high-level human attributes (e.g., gender) into feature representations

The importance and the sheer amount of human face photos make manipulations (e.g., search and mining) of large-scale human face images a really important research problem and enable many real world applications.Our goal in this paper is to address one of the important and challenging problems – large-scale content-based face image retrieval. Given a query face image, content-based face image retrieval tries to find similar face images from a large image database. It is an enabling technology for many applications including automatic face annotation, crime investigation, etc. Traditional methods for face image retrieval usually use low-level features to represent faces but low-level features are lack of semantic meanings and face images usually have high intra-class variance (e.g., expression, posing), so the retrieval results are unsatisfactory (cf. Figure 1 (a)).

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In this work, we provide a new perspective on content base face image retrieval by incorporating high-level human attributes into face image representation and index structure. As shown in Figure 1, face images of different people might be very close in the low-level feature space. By combining low-level features with high-level human attributes, we are able to find better feature representations and achieve better retrieval results. The similar idea is proposed in using fisher vectors with attributes for large-scale image retrieval, but they use early fusion to combine the attribute scores. Also, they don't take advantages of human attributes because their target is general image retrieval. Human attributes (e.g., gender, race, hair style) are high level semantic descriptions about a person. The recent work shows automatic attribute detection has adequate quality (more than 80% accuracy) on many different human attributes. Using these human attributes, many researchers have achieved promising results in different applications such as face verification, face identification, keyword-based face image retrieval, and similar attribute search.

These results indicate the power of the human attributes on face images. Although human attributes have been shown useful on applications related to face images, it is non-trivial to apply it in content-based face image retrieval task due to several reasons. First, human attributes only contain limited dimensions. When there are too many people in the dataset, it loses discrim in ability because certain people might have similar attributes. Second, human attributes are represented as a vector of floating points. It does not work well with developing large scale indexing methods, and therefore it suffers from slow response and scalability issue when the data size is huge.

To leverage promising human attributes automatically detected by attribute detectors for improving content-based face image retrieval, we propose two orthogonal methods named attribute-enhanced sparse coding and attribute-embedded inverted indexing. Attribute-enhanced sparse coding exploits the global structure of feature space and uses several important human attributes combined with low-level features to construct semantic codeword in the offline stage. On the other hand, attribute-embedded inverted indexing locally considers human attributes of the designated query image in a binary signature and provides efficient retrieval in the online stage. By incorporating these two methods, we build a large-scale content-based face image retrieval system by taking advantages of both low level (appearance) features and high-level (facial) semantics. We show that the proposed methods can leverage the context information from human attributes to achieve relative improvement up to 43.55% in mean average precision on face retrieval task compared to the existing methods using local binary pattern (LBP) and sparse coding. We also analyze the effectiveness of different human attributes across datasets and find informative human attributes.The rest of the paper is organized as follows. Section II discusses literature survey. Section III describes our proposed system on the face image retrieval problem and the promising utilities of human attributes. Section IV introduces the algorithm used for image retrieval. Section V gives the experimentalresults, and section VI concludes this paper.

II.LITERATURE SURVEY

In this work, they aim to utilize automatically detected human attributes that contain semantic cues of the face photos to improve content based face retrieval by constructing semantic code words for efficient large-scale face retrieval. By leveraging human attributes in a scalable and systematic framework, they propose two orthogonal methods named attribute-enhanced sparse coding and attribute embedded inverted indexing to improve the face retrieval in the offline and online stages [1]. Due to the exponential growth of the social media like face book, flicker etc. photos of people became one of the highly interested area. Dealing with human faces are more challenging because most of the human faces are similar in the low level appearance. The content based face image retrieval using the low level attributes like posing, expression etc. Thus the retrieval results are unsatisfactory. This problem can be solved by combining low level features with high level features. Two methods named attribute enhanced sparse coding and attribute embedded inverted indexing are proposed to achieve better retrieval results [2].

