Engineering,Technology and Techniques

Vol.60: e17160480, January-December 2017
http://dx.doi.org/10.1590/1678-4324-2017160480
ISSN 1678-4324 Online Edition

BRAZILIAN ARCHIVES OF BIOLOGY AND TECHNOLOGY

A N I N T E R N A T I O N A L J O U R N A L

Face Image Retrieval of Efficient Sparse Code words and Multiple Attribute in Binning Image

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ABSTRACT

In photography, face recognition and face retrieval play an important role in many applications such as security, criminology and image forensics. Advancements in face recognition make easier for identity matching of an individual with attributes. Latest development in computer vision technologies enables us to extract facial attributes from the input image and provide similar image results. In this paper, we propose a novel LOP and sparse codewords method to provide similar matching results with respect to input query image. To improve accuracy in image results with input image and dynamic facial attributes, Local octal pattern algorithm [LOP] and Sparse codeword applied in offline and online. The offline and online procedures in face image binning techniques apply with sparse code. Experimental results with Pubfig dataset shows that the proposed LOP along with sparse codewords able to provide matching results with increased accuracy of 90%.

Key words: Face Retrieval, LOP, Multiple face attribute, sparse representation, indexing

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INTRODUCTION

Camera and internet connectivity enable smart phone users to upload photo in internet. Smart phone applications leads to image search for various applications like criminal investigation, banking smart-card application etc. Image based search involve an input query image and retrieval of similar image to the input image from database. Image retrieval systems consist of low-level features such as colour, texture and shape. Image retrieval systems with colour and shape features perform with low results. In addition, Facial Feature like expression, pose, illumination, gender, race and hairstyle as input for image retrieval results with high performance. Feature extraction from image pixel play an important role in facial image retrieval. The facial and image content features forms the multiple attribute retrieval system.

Multiple attribute help to identify similar images from the database and index the results depending on their similarity. However, factors such as illumination, expression, side pose, and occlusion make hard to extract the multiple attribute features of face image. Similarly, the less no of attributes from images give more mismatch image. Until now and then, many researchers concentrate on Multiple attributes of, image retrieval system still the level of perform is a challenging task. The problem is due to the accuracy in the exact facial feature extraction during different lighting and pose.

In this paper, we propose image retrieval with Local Octal Pattern [LOP] and sparse code words detects the facial attribute feature. Sparse code words provide additional features of face image. These sparse code features improve accuracy of image retrieval from the database and also the same procedure obtains for the face images with binning techniques.

RELATED WORK

Image retrieval systems develop rapidly due to the globalization. The retrieval system need more efficient algorithm with accuracy for huge database[1,2]. The database of the image increases as storage capacity of the servers increases. The size of database leads for the more new algorithm in retrieval system[3,4]. The process of developing the new algorithm is everlasting. As a result, the image retrieval algorithms combine with many other machine-learning systems to produce an efficient result in retrieval[5,6]. The image retrieval integrates with the discriminative learning for face detection. In the face detection, the faces images with bounding rectangles and facial landmark locations collected for all the images in the database and the corresponding discriminative classifiers obtained[7,8]. For the collected classifiers, a voting based method of image retrieval is applied. The voting method produces an accurate method without resorting and scanning[9,10]. The method gives more negative retrieval results for various illumination and side pose of the face images. Further, retrieval system execute with the attribute of the face image[11,12]. The attributes such as age, race, hair, colour, smiling, bushy eyebrows, etc. consider for retrieval to the pubfig database. The attributes retrieval performs low results due to pose variations[13]. However, low-level image features such as shape and texture of the images apply for retrieval system. The shape and texture features obtained from the small regions, in single image with local binary pattern for face identification[14,15]. The local binary pattern histogram of face and nearest neighbourhood classifier for face recognition perform better than PCA, Bayesian, Intra/extra personnel classifier and elastic bunch graph matching[16]. In addition the shape and texture feature execute efficiently on FERET face database, which includes differential facial expression, lighting and aging of the subjects. As an extension, shape feature in terms of active shape model use to locate the frontal view of upright faces[17,18]. The extension in active shape incur due to fitting more landmarks that are actually needed, selectively using two instead of one dimensional landmark templates, adding noise to the training set, relaxing the shape model where advantageous, trimming covariance matrices by setting most entries to zero and stacking two active shape models in series[19.20]. However, local binary pattern to recognise the face replaced with local octal pattern. The local octal patterns (LOP) do well than local binary pattern, local ternary pattern, and local tetra pattern[21]. The LOP calculates the diagonal, horizontal and vertical directions of the pixels using first derivatives and thereby encodes eight distinct values about the relationship between the referenced pixel and its neighbours[22]. Further, the retrieval system improves the positive images, when face attributes and positions is included. The face attributes consists of nine attributes such as female, male, kid, youth, elder, Caucasian, Asian and, African. Along with the face attributes and aesthetics filter, enhance the face images with poor photographic qualities[23]. The attributes with domain knowledge allows the humans to interactive paradigm, as feedback to the classifier for face recognition. The attributes can extend with more number of attributes and form a multiple attribute query search for face recognition[24]. The multiple attributes obtain from the statistical extreme value theory and the probability scores the attributes. The multiple attributes increases the results with contextual attributes. The multiple attributes with dictionary learning algorithm for sparse code in face recognition incorporates data and attribute similarities. The dictionary-learning algorithm measures the distance of data and attribute to evaluate the positive images[25].

