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Multiple feature descriptors based model for individual identification in group photos

Kapil Juneja

Department of Computer Science and Engineering, Maharshi Dayanand University, 307, Sector 14, Rothak 124001, Haryana, India

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ABSTRACT

Detection of person in the crowd is most exigent facial recognition aspect. Faces in a group can comprise the criticality of face localization, partial occlusion, and facial overlapping and real time background scenes. In this paper, single and multiple persons recognition is provided for group pictures. This offered method at first localized the facial area of the individuals. These identified faces are divided in full or the partial view clusters by observing the oval map. While performing the recognition, separate algorithms will be applied to both facial groups. Full face recognition is here implied using LBP, Gabor and structured feature fusion based distance analysis method. These methods will be applied individually and jointly to identify the facial image. Partial face recognition is here implied using discriminative structural analysis. This structural formation is here obtained using structure points and base curve identification. Maximum structural points and curve ratio map is considered as the identified image. Group images are captured at home, office, classroom and roadside with multiple situations. The experimentation interpretation is measured disjointedly for full view and partial view images obtained from complex scenes and scenarios. The evaluation is here applied to perform the facial region identification and the group photo recognition. The facial region extraction is applied on eight datasets. These datasets are IMM, Caltech, CMU, Bau, FDDB, LFW, Pointing and Self Collected Dataset. The facial extraction is applied on complex background images with single and multiple faces. The comparative evaluation shows that the localization stage of proposed model has reduced the FAR and FRR. The complete recognition model is applied on real time family dataset, random web celebrity dataset associated with LFW and FDDB datasets. The evaluation is provided for recognition of front and partial face images in different scenarios. The comparative results of facial recognition are evaluated against PCA, ICA and PCA-LDA methods. The results conclude that the proposed methods have improved the accuracy for both full and partial faces.

1. Introduction

Group photos are most standard captured photos form in ongoing scenarios either as family photos, occasion driven to capture photos or the image frame of any surveillance system. Group photo recognition can be implied in various application areas includes classroom attendance system, door surveillance cameras, etc. Sometimes, while performing the recognition the individual person image is not available or the recognition system is connected directly to the video camera device which can capture individual or group photo. In such case, recognition system is required to apply on faces present in group images. This kind of recognition system is effectively required in real scenes such as crime site monitoring through surveillance cameras. The recognition system applied to group photos is associated challenges. The first challenge to the system is to identify the facial region of each person in the image. This view region can be full or the partial. As the gathering increases or the scene complexities are high, facial region of a person can be overlapped by another person or some scene object. In Fig. 1, person 6 is partially overlapped by a person 7 which hide some of the facial information of that person. Pose variation (Takallou and Kasae, 2014), side view and the directions can be different for different person as depicted here in person 1, 2 and 3. All are having different head directions. Such kind of direction, sometimes gives only the side view of the person. In such scene specific capturing, the directional and distance measures from camera points can be differ. The camera centralized direction for person 1 and 8 are completely opposite whereas the distance aspect for person 7 and 3 are completely different. Based on this viewpoint, the

E-mail addresses: kapil.juneja81@gmail.com, kapil.juneja.1981@ieee.org
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1319-1578/

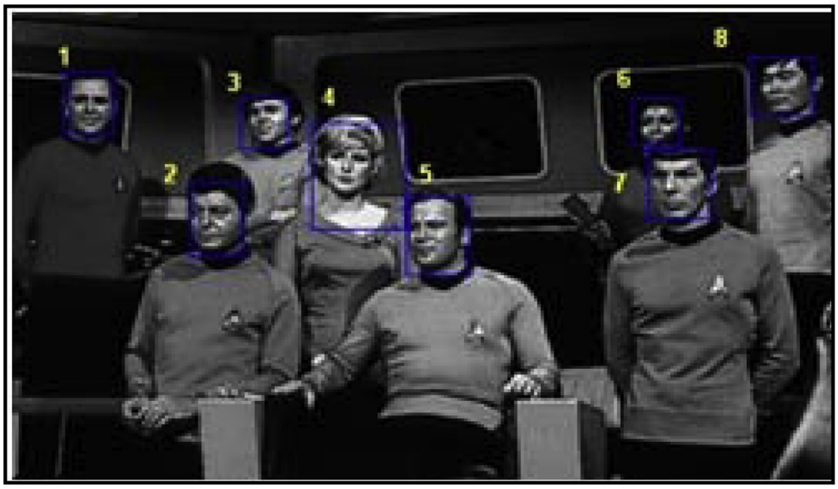


Fig. 1. Sample Group Image.

size of facial image can be different. These all differences signify that the group photo capturing requires a lot of pre-processing to transform each of facial images as individual face. In this paper, to perform facial recognition on the group photo, an exclusive process for facial region segmentation is applied as well as to identify the individual facial image from the group.