Soft biometric traits embedded in a face (e.g., gender and facial marks) are ancillary information and are not fully distinctive by themselves in face-recognition tasks. However, this information can be explicitly combined with face matching score to improve the overall face-recognition accuracy. Moreover, in certain application domains, e.g., visual surveillance, where a face image is occluded or is captured in off-frontal pose, soft biometric traits can provide even more valuable information for face matching or retrieval. They propose to utilize demographic information (e.g., gender and ethnicity) and facial marks (e.g., scars, moles, and freckles) for improving face image matching and retrieval performance [3]. In this work, they aim to utilize automatically detected human face attributes that contains

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semantic cues of the face hotos, it improve content based face retrieval by constructing semantic code words for efficient large scale face retrieval. Mainly we propose two methods named Attribute- Enhanced Sparse Coding and Attribute Embedded Inverted Indexing. These two methods will improve the face retrieval in the online and offline stages [4]. They present two novel methods for face verification. Our first method – “attribute” classifiers – uses binary classifiers trained to recognize the presence or absence of describable aspects of visual appearance (e.g., gender, race, and age). Second method – “simile” classifiers – removes the manual labelling required for attribute classification and instead learns the similarity of faces, or regions of faces, to specific reference people. Neither method requires costly, often brittle, alignment between image pairs; yet, both methods produce compact visual descriptions, and work on real-world images [5].

III.PROPOSED SYSTEM

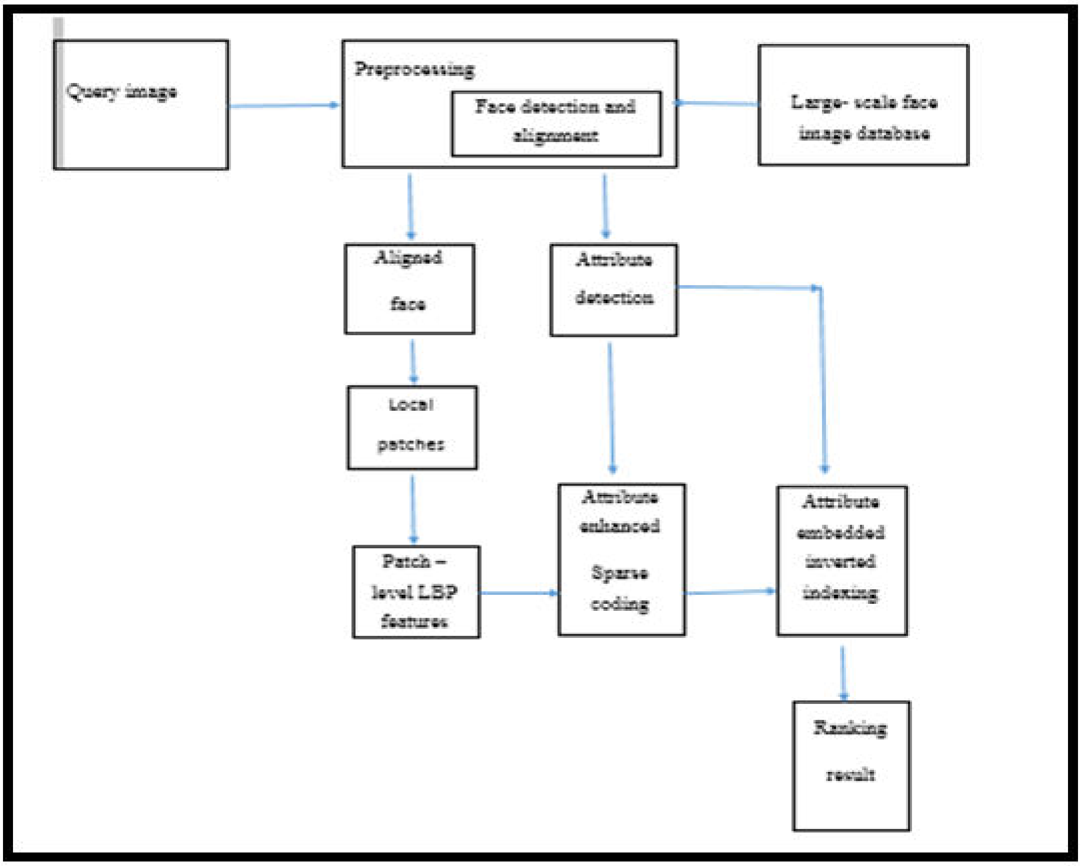

Fig 2: Block diagram of system

3.1Block diagram Description

3.1.1Preprocessing:

In this phase we first process the query image. Pre-processing removes the background and identifies the face region. In mat lab, infielder and image just is used to filter the face and remove the background region. The noisy data from the query image is also removed here. By extracting the face region, it can be divided into multiple grids. From

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the grid points, Local patches are extracted and by using the patches LBP features are obtained. From every LBP descriptor sparse code words are quantized.

In face recognition technology mostly we crop only face region using pre-processing method and we normalize the posing, lighting etc. By doing these steps we are ignoring hair, color, and skin etc., rich semantic cues are ignored so while performing pre-processing we cannot get the correct semantic description about the image. For example hair is one of the major attribute in deciding whether the image is the man or women. In that case it fails to identify the correct semantic meaning of the face. After pre-processing step the information are lost to find the attribute of the images. And when the faces are cropped then it will fail to compare the cropped version with uncropped. So only by using the surrounding context of the face we can get the exact semantic meaning of the image.

3.1.2 Attribute Enhanced Sparse Coding:
It describes the automatic detection of human attribute from the image and also creates the different sparse coding. These collections of sparse coding represent the original image.

3.1.3 Attribute embedded inverted indexing:
It collects the sparse code words from the attribute enhanced sparse coding and check the code words with the online feature database and retrieve the related images similar the query image.For every image in the database face detector is used to detect the location of face region. 73 possible attributes can be taken. For example hair, color, race, gender etc. Active shape model is used to mark the facial landmarks and by using that land mark alignment of the face is done. For each face component 7*5 grid points are taken. Each grid will be a square patch. These grid components include eyes, nose, mouth corners etc.

LBP feature descriptor is used to extract features from those grids. After extracting the features we quantize it to code words known as sparse coding. All these code words are summed and generate a single pattern for the image. These steps are obtained by using attribute enhanced sparse coding. Before storing the image in database an index number will be provided toit and by using that index number we can identify the image.

VI. ALGORITHM USED FOR IMAGE RETRIEVAL

4.1 LBP Pattern (Local Binary Pattern)
Local binary patterns were introduced by Ojala et al as a fine scale texture descriptor. In its simplest form, an LBP description of a pixel is created by thresholding the values of the 3*3
Neighbourhood of the pixel against the central pixel and interpreting the result as a binary number

The LBP feature vector, in its simplest form, is created in the following manner:

- Divide the examined window into cells (e.g. 16x16 pixels for each cell).
- For each pixel in a cell, compare the pixel to each of its 8 neighbours (on its left-top, left-middle, left-bottom, right-top, etc.). Follow the pixels along a circle, i.e. clockwise or counter-clockwise.
- Where the centre pixel's value is greater than the neighbour's value, write "0". Otherwise, write "1". This gives an 8-digit binary number (which is usually converted to decimal for convenience).
- Compute the histogram, over the cell, of the frequency of each "number" occurring (i.e., each combination of which pixels are smaller and which are greater than the centre). This histogram can be seen as a 256-dimensional feature vector.
- Optionally normalize the histogram.
- Concatenate (normalized) histograms of all cells. This gives a feature vector for the entire window.

The feature vector can now be processed using the Support vector machine, extreme learning machines, or some other machine-learning algorithm to classify images. Such classifiers can be used for face recognition or texture analysis.

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4.2 Attribute Embedded Inverted Indexing (AEI)

The methods described in Section IV-B aim to construct codewords enhanced by human attributes. In this section we describe the second method that can utilize human attributes by adjusting the inverted index structure.

1) Image ranking and inverted indexing: For each image, after computing the sparse representation, we can use codeword set $C^{(i)}$ to represent it by taking non-zero entries in the sparse representation as codewords. The similarity between two images are then computed as follows,

S (i; j) = $\left\| C^{(i)} \cap C^{(j)} \right\|$

The image ranking according to this similarity score can be efficiently found using inverted index structure.