TABLE I - Literature Review

S.No	Year	Authors	Title	Proposed Method	Findings
1	2001	P. Viola and M. Jones	Rapid object detection using a boosted cascade of simple features [10]	Machine Learning Approach	Visual object detection that is capable of process images extremely speedily and achieving high detection rates
2	2009	J. Mairal, F. Bach, J. Ponce, and G. Sapiro,	Online dictionary learning for sparse coding [1]	Online optimization algorithm based on stochastic approximations.	The retrieval system need more efficient algorithm with accuracy for huge database
3	2010	Z. Wu and H. Shum	Scalable Face Image Retrieval with Identity-Based Quantization and Multireference Reranking [11]	Inverted index based on local features	Face images with good recall, while the multi-reference re-ranking with global hamming signature leads to good precision.
4	2011	R. S. Feris and L. S. Davis	Image Ranking and Retrieval based on Multi-Attribute Queries [8]	Multi-attribute query based	Attributes are independent both single object and multiple object categories
5	2011	Y.-H. Lei, Y.-Y. Chen, L. Iida, B.-C. Chen, H.-H. Su, and W. H. Hsu	Photo search by face positions and facial attributes on touch devices [4]	Block-based indexing approach	It achieved high performance but the database of the image increases as storage capacity of the server's increases. The size of database leads for the more new algorithm in retrieval system

6	2012	S. Murala, R. P. Maheshwari, and R. Balasubramanian	Local tetra patterns: A new feature descriptor for content-based image retrieval [2]	LTrPs method	The retrieval system need more efficient algorithm with accuracy for huge database.
7	2012	W. J. Scheirer, N. Kumar, P. N. Belhumeur, and T. E. Boult	Multi-attribute spaces: Calibration for attribute fusion and similarity search [3]	To construct normalized “multi-attribute spaces” from raw classifier outputs, using statistical Extreme Value Theory	The database of the image increases as storage capacity of the servers increases. The size of database leads for the more new algorithm in retrieval system.
8	2013	B. C. Chen, Y. Y. Chen, Y. H. Kuo, and W. H. Hsu	Scalable face image retrieval using attribute-enhanced sparse codewords [15]	Attribute-enhanced sparse coding and Attribute embedded inverted indexing	In this paper, proposed automatically detected human attributes to improve content based face retrieval by constructing semantic codewords.
9	2013	X. Shen, Z. Lin, J. Brandt, and Y. Wu	Detecting and aligning faces by image retrieval [7]	voting-based method	Faces may be detected by choosing the modes from the voting maps, without resorting to exhaustive sliding window-style scanning.
10	2014	S. Suchitra, S. Chitrakala, and J. Nithya	A Robust Face Recognition using Automatically Detected Facial Attributes [9]	Local Octal Pattern (LOP) feature descriptor with automatic facial attributes	In this paper, facial feature extraction done by LOP with automatic facial attributes. It improved the accuracy of the face retrieval system but still some of the attributes will decrease the performance
11	2014	I.Sudha, V.Saradha, M.Tamilselvi, D.Vennila	Face Image Retrieval Using Facial Attributes By K-Means [19]	Facial Attributes By K-Means algorithm	It achieved immediate retrieval in a very large-scale dataset by raising the face retrieval in the offline and online stages. The proposed automatic method allows the recognition and their time characteristics (i.e., sequences of time segments: neutral, start, height, and balance).
12	2015	Jun Liu, Xiaojun Jing, Songlin Sun, Zifeng Lian	Local Gabor Dominant Direction Pattern for Face Recognition [24]	Local gabor dominant direction pattern (LGDDP)	The LGDDP convolve query images with Gabor filters to produce resultant images of multiple scales. The output images contain pixels encoded with LGDDP. In addition, nearest neighbour classifier help classify face images.
13	2016	J.H. Na, H.J. Chang	Blockwise collaborative representation-based classification via L_2-norm of query data for accurate face recognition	Blockwise collaborative representation-based classification	A blockwise collaborative along with L_2-norm data set propose for face recognition from images. The image divides into blocks for representation coefficients estimations. In addition, conventional reconstruction method employ for classification of query