Background scenes in such group photos can also create confusion if it overlaps the facial object partially or the scene color, lighting or contrast mix with facial region. But if the background scene is known which is the genuine phenomenon on such images, then the background mask can be applied to identify the facial region easily.

The application area of such recognition system is very wide which can be applied for identification of crime suspects. The suspects can be identified even on social media and online shared pictures. Group photos shared on social media can be analyzed to identify some prime suspect. Accidental captured photographs or the sting captured photos and video frames can be used for identification of suspects.

1.1. Problem statement

Group photos are the real time photo capturing in real scenes includes the Parks, Hospitals, Railway stations etc. As these photos can be captured using some fix camera, CCTV cameras or the accidental capturing, It is almost impossible to get the clear view of some suspect. The identification of the suspect using the partial captured face and under real time capturing challenging is quite critical. Because of this there is the requirement of a complete model that can identify the facial objects from group photos as well as apply the separate feature measures on full and partial face images to improve the facial recognition. In this paper, a complete framework is provided to cover these common problems of group photo recognition.

Before working with the application area of group photo recognition, most of the criticalities are pragmatic and reasonably a supreme elucidation is provided. This framework acknowledged each of face independently in the group photo and categorizes them in packs and fractional vision images. Later on the separate algorithmic implication is applied to extract the representative featured forum. This featured outline is applied on individual facial feature with some extent map to identify the maximum mapped image with the specification of the lower limit. The work is implied on self captured images databases.

The paper has provided a robust and reliable solution for facial recognition on group images. Based on observations, separate algorithmic solutions are suggested for full and partial face recognition. In this section, the requirement and the complexities of group photo recognition is provided. The ground reliability relative to the application and the problems in the recognition process is discussed. The method provided in this paper considered all such criticalities. In Section 2, a discussion on the earlier researcher's contribution and the significance of work model is discussed. In Section 3, the framework provided for group photo recognition is provided. In Section 4, the algorithmic specification of full face recognition is provided and discussed. In Section 5, the subframework for partial face recognition is provided using ratio driven recognition. In Section 6, the experimentation on real time captured photos and web captured photos is provided and discussed.

2. Related work

Group photo recognition (Liao et al., 2014; Kaur and Kaur, 2013; Shelke, 2013) is rare and complex application area which is considered by lesser researchers. This application area still requires a lot of consideration of researchers. Most of researchers provided work on application (Manyam et al., 2011) specific group photo recognition, including student authentication system (Tamimi et al., 2015), crime investigation (Manjula and Santhosh Baboo, 2012) etc. The base of these recognition systems is identifying the facial region and separates the individual face image. Researcher's applied the clustering method (Barr et al., 2014) to locate the group faces. The clusters can be formed here based on the constraint observations (Junjea, 2015), including pose variation, distance variation or illumination variance (Juneja, 2015). The distance ensemble clustering is applied to improve the classification algorithm. The constraint clustering is offered by the researchers at an earlier phase to reduce recognition error. The distance formed clustering with connected component model generates the component weight and keep similar wait components in one group. The reliability of the classification method depends on the clustering method.

To apply the recognition algorithm appropriately, it is required to observe the basic facial characterization to convert the image to normalized image. Xu et al. (2016) designed a framework to convert facial data set to axis-symmetrical form to enhance the accuracy of face recognition. This virtual normalized image processing reduced the negative effects of pose, illumination and geometric variations in image. Author achieved the higher accuracy with lesser computational work at recognition stage. Haghighat et al. (2016) normalized the facial image to improve the capability of recognition process against non-frontal and variant illumination problems. Author used the Active Appearance Model to improve the facial features and make it compatible to the standard featured form.