2) Attribute-embedded inverted indexing: To embed attribute information into index structure, for each image, in addition to sparse codewords$C^{(i)}$ computed from the facial appearance, we use a db dimension binary signature to represent its human attribute, $b^{(i)}$:

$$b_j^{(i)} = \begin{cases} 1 & \text{if } f_a^{(i)}(j) > 0 \\ 0 & otherwise, \end{cases}$$

The similarity score is then modified into,

$$S(i,j) = \begin{cases} ||c^{(i)} \cap c^{(j)}|| & \text{if } h(b^{(i)}, b^{(j)}) \leq T \\ 0 & otherwise, \end{cases}$$

Where h(i; j) denotes hamming distance between i and j, and T is a fixed threshold such that 0 ≤T ≤ d_b. As shown in Figure 5, attribute-embedded inverted index is built using the original code words and the binary attribute signatures associated with all database images.

4.3 Attribute-enhanced sparse coding (ASC)

In this section, we first describe how to use sparse coding for face image retrieval. We then describe details of the proposed attribute-enhanced sparse coding. Note that in the following sections, we apply the same procedures to all patches in a single image to find different codewords and combine all these codewords together to represent the image.

4.3.1 Sparse coding for face image retrieval (SC):

Using sparse coding for face image retrieval, we solve the following optimization problem:

$$\min_{D,V} \sum_{i=1}^{n} ||x^{(i)} - Dv^{(i)}||_2^2 + \lambda ||v^{(i)}||_1$$

Where x (i) is the original features extracted from a patch of face image i.e., D ∈ R^{dxk} is a to-be-learned dictionary contains K centroids with d dimensions. V = [$V^{(1)}$;$V^{(2)}$; $V^{(3)}$; ::::::::: $V^{(n)}$] isthe sparse representation of the image patches. Randomly sampled image patches as dictionary can achieve similar performanceas that by using learned dictionary (< 2:7% relative improvement in their experiments) if the sampled patches provide a set of over complete basis that can represent input data.

V.RESULT

In the experiment , Whenever query image is given as input to the system,Only facial position of the image is separate from query image.after that patch generation and codeword assignment is done using attribute enhanced sparse coding. The collection of sparsecoding represent the original image.

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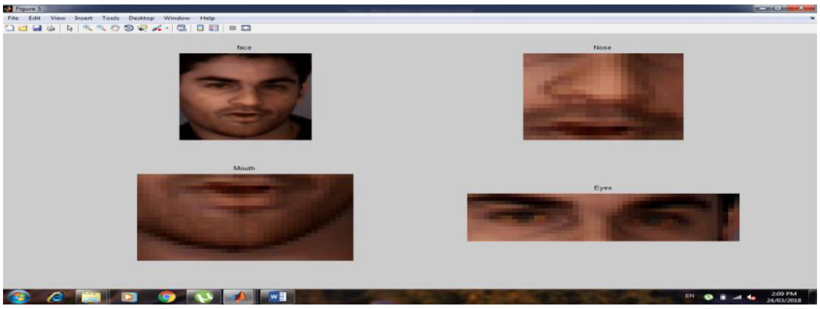

Fig 3: Patch generation of query images

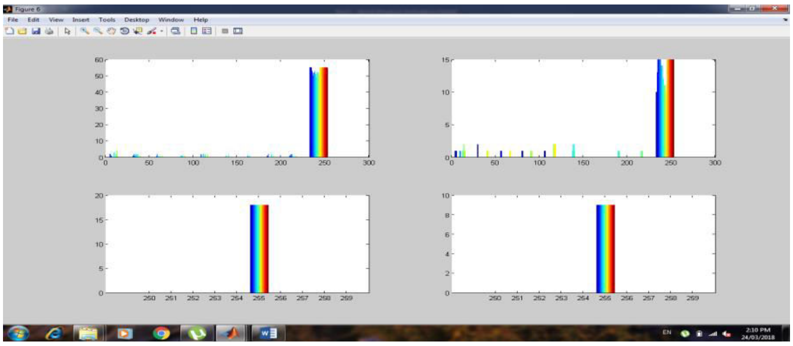

Fig 4: Codeword assignment

This system use rich sematic cues such as hair color, gender, race for image retrival and obtain ranking images.