			[25]		image.
14	2016	Cuiming Zou, Kit Ian Kou, Yulong Wang	Quaternion Collaborative and Sparse Representation With Application to Color Face Recognition [26]	Quaternion Collaborative and Sparse Representation	Quaternion CRC (QCRC) in addition with quaternion SRC (QSRC) using quaternion ℓ_1 minimization employ for face recognition. The QCRC and QSRC perform better than CRC and SRC method. The CRC and SRC method use for face recognition from gray scale image.
15	2016	Yang Hui-xian, Cai Yong-yong.	Adaptively weighted orthogonal gradient binary pattern for single sample face recognition under varying illumination [27]	An improved version of AWOGBP and PCA method	An improved version of AWOGBP and PCA method overcome illumination barrier in precise face recognition.
16	2016	Tomás Mantecón, Carlos R. del-Blanco, Fernando Jaureguizar, Narciso García	Visual Face Recognition Using Bag of Dense Derivative Depth Patterns[28]	Dense Derivative Depth Patterns	The authors propose depth camera to discriminate face with high accuracy. The face images recognize faces with different pose in all directions.

PROPOSED MEHTOD

Dataset:-Pubfig consists of real-world images of public figures collected from the internet. The Pubfig database contains 58,797 face images of 200 people collected from the internet with different conditions such as illumination, pose etc. From the dataset, 30 images, people of 15 images taken for experiments. The Pubfig dataset is larger [over 60000 images] and deeper [300 images per individual]. The dataset applies for feature extraction, multiple-query attributes, and sparse codewords.

The architecture of an efficient sparse codewords for multiple attributes work with dynamic human attributes. The dynamic attributes in the architecture such as smiling, glasses, and hairstyle. The architecture of multiple attributes executes in two stages namely online and offline stages. The offline process is to train stages in the database for similarity matches. The online process is to get the similar images in the database for the given input query image. Initially, the images are pre-processed before given as an input to online and offline process. The pre-processing step involves getting the aligned faces for retrieval phase. In pre-processing viola-jones, face detector detects the face in database and the active shape model detects the face landmarks. The output of pre-processing provide the face image with align. The figure 1.shows the system architecture for an efficient sparse codewords using multiple facial attributes in face image retrieval system.

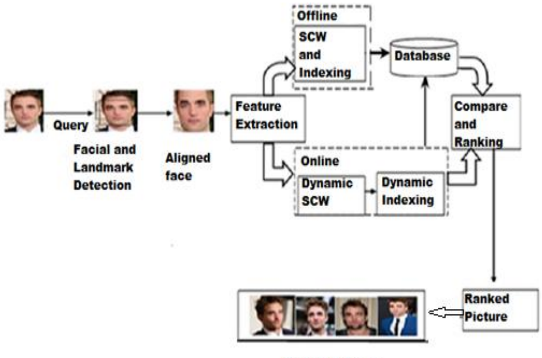

Figure 1. System Architecture for an efficient sparse codewords using multiple facial attributes in face image retrieval system

The steps in pre-processing are face detection, face landmark detection, and face alignment. In face detection, the faces under different pose and illumination detect with viola-jones method. The landmarks in the face obtain with active shape model. The model locates the landmarks, which distinguish the point in the face for extracting the features, for example the location of right eye pupil. The alignment of face obtains from the elimination of background object as shown in figure 2.

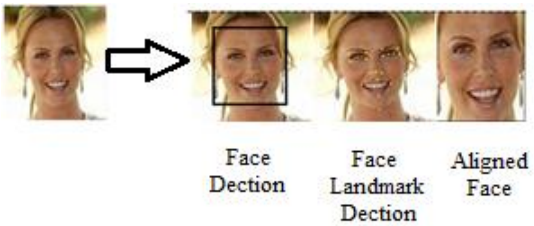

Figure 2: Pre-processing steps for face image retrieval system

The feature extraction in the face after face alignment obtain with LOP (Local Octal pattern).The LOP encodes the relationship between the centre pixel and the reference pixel base on the direction of the centre pixel gc. The LOP algorithm executes as below.