The quality of face recognition against different complexities and criticalities depends on the generate feature space. Most of researches to optimize the recognition process are based on the way of feature subset generation. Gabor filter (Abhishree et al., 2015) is one such filter that process at different specified angles to generate Gabor image. Mahbubur Rahman et al. (2016) used the discriminatory feature set formed using global and local features. The heuristic method using fixed order moment was selected as 2D feature space to improve the recognition accuracy. A hybrid feature descriptor was introduced by applying the Zernike moment (Fathi et al., 2016) on Gabor filter result. Author combined the global feature along with local feature form to improve the accuracy of recognition method. Liu et al. (2016b) used the local structural observation based on overlapped local patches. The entropy estimation with probability distribution observation is used to obtain phase feature. The method used the multiple features for multiphase classification of facial image. Discriminant (Juefei-Xu and Savvides, 2016) Information is the dimension reduction based subspace feature form extracted using LDA (Linear Discriminant Analysis), UDP (Unsupervised Discriminant Projection) and LPP (Locality Preserving Projections) methods. To generate the multi aspect features, a more effective Zernike (Fathi et al., 2016) moment applied Gabor filter was used. This feature space provides the rotation invariant and multi-scaled feature descriptor to attain robust facial recognition. Another improvement to Gabor features was provided by incorporating the block feature analysis using entropy weight (Cament et al., 2015) assignment. This improved local normalization method provided the compensation against pose variant and illumination variant feature enhancement. The Gabor feature can be combined with some statistical measures to generate Unit Length Normalization (ULL) (Thiyagarajan et al., 2010), Zero Mean and Unit Variance methods. The normalized methods are applied under different feature classifiers to improve the facial recognition. The Gabor based statistical modeling can be applied under Graph Matching (Zhao et al., 2009) to generate the local landmarks. This local alignment based landmark mapping able to provide profile and shape robust facial features in more extensive form. The Gabor filter bank (Serrano et al., 2011) with Gaussian width can be applied to achieve robustness against turned faces, illumination, and facial expression and occlusion problems. The holistic and analytical features composition is able to improve the recognition accuracy.

The descriptive features under different aspects can be extracted to improve the computational simplicity, robustness and accuracy. LBP (Local Binary Pattern) is such feature form that represents textural properties based on extensive neighborhood analysis and generates different feature patterns. LBP can be applied on Image region space or on histogram region (Yang and Chen, 2013) space to motivate the feature utilization in classification methods. A weighted extended local binary pattern with pyramid (Gao et al., 2013) transformed method was used to generate local sub-feature map. More clear observation in local regions was provided under different critical problems including occlusion, expression and illumination change. The mutual information extraction using LBP structure (Ren et al., 2015) learning was provided based on pixel difference analysis was considered as strongly correlated feature selection method. The spatial feature patterns with incremental pixel difference were obtained to improve dynamic facial recognition.

Fusion Process is the merger of two or more technologies or methods defined at same level. The fusion process can be applied at filtration stage, feature generation stage or at recognition stage to improve the accuracy and efficiency of facial recognition. Zhang et al. (2016) used same strategy at feature generation stage using LBP (Local Binary Pattern) and Gabor filters. The combined method provided the robustness against textural variation, structural variation and geometric variation in facial images. A feature fusion based on Euclidean and Manifold (Chen et al., 2015) structures are considered to generate the discriminate feature space. A structural quantified measure under local preserved projection was provided using this fusion process. The combined structural features area able to provide higher recognition rate.

Different optimization and featured trained methods are identified by different researchers to improve the facial recognition. Liu et al. (2016a,b) has given a label based learning method based on modified flexible manifold embedding (FME). Author also used the score fusion scheme to predict the labels appropriately. Another improvement to machine learning approach using voxal (Li et al., 2016b) based morphometry analysis. A linear regression method based predictive model is defined to identify the path physiological condition in patients.