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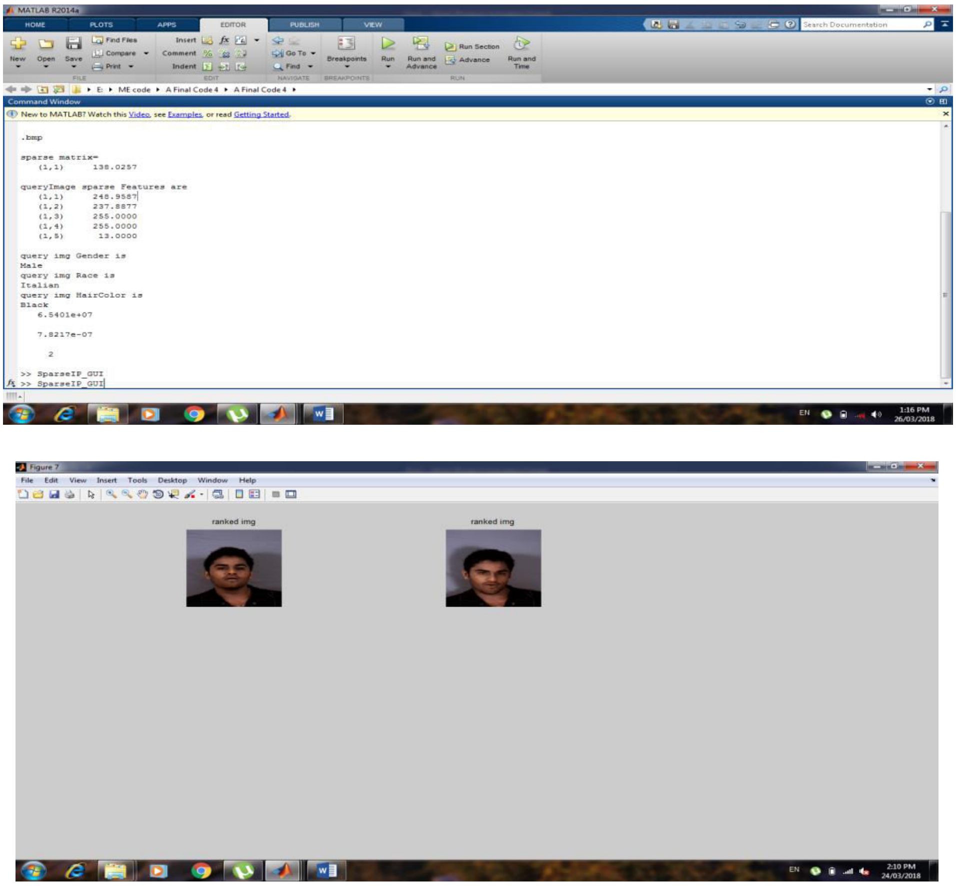

Fig 5: Ranking Images

VI.CONCLUSION

We propose and combine two orthogonal methods to use automatically detected human attributes to significantly improve facial image recovery based on content. To our knowledge, this is the first proposal to combine low-level functions and automatically detected human attributes for retrieving facial images based on content. Attribute-spaced coding takes advantage of the global structure and uses various human attributes to construct words with semantic codes in the offline phase. The inverted indexing incorporated in the attributes also considers the signature of the local attributes of the query image and still guarantees efficient recovery in the online phase. The experimental results show that using the code words generated by the proposed coding scheme, we can reduce the quantization error and obtain significant gains in facial recovery in two sets of public data; The proposed indexing scheme can be easily integrated into the inverted index, thus maintaining a scalable framework. During the experiments, we also discovered some information attributes for facial retrieval through different data sets and these attributes are also promising for other applications (for example, face verification).

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