-----Algorithm of LOP---------------------------------

i. ***Load the image and convert it into grayscale.***

ii. ***Calculate the first-order derivatives in diagonal (g_d), vertical (g_v) and horizontal (g_h) directions with respect to center pixel, g_c.***

$$I^1_{0^o}(g_c) = I(g_h) - I(g_c)$$

$$I^1_{45^o}(g_c) = I(d) - I(g_c)$$

$$I^1_{90^o}(g_c) = I(g_v) - I(g_c)$$

iii. ***Direction of each pixel is calculated by***

$$\begin{array}{ll} 1, & I^1_{0^o}(g_c) \geq 0 \text{ and } I^1_{90^o}(g_c) \geq 0 \\ 2, & I^1_{0^o}(g_c) < 0 \text{ and } I^1_{90^o}(g_c) \geq 0 \\ 3, & I^1_{0^o}(g_c) < 0 \text{ and } I^1_{90^o}(g_c) < 0 \\ 4, & I^1_{0^o}(g_c) \geq 0 \text{ and } I^1_{90^o}(g_c) < 0 \\ 5, & I^1_{0^o}(g_c) \geq 0 \text{ and } I^1_{45^o}(g_c) \geq 0 \\ 6, & I^1_{0^o}(g_c) < 0 \text{ and } I^1_{45^o}(g_c) \geq 0 \end{array}$$

$$7, \quad I^1_{45^o}(g_c) < 0 \; and \; I^1_{90^o}(g_c) < 0$$
$$8, \quad I^1_{45^o}(g_c) \geq 0 \; and \; I^1_{90^o}(g_c) < 0$$

iv. ***Calculate the 8-bit tetra pattern for each centre pixel, and three binary pattern are generated from them***
v. ***Calculate the histograms of binary patterns***
vi. ***The magnitude of centre pixel can be calculated as***

$$M_{I^1(g_p)} = \sqrt{(I^1_{0^o}(g_p))^2 + (I^1_{45^o}(g_p))^2 + (I^1_{90^o}(g_p))^2}$$
$$LP = \sum_{p=1}^{P} 2^{(p-)} * f_1(M_{I^1(g_p)} - M_{I^1(g_c)})$$

vii. ***Construct the feature vector***
viii. ***A given query image and images in the database is compared and a set of similar images is retrieved***

In the algorithm, first-order derivatives calculate the diagonal, horizontal, and vertical direction pixels. From the pixels, a centre pixel of 8-bit tetra pattern is obtained. The patterns divide into four parts from the calculated directions. Finally, three binary patterns generate from each direction as a total of 12 (4*3) binary patterns.
The LOP algorithm fixes the pixel of matrix in the face as centre pixel, horizontal, vertical and diagonal pixels. The diagonal pixel thresholds the centre pixel and interprets the binary number as result. Further, the adjacent pixel of centre pixel considers as centre pixel and threshold and the process continue for the entire adjacent pixel. From the process, the feature of face component extraction is efficient, due to the consideration of each pixel as centre pixel as shown in figure 3. However, the facial image for test cases capture with 300 dpi camera. In addition, any flaws in camera and different resolutions have trivial impact on recognition.

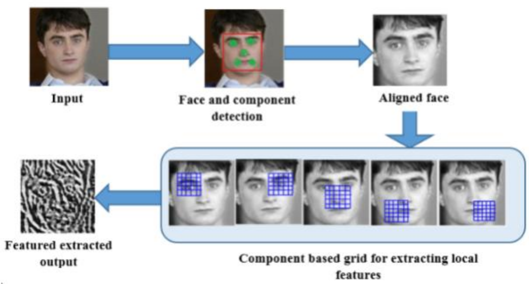

Figure 3. Facial feature extraction using Local Octal Pattern (LOP) feature descriptor

Multiple Attributes Sparse Codewords Dictionary Learning (MASCDL):
The sparse codewords applies in the face image as a feature, a linear combination of the column vectors of the dictionary. The sparse coding for face image retrieval as follows

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

Subject to $\|D_{*j}\|_2^2 = 1, \; \forall_j$

Where $x^{(i)}$ the original feature extracts from a patch of face image i, $D \in R^{dXK}$ to-be-learned dictionary contains K centroids with d dimensions. $V = [\vartheta^{(1)}, \vartheta^{(2)}, \vartheta^{(3)}, \ldots . \vartheta^{(n)}]$Sparse represent of the image in patches. The constraint on each column of $D(D)_{*j}$is to keep D to become arbitrarily large.

Face attributes dynamically change, a challenging task in face image retrieval. The multiple attributes from face image achieve better retrieval results. The face image multiple attributes convert to attributes scores after combining with extracted features and attributes to generate attribute enhanced sparse code words. The extracted feature of image is of low-level features such as shape and colour, which lacks in semantic meaning. However, the low-level feature combines with high-level human attributes to form a better feature representation for image retrieval. The high level attributes are asian, white tone and brown eyes.