In high formed clustering, the pose (Li et al., 2014) is major constraint that can increase the recognition time error. The landmark work on pose difficulty resolution is required based on the adjustments at feature dimensions. Semantic observation respective to shape, texture and displacement field is provided to obtain the comparative observations on segmented region. These constraints are observed with neighbor level confidence measures to identify the cluster members. These parameter directed observation is more critical for 3D database (Min et al., 2014). These databases suffer from dimension specific occlusion and illumination. Data uncertainty (Xu et al., 2014) and modality increases in such database. The dynamic methods are applied to acquire the structural and environmental specific details that are potentially represented as facial landmark. These landmarks are required to observe respective to various facial variations in controlled conditions. Some adaptive (Wang et al., 2014) and dynamically robust methods are required for reliable and robust recognition formulation. Correlation structured map and sample structured analysis is required to gain the requirement method observations so that the accuracy of recognition process will be improved. To handle such uncertain data, object and situational variation, different trained filters (Rong et al., 2009; Xu et al., 2014) are applied before applying the classification methods. These methods capable the raw images to more interactive, real time and online recognition (Mallauran et al., 2005; Fazl-Ersi et al., 2008) applications. The rule formulation can be distance (Gunjan Dashore and Cyril Ra, 2012) driven or based on some intelligent classification methods. This proposed framework also covered all the real time criticalities and observation to achieve high recognition rates. The framework and the algorithmic stages corresponding to the work are given in the next sections.

3. Proposed framework

The objective of this framework is to provide accurate individual face recognition for a group image of the personage face dataset. The dynamic instinctual analysis improves the potential to apply it for diverse applications including crime investigation, classroom attendance or cyber crime detection. The framework shown in Fig. 2 is able to provide some key solutions with better recognition of individual from group photos. Kinetic observations are applied on each stage of work, including facial region segmentation, facial categorization, featured information extraction and recognition. The dynamic behavior of the algorithmic methods qualified with expected problem derivation. The structural and statistical methods are cooperatively functional here variant window specification.

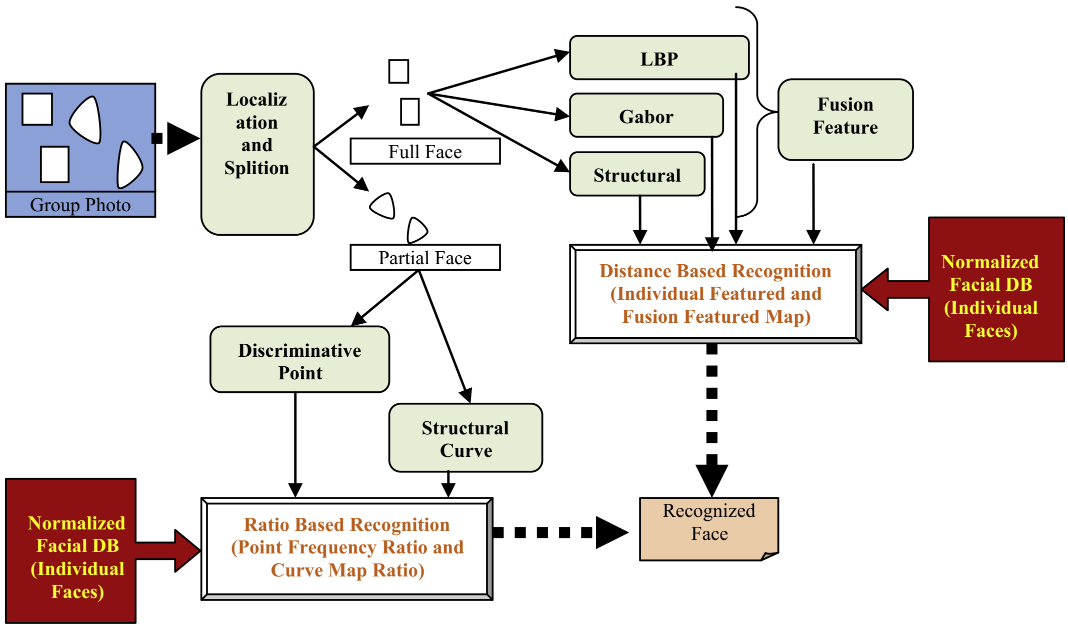


Fig. 2. Proposed Framework.

