# AESC technique for scalable face image retrieval

Karche S. N.[1], Mulani A. O.[2]
[1]PG Student, [2]Assistant Professor
[1, 2]*Electronics & Telecommunication Department,*
*SKNSCOE Korti Pandharpur, Solapur University Solapur, MS, India*
[1]sonalikarche@gmail.com, [2]aksaltaaf@gmail.com

***Abstract: Photographs with individuals (e.g., family, companions, superstars, and so on.) are the real enthusiasm of clients. In this way, with the exponentially developing photographs, extensive scale content-based face picture recovery is an empowering innovation for some rising applications. Many literatures use naturally recognized human characteristics that contain semantic prompts of the face photographs to enhance content based confront recovery by building semantic code words for effective huge scale confront recovery. By utilizing human properties in a versatile and deliberate system, we reviewed two orthogonal techniques attribute-enhanced sparse coding and attribute embedded modified ordering to enhance the face recovery in the disconnected and online stages. This paper also provides a survey on different techniques for Scalable Face Image Retrieval Using Sparse Code words.***

***Keywords:Content-based image retrieval, face image, human attributes.***

## I. INTRODUCTION

Because of the prominence of advanced gadgets, individuals can effortlessly catch a photograph and share it utilizing the web by different online instruments like Facebook, Flickr, speedier, twitter, and so forth. Among these unlimited computerized pictures and photographs shared on the web, a major rate of them are photographs identified with human countenances. Since human countenances are firmly identified with social exercises of individuals. The exponential development of facial pictures has made numerous examination issues and open doors for an assortment of certifiable applications. The challenges like extensive scale confront picture recovery is found in recovery method as substance based face picture recovery. In conventional face recovery techniques low level components are used to speak to faces. Be that as it may, the disadvantage of low level elements is that they absence of semantic implications though confront pictures have change in expressions, posturing, and so on. Confront pictures of various individuals may coordinate as indicated by low level components. This may create vague result. By joining abnormal state human properties and low level components; better recovery comes about are accomplished alongside better representation of highlight. To solve this issue propose to use identity based quantization and propose to use identity-constrained sparse coding, but these methods might require clean training data and massive human annotations. The proposed techniques provide a new perspective on content-based face image retrieval by incorporating high-level human attributes into face image representation and index structure.

## II. LITERATURE REVIEW

There are different theories related to attribute enhanced sparse coding (AESC) for scalable face image retrieval by different authors. The surveyed literature on AESC technique for scalable face image retrieval is as follows:

D. Hema R et.al [1] proposed system has two methods for automatically detecting human attributes and map retrieval Proposed system uses combination of low level as well as high level features combination to retrieve the probably similar image extraction. Attribute-enhanced sparse coding uses multiple human attributes to construct semantic code words in the offline stage which describes all global structure of image. Attribute-embedded inverted indexing considers the local attribute signature of the query image and ensures efficient retrieval of image in online stage.

Le An et.al [2] proposed an attribute-driven face image retrieval method. It provides attribute information to transform the low-level features to attribute-driven features in a supervised manner. The transformation is learned using Local Fisher Discriminant Analysis (LFDA). Binary encoding of attribute-driven features is applied to ensure scalability since the retrieval using Hamming distance with binary codes is very efficient. After initial retrieval, the top ranked results enter a re-ranking process in which an appearance-based distance using low-level features and an attribute-based distance using attribute- driven features are combined to obtain are fined ranking.

M. Balaganesh et.al [7] discussed two orthogonal methods used to utilize automatically detected human attributes to significantly improve content-based face image retrieval. This is the first proposal of combining low-level features and automatically detected human attributes for content-based face image retrieval.

M. Bhagat et.al [9] proposed system two orthogonal methods are combined to utilize automatically detected human attributes to significantly improve content-based face image retrieval by combining low-level features and automatically detected human attributes for content based face image retrieval, the image retrieval is efficient. Attribute-enhanced sparse coding uses automatically detected human attributes to construct semantic 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 in the online stage. This technique may reduce the quantization error and achieve salient gains in face retrieval on two public datasets. As encryption algorithm is applied on final output; the chances of attack on output get reduced in case of online stage.

Bor-Chun Chen et.al [10] proposed two orthogonal methods named attribute-enhanced sparse coding and attribute embedded inverted indexing to improve the face retrieval in the offline and online stages. In this method combining low-level features and automatically detected human attributes for content-based face image retrieval. Attribute-enhanced sparse coding exploits the global structure and uses several human attributes 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 in the online stage. Proposed system reduce the quantization error and achieve salient gains in face retrieval on two public datasets; the proposed indexing scheme can be easily integrated into inverted index, thus maintaining a scalable framework. Also discover certain informative attributes for face retrieval across different datasets and these attributes are also promising for other applications (e.g., face verification).

Walter J.Scheirer et.al [12] formalized the notion of multi attribute spaces and shown how to calibrate attribute values into probabilities that an image exhibits a given attribute. Also shown that principled probabilistic approach to score normalization greatly improves the accuracy and utility of face retrieval using multi-attribute searches, and allows for the new capability of performing similarity searches based on target attributes in query images. Publicly released calibration code on companion website

D. Wang et.al [13] investigated the retrieval-based face annotation problem and presented a promising framework to attack this challenge by mining massive weakly labelled facial images freely available on website. To improve the annotation performance, a novel Weak Label Regularized Local Coordinate Coding (WLRLCC) algorithm, which effectively exploits the principles of both local coordinate coding and graph-based weak label regularization.