In sparse representation to consider human attributes, we must use dictionary selection to force images with different attribute values to contain different code words. However, for a single human attribute, we divide dictionary centroids into two different subsets and they are the images with positive attribute scores and images with negative attribute scores. The positive male attributes score occupies the first half of the dictionary centroids. If the image has negative male attribute score then occupies the second half of the dictionary centroids. Similarly, doing the above process the different attributes have different codewords. In addition, for multiple attributes, we divide the sparse representation into multiple segments based on the number of attributes, and each segment of sparse representation generates a single attribute. The algorithm for MASCDL executes as below

---

a) ***INPUT: Training signals Y;***
b) ***OUTPUT: Learned dictionary D, Encoded sparse features V;***
c) ***Main Procedure:***

i. ***Initialization: D0 , $\rho > 1$, $K \in N$ and $b > a > 0$***
ii. ***do (for all image)***
iii. ***for K = 0, 1, . . . , K***
iv. ***// sparse representation of the image patches***
v. ***calculate V = [$\vartheta^{(1)}, \vartheta^{(2)}, \vartheta^{(3)}, \ldots .. \vartheta^{(n)}$]***
vi. ***end***
vii. ***for K= 0, 1, …, K***
viii. ***calculate each column D = D $\left(D_{*j}\right)$***
ix. ***end***
x. ***repeat each data points in the image***
xi. ***compute the distance of ϑ_q to each centroid $\overline{\vartheta^{(k)}}$***
xii. ***end***
xiii. ***update K = D $\in R^{d\,X\,K}$***
xiv. ***until no new assignment occurs***

The output of sparse coding the images with most features matching is listed and indexed. Sparse coding attribute score transforms with linear transformation in the interval of variation for current attribute. The transformed score calculates with the formula of

$t_{h_i} = LB_i + \frac{(h_i - L_i)}{(H_i - L_i)} * UB_i - LB_i$---(2)

Where,

h_i - Attribute score
L_i - Lowest of attribute score
H_i - Highest of attribute score
UB_i - Upper bound of interval of variation
LB_i - Lower bound of interval of variation

However, Normalize the attribute score of all the attributes so that to sum up to the number of attributes. The normalized values are the dynamic weights of each of the attributes.

EXPERIMENTS

The block diagram as in figure 7 shows the workflow of the retrieval process.We compare LBP and LOP feature descriptor and Single face attribute and multiple face attribute.LBP threshold centre pixel with each pixel in 3X3 neighbourhoods whereas LOP encodes relation between the centre pixel and reference pixels on horizontal, vertical and diagonal direction using first order derivate. A grid of 5X7 draws at each face component to get local facial features. Single face attribute may give importance to that attribute only. Multiple attributes combine to give semantic meaning to the query image for similarity match. For example, query image has a multiple attribute as brownish hair young woman having three attribute, which uniquely describes the query image to find similarity match with the database at the testing stage. The pubfig databases consist of facial images from western origin with variations such as male, female and facial images of people belonging to different regions. Facial images of people belonging to different regions such as, people from Asian and European have distinct facial features. The facial features of people in same region have little differences, which other algorithms fail to recognise. Local octal pattern algorithm extract feature from facial images with little difference. The steps involved in LOP algorithm of face recognition as follows.

The Figure 4 shows the aligned face from the face dataset. The face dataset images trains and give similar face images as same as the query image. Pre-processing steps to detect the face and detected face alignment output is as given below.

Figure 4. The output of the pre-processing stage - aligned Face

Once the pre-processing completes, the feature extraction of the given query face image is done and the Figure 5 shows that the output of the feature extraction using LOP which is given below.

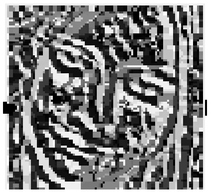

Figure 5. Extracted facial feature representation using LOP algorithm

After multiple query selection, sparse codewords for the attribute selected and feature extracted are obtained, indexed and similar face results are retrieved from the database trained. Figure 6 shows that the intermediate results.

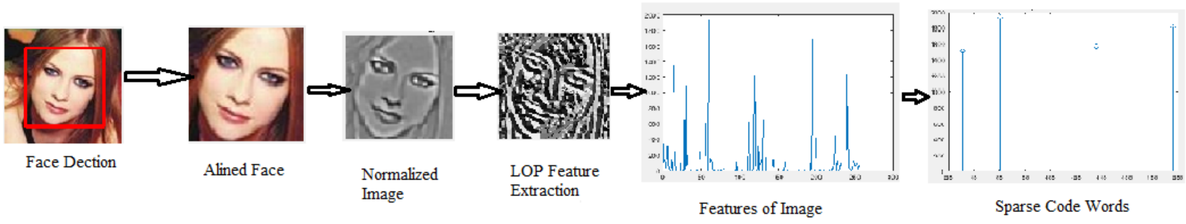

Figure 6. Intermediate results for the proposed method

The parameter in design of dictionary leads to the variation in performance. Parameter Setting of SC and ASC we need to decide parameter λ and dictionary size K. However, in our proposed system, we run different dictionary sizes from 100 to 3200 and λ from 10^{-6} to 10^{-1}, whereλ is too large (λ = 10^{-1}), almost all entries in sparse representation become zero, so the performance will drop. When λ and K are set properly (λ= [10^{-6}; 10^{-2}]; K = [100; 3200]), the performance of SC is stable. Throughout the experiments, we use mean Average Precision (mAP) to measure the performance.