The input (MImg) taken to model is multi person high resolution color or grayscale image with a random background scene. Input image can have multiple facial instances, but should not include extremely close or interacting facial group such as kissing image, affectionate images, etc. The model will work where individual face can be identified clearly whether with a complete or partial view. After setting up the constraints, the improvement to the input image is done to equalize the feature constraints using histogram equalization method. A first dynamic process without applying any mask or template is applied to obtain the facial objects or regions. Each of the extracted facial regions is described by a separate image. As the camera distance from different images can be different, size level adjustments are done based on the largest size facial object. These adjusted facial regions are evaluated on a defined oval applied on each facial region.

The faces that qualify oval structure are considered full view faces and placed in the same group. The rest of the facial images are considered as partial view faces. After categorizing the individual faces, the separate feature extraction and recognition methods are applied. As the full face images are front face images with plenty of decisive information. This information extraction is applied using LBP (Local Binary Pattern), Gabor and structural methods. LBP generates textural features present the descriptive information in unified form independent to illumination and computational incapability. Local primitives for facial descriptors are obtained to account the coherent features. Gabor filter is a direction independent linear measure that generates the feature pattern from multiple viewpoints. The characteristics generations are based on frequency, edge and orientation vectors in spatial domain. Kernel function is applied to cell specification to gain the perceptual features. The structural features are disguised in the scheme to represent the information regions. Most qualified points in each region are taken to represent facial structure. After capturing these distinguish features on each full view face, the distance based mapping is applied to DB images. The kernel specific map is applied to identify the maximum recognized facial image. The reorganization process applies to individual and combined feature method. To combine the featured information, fusion process is applied on facial image. Based on these distance observations for four different feature patterns, maximum matched image is considered as a qualified image for full facial map.

Second extracted partial facial group is a more critical group to the lesser facial region. This lesser information is considered as discriminative facial region, which is quantified under discriminative feature evaluation methods. This evaluation is done in two phases. In the first phase, the discriminating feature obtains are extracted to represent information regions on face image. The segment driven information quantification is applied based on texture, visibility and edge information. The point table is composed as the discriminating feature points. Another discriminating observation is taken based on the curve identification as connected edge pints. The high frequency and edge featured observations are applied to generate discriminative curve for facial image. These discriminative points and curve compare with database image discriminative features. This comparison is applied respective to positional and intensity value observations. The maximum ratio of points mapping is considered as outcome image obtained from sub-model.

From the model, it is understood, to apply the individual face recognition, it is required to first identify the facial regions and categorize them respective to available facial information. In this section, these two stages are described.

3.1. Individual face identification

Group images captured through still or video cameras in real time scenarios. These videos or images can have known or unknown scene. To acquire the facial objects from an image, it is required to remove these complex real time backgrounds and extract the facial region. If the background scene is known, then a clear subtraction method can be applied. Such background mask based removal is shown in Fig. 3(a)–(c). If the scene is captured through a video camera and the group persons are not stationary, then the movement analysis between the movie frames can be observed to identify the similarity between the frames as shown in Fig. 3(e)–(g). If a stationary image with the unknown scene is available, then some intelligent observation is required to identify the individuals. To extract facial region, skin color regions are detected after adjusting the colors and color mode.

During preprocessing, light and color compensation is provided by adjusting the light interferences. Each layer of RGB is adjusted by adding some color tolerance to average color value. This bal-