U. Park et.al [14] developed a soft biometric traits-based face matching system. It uses gender and ethnicity information and facial marks. This soft biometric matcher can be combined with any face matcher to improve the recognition accuracy. Also show that facial marks can help in discriminating identical twins. With the proposed soft biometric matcher, users can issue semantic queries to retrieve images of interest from a large database.

Zhong wu et.al [15] designed a face image retrieval system with novel components that exploit face-specific properties to achieve both scalability and good retrieval performance, as demonstrated with a one-million face database. Learning algorithm to automate this process to further improve the visual word vocabulary for face. This system is highly scalable, and we plan to apply it on a web-scale image database using a computer cluster.

## III. PROPOSED SYSTEM

At the point when query picture is given, then the objective of face picture recovery is to locate the positioning result from most to minimum comparable face pictures in a face picture database. Proposed techniques has fallowing objectives:

- Design sparse coding method which combines automatically detected high level features with low level features for better image representation to achieve improved face retrieval result.
- Use regression technique for efficient and fast retrieval result.
- Use randomly sampled image patches as dictionary instead of learned dictionary. Because learning dictionary with a large vocabulary is time-consuming process (training 175 codebooks with 1600 dimension takes more than two weeks to finish), so aim to just use randomly sampled image patches as dictionary and skip the time-consuming dictionary learning step by fixing dictionary D.
- Design dictionary selection process to force images with different attribute values to contain different codewords.

### A. System Overview

Both database images and query image will go through same procedure as shown in fig 1: First step is image pre-processing. In pre-processing stage, first step is to find location of face from input image and then find components of face. Human attributes are detected from given face. After that, face alignment is done to extract low level features. From detected facial components local patches extracted and 9-dim LBP features computed. These are called local feature descriptors. After obtaining local low-level LBP features and attributes scores, our aim to combine these features to semantically represent image. To the best of our knowledge, this is the first proposal of such combination for content-based face image retrieval. For that purpose, proposed attribute-enhanced sparse coding method is applied to construct sparse codewords for that image.

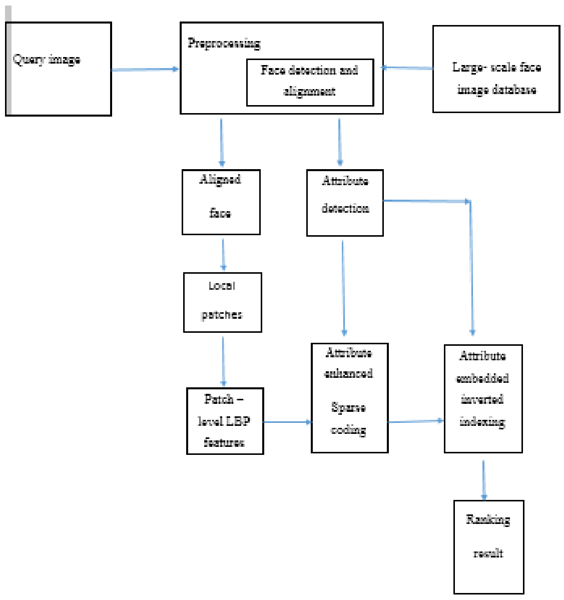


Fig. 1 Block Diagram of Proposed System

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Query image will go through the same procedure to obtain sparse codewords and human attributes, and use these codewords to retrieve images from dataset. For efficient retrieval from dataset images regression technique is use*d*

### B. Methodology

Step1: Image preprocessing
Step2: Attribute detection
Step3: Patch-level LBP feature computation
Step4: Attribute-enhanced sparse coding
Step5: Regression technique
Step6: Retrieval result

#### 1) Image preprocessing

For every image in the database, first Viola-Jones face detector is applied to find the locations of faces. To locate 68 different facial landmarks on the face image Active shape model is applied. Using these facial landmarks, barycentric coordinate based mapping process is applied to align every face with the face mean shape.

#### 2) Attribute detection

Before face alignment in preprocessing stage attribute detection is needed. Attribute detection framework from used to find human attributes from located face. For automatic attribute detection, attribute classifier is trained using various labeled images from internet which measures the presence, absence, or degree to which an attribute is expressed in images.

#### 3) Patch-level LBP feature computation

Three components detected from face image, nose tip, and two eyes. From each detected facial component 81 grids are extracted, where each grid is square patch. Hence, in total we have 243 grids from aligned face. From each grid, an image square patch is extracted and a 9-dimensional uniform LBP features computed.

#### 4) Attribute-enhanced sparse coding

This coding method is applied to all patches in a single image to find different codewords and finally combine. All these codeword together to represent the images.

## IV. CONCLUSION

Scalable face image retrieval utilize automatically detected human attributes to significantly improve content-based face image retrieval. This system combining low-level features and automatically detected human attributes for content-based face image retrieval. Attribute-enhanced sparse coding exploits the global structure and uses several human attributes to construct semantic-aware codewords in the offline stage and also used regression to further improvement. This technique may reduce the quantization error and achieve salient gains in face retrieval on two public datasets. By using the AES the chances of attack on output get reduced in case of online stage.

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