In proposed system to highlight semantic-rich sparse codewords representations, we compare and the conventional sparse coding method and MASCDL as shown below in figure 7.

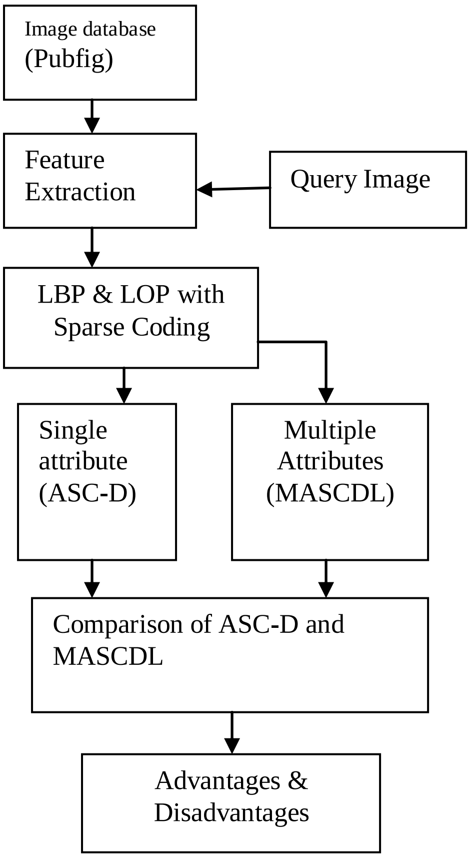

Figure 7: Block diagram-Workflow of retrieval process in proposed method

The Table II shows the comparison of LBP and LOP with MAP. The mAP is defined, as mean Average Precision (mAP) for a set of queries is the mean of the average precision scores for each query.

$$MAP = \frac{\sum_{q=1}^{Q} AveP(q)}{Q} \quad \text{---- (3)}$$

Wherein Q the number of queries.

The performance evaluates the each query images and their corresponding precision value calculates using the above formula. From the tabulation, we conclude that LOP able to retrieve almost accurate face images and reduced the retrieval of false positive images than its counterpart LBP.

IMAGE BINNING

The images with insufficient illumination play a vital task in image recognition. The proposed algorithm does not require any changes in image sensor or frame memory. Apply Image binning technique for the aligned face. After improving brightness and anti-saturation of local region of the face image and then extracting facial features using LOP feature descriptor. The low light image enhances using either sensor based binning or digital based binning. The digital binning algorithm improves brightness and anti- saturation of local regions. Sensor pixel binning sensitivity is increased by adding multiple pixels in one bin and decreasing spatial resolution. Sensor pixel binning avoids reuse of combined pixels, which reduces spatial resolution inversely proportional to bin size. However, digital pixel binning gathers multiple pixels values and reuses pixels of adjacent bins, which preserves spatial resolution. However, digital pixel binning gathers multiple pixels values and reuses pixels of adjacent bins. The adjacent bins combined improves signal to noise ration and increases the read speed of an image The digital pixel binning works figure 8 as shown in below

