2. Locating facial landmark.
3. Extract image patch.
4. LBP feature for each patch.
5. Quantize every descriptor into codewords using attribute enhanced sparse coding.
6. Use this codewords with binary signature to retrieve image in the index system.

- **Attribute-Enhanced Sparse Coding (ASC)**

Sparse coding is one of the approaches for face image retrieval. In our proposed work, we used an attribute-enhanced sparse coding applied to all the patches of a single image. The codeword's are then combined together for representing a single image. Let us discuss the process of sparse coding for image retrieval.

a) Sparse Coding for Face Image Retrieval (SC): The sparse coding technique for face image retrieval is a combination of two processes: dictionary learning and sparse feature encoding. Learning the dictionary which is a large vocabulary is a time consuming process. Hence, the author Coa tes et al. has suggested an idea of using randomly sampled image patches as dictionary. The use of the sampled image patches produces similar result than using a learned dictionary. After learning the dictionary, we solve the problem by LARS algorithm. Then we identify the nonzero entries as codeword's of images. The codeword's of 175 different grids would never match to each other enabling to encode the spatial information into sparse coding.

b) Attribute-Enhanced Sparse Coding (ASC):
For sparse representation of human attributes, we enforce the process of dictionary selection (ASC-D), for assuring every image with different attributes should contain different codeword's. As shown in figure 5, for every human attribute, the dictionary is divided into two dissimilar subsets. One subset is used by the images with positive attribute scores and the other subset is used by the images with negative attribute scores. Due to these dissimilar subsets, we can surely have non-identical codeword's.

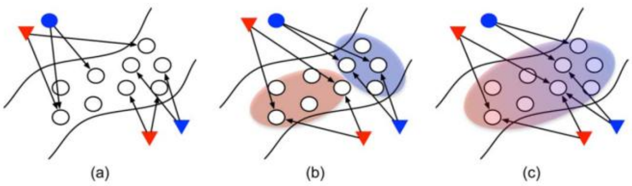

Figure 5: Comparison between attribute enhancing coding methods: SC, ASC-D and ASC-W.

- **Attribute Embedded Inverted Indexing (AEI)**

The above approach included the construction of codeword's from human attributes. The second approach for utilizing the human attributes is discussed in this section. The human attributes are used by adjusting the inverted index structure.

a) Image Ranking and Inverted Indexing: After the images are represented in sparse representation, the codeword's can be used for representing. There is a set of codeword's say c(i). The computation of similarity between two images is done as follows:
$S(i,j)=||c(i)\backslash c(j)||$

The ranking of image based on these similarities can be efficiently found using inverted index structure.

b) Attribute-Embedded Inverted Indexing*:* We can use a binary signature for embedding the attribute information into index structure. The signature is a dimension binary signature used for representing the human attributes. The sparse codeword's set c(i) with combination with the signature b(i) represents the attributes as:
$b(i) = 1$ if $f(i)(j)>0$
0 otherwise.
The attribute-embedded inverted index is constructed with the features of database images. These features include the codeword's and binary signature of the image.

5. Contribution

We have added some more function to existinig system .We have provided other retrieval system by using the query. By using this query we can retrieve the image on the basis of attributes. This query base retrieval gives the different result as compare to the image base retrieval. This query base retrieval use the same database as the image base retrieval database.

6. Result Set

For every image in database we are applying Haar-cascade algorithm which detect the face As shown in the below figure query image is seleced then the face is detected after detecting the face face get crop from query image patches are find.

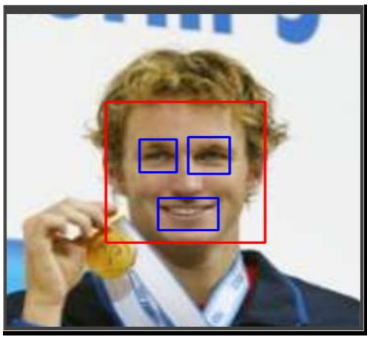

Figure 6: Query image with detected face

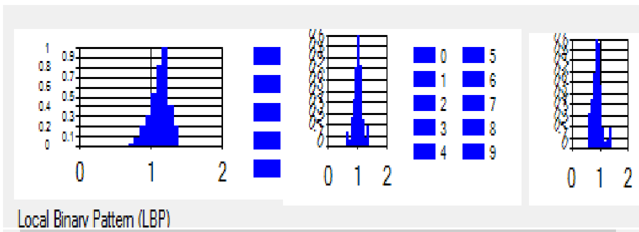

Figure 7: Local Binary Patterns.

Figure 8: Retrieval result.

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Local binary patterns are find for each patch of image .It goes through sparse codeword's and human attributes and use these codeword's with binary attribute signature to retrieve image in the system.

7. Conclusion

We combine two methods to utilize automatically human detected attributes to significantly improve content-based face image retrieval. Attribute-enhanced sparse coding uses several human attributes and exploits the global structure. These human attributes used to construct semantic aware codeword's in offline situation. Attribute-embedded inverted indexing considers local attributes of the query image and used for retrieval in online situation. The proposed scheme can easily integrated into inverted index to maintain a scalable framework. We invented methods which dynamically decide the importance of the attributes to exploit the contextual relationships between them.

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