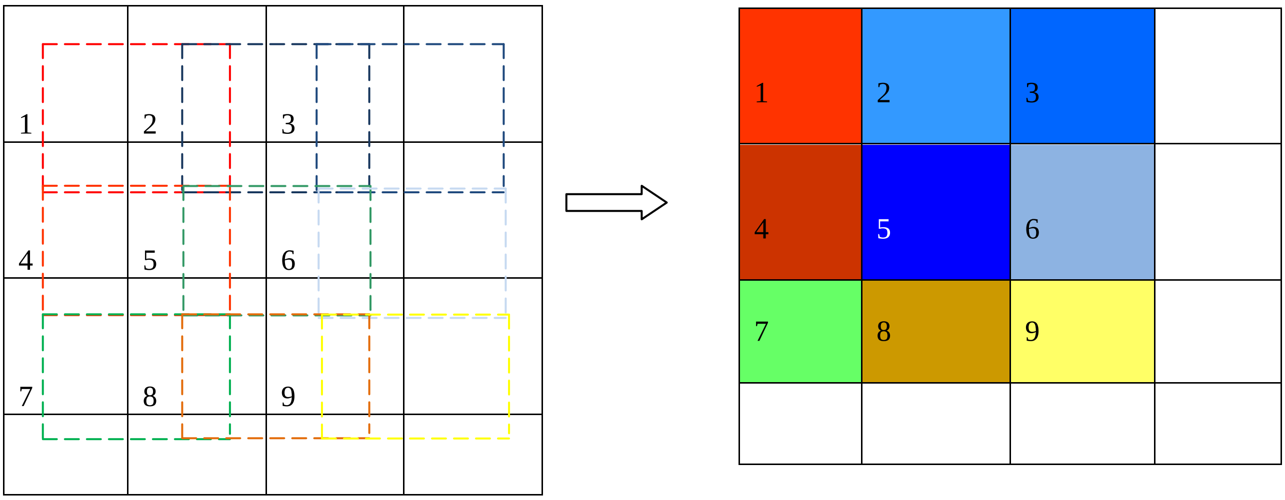

Figure 8. The digital pixel binning implements in the aligned face

TABLE II - Comparison of LBP and LOP algorithms

Dataset	PubFig	Dataset	PubFig
# of Queries	20	# of Queries	20
Performance	MAP	Performance	MAP
LBP	11.6%	LOP	19.2%
ATTR	15.1%	ATTR	17.1%
SC	14.7%	SC	15.4%

The multiple attributes sparse codewords dictionary Learning (MASCDL) and ASC-D performance analysis with various attributes is discussed. However, theTable III shows the mAP of multiple attributes sparse codewords dictionary learning based on single attribute up to 12.2% improvement in Pubfig dataset whereas the proposed method MASCDL increases to 50% more compare to ASC-D. We also notice that using certain attributes (smiling, frowning, harsh lighting, etc.) will decrease the performance in Pubfig dataset.

TABLE III - Comparison of Single Attribute using ASC-D and MASCDL

Attribute	Pubfig Dataset	
	ASC-D	MASCDL
Eye Glasses	15.9%	18%
Smiling	11.8%	14%
Teeth Not Visible	10.9%	15%
Black Hair	13.4%	17%
Male	16.1%	16%

The performance on multiple attributes shows in Table IV. The mAP of multiple attribute sparse codewords dictionary learning is tabulated. The ASC-D achieves up to 27.9% relative improvement in Pubfig dataset and the proposed method MASCDL achieve an increase of 30%.

TABLE IV - Comparison of multiple face attributes on ASC-D and MASCDL

Multiple Face Attributes	Pubfig Dataset	
	ASC-D	MASCDL
Eye Glasses/ Asian/ Smiling	15.9%	19%
White/ Smiling/ Asian	11.8%	14%
Teeth Not Visible/ Black/ Eye Glasses	10.9%	13%
Black Hair/ Male/ Teeth Not Visible	13.4%	16%
Male/ Eye Glasses/ Smiling	16.1%	21%

The Figure 9 shows that the performance of comparison between LBP and LOP, single attribute and multiple attribute in Pubfig with different threshold values (T). When T is large, the performance will converge to SC because it ignores the attribute signature. When T is small, the performance will improve, but when T is too small, the performance will drop dramatically. However, the reason for the phenomenon is due to two reasons. First, attribute detection error; when T is too small, the algorithm cannot tolerate attribute detection error, so the performance will drop. The Second, some attributes are not effective for identifying a person, and these attributes will cause the performance drop when T is too small.

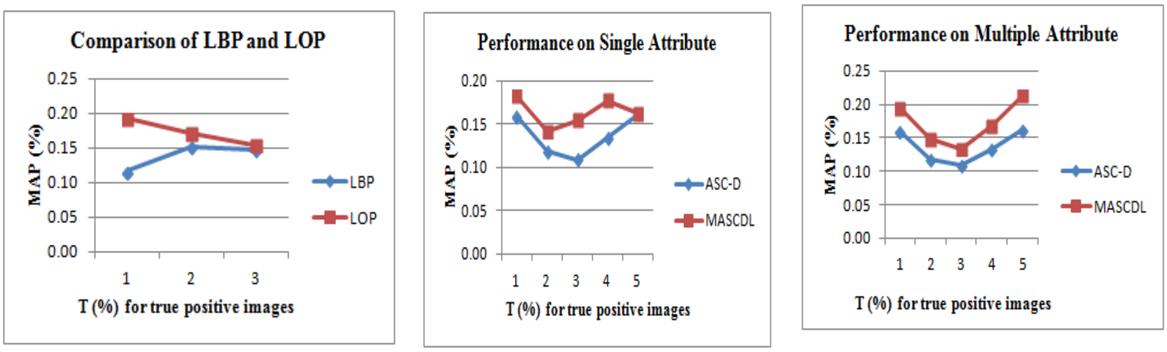

Figure 9. Performance analysis (a) LBP and LOP (b) single attribute (c) multiple attributes in Pubfig Dataset using different threshold values (T)

The digital pixel binning technique implements in the aligned face, to improve the spatial resolution of the given face image and then apply LOP local descriptor on the aligned face to extract the facial components. Figure 10 shows different parts of face using image binning technique implements in LOP algorithm. The binning in the face image improves the positive images in the retrieval. The spare codewords performs well in image binning than normal images.

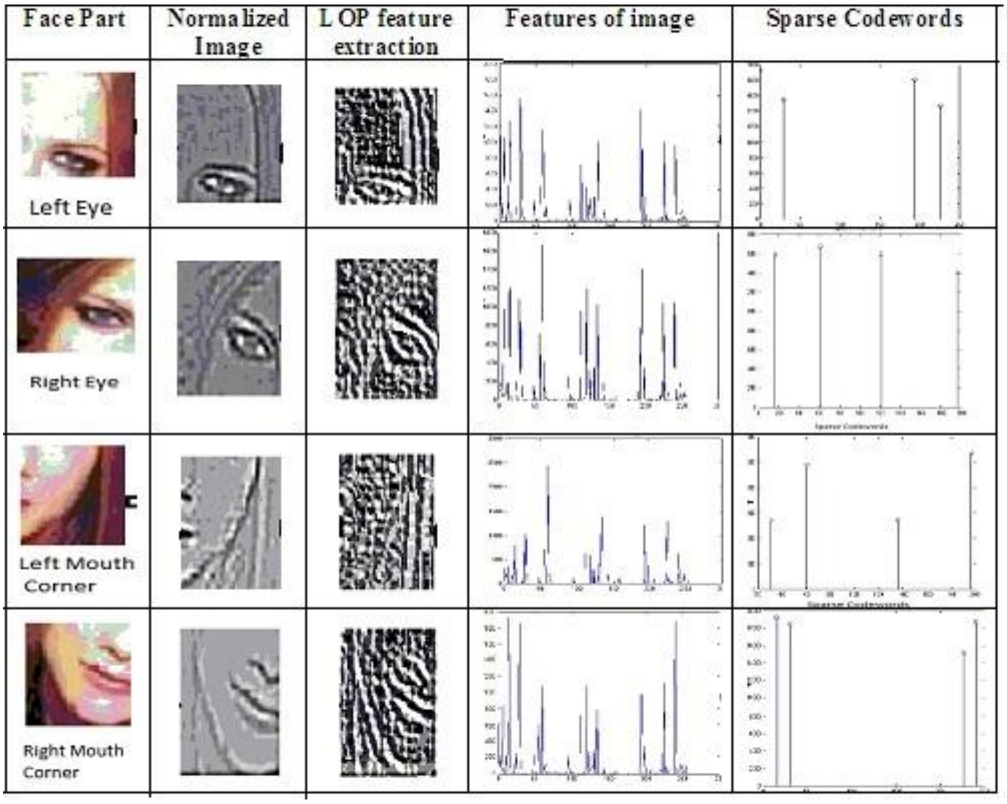

Figure 10: Different parts of face using image binning technique implements in LOP algorithm

Figure 11 shows an example of retrieval results from the proposed method MASCDL. The red boxes indicate the false positives, and each image is its rank in the retrieval results. In the figure (a) show how the selected the multiple face attributes of asian, male and smiling, the retrieval results are improvement, because no false positives images. In the (c) the selected multiple face attributes are female, white and teeth not visible the retrieval results are improvement, because no false positives images. In addition, in the (b) and (d) the failure case is due to select the wrong multiple face attributes for the query image such that we are unable to detect correct human attributes and reliable codewords. e) Even the query image has some occlusions; we can still find certain results because the codewords and attributes can capture additional information from the face region.

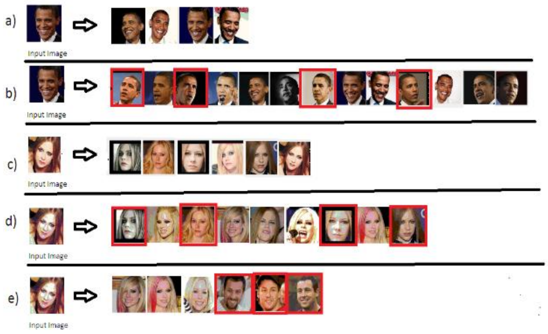

Figure 11. Retrieval results using the proposed method

CONCLUSION

The Low-level features of face image and high level intra-class variance such as illumination, pose and expression still a challenging task. However, the proposed approach could detect similar match face from the database with multiple attribute sparse codewords dictionary learning algorithm. In addition, the low-level feature combines the sparse representations with multi-attribute to get semantic information to represent image. Further, the experimental result shows the multiple attribute information and enhanced LOP feature extraction, we can solve the issues of high-level user expectation and fulfill lack in contextual relationships. Current methods show that significant improvement in retrieval. Scalability, recognizing facial image with pattern in expression and issue in identifying age of human face for a same person will be the future enhancement.

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Received: February 03, 2016;
Accepted: July 14, 2016