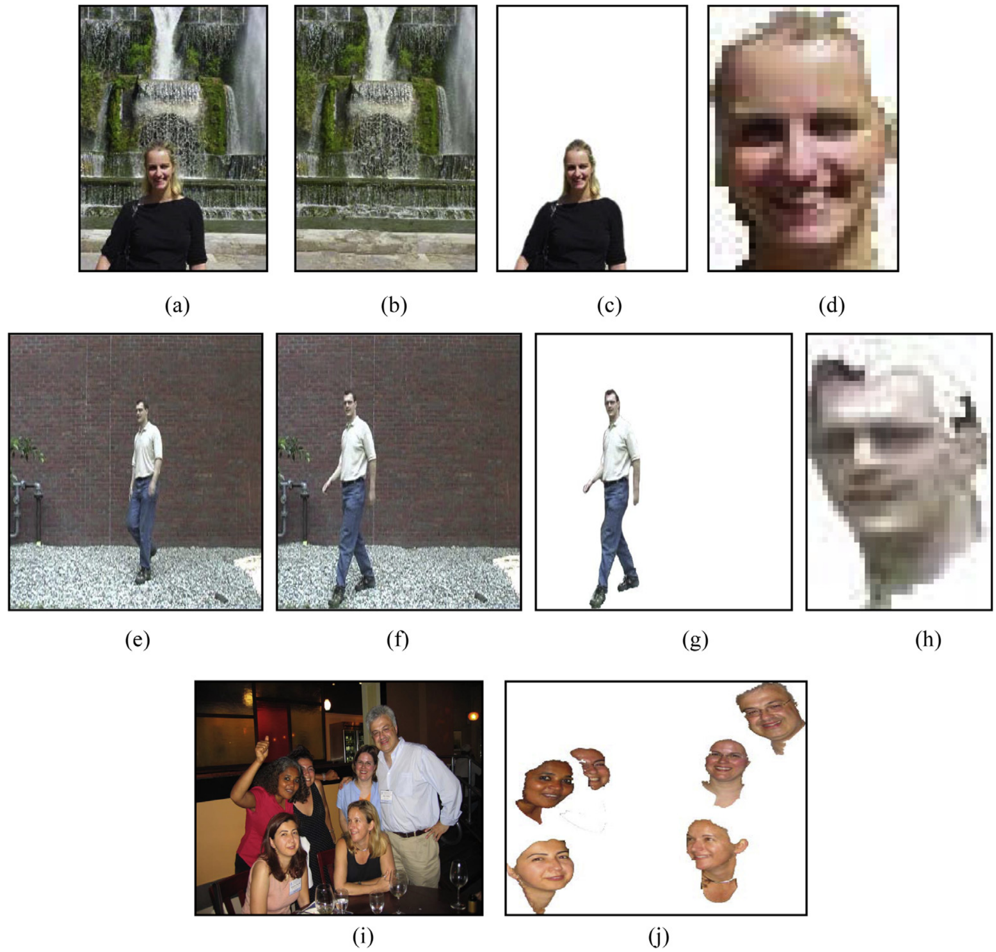


Fig. 3. Facial Region Segmentation in single, group images and videos (a)–(c) person region segmentation for known scene over still image (e)–(g) facial segmentation on videos based on object moment analysis (i) group image with unknown scene (d), (h), (j) skin region identification based on Gaussian enabled color model analysis.

anced image is transformed in YCbCr color space and processed on Luminance layer along with skin thresholding for facial region selection. At the final stage, Gaussian distribution is combined to achieve the color difference and the luminance independent skin selection and to avoid facial overlapping. Hole filling is applied to avoid the smaller skin regions, including hands, feet, etc. The algorithm implementation of this model is shown in Table 1.

The algorithm defined in Table 1 equalizes the color features applied to the RGB model. Intensity observation on each layer is applied using statistical derivations. The reformation of illumination invariant image is performed using average intensity to intensity difference analysis. This color space conversion is applied on reforming the image to YCbCr model. To identify the skin color, analysis on 50+ real time group images is done to decide the threshold limit. This limit is applied on the luminance layer to getting skin regions over the image. Gaussian filter respectively to mean is applied to obtain the region invariant to luminance filter. This process generates the skin segment over the image. To deduce the regions obtained as smaller chunks are removed by applying the condition on area size. Finally the highly accurate skin segmentation is obtained as shown in Fig. 3(d), (h) and (j).

3.2. Oval map based face view categorization

Skin region wrenching applied on multi-person image spotted all persons in the image. These face areas are of different size because of distance from camera, pose or the occlusion. To apply the recognition it is essential to turn, then in the individual face image. Each face image must be explicated with identical geometric features. A size level individual face reformation is applied respective to frontal and larger facial image. These sizes adjusted facial images are considered as test images for the recognition process. But to apply the recognition feature method, it is required to categorize the images based on facial view content observation. For this categorization, the oval map is applied on facial images as shown in Fig. 4. This oval is divided into N smaller segments at the circumference points. Each segment point is evaluated for facial connection. The number of connection points on circumference segments is evaluated dynamically and compared with a defined limit to identify the face is full face or the partial. This evaluation categorizes the individual test set as full face testset and partial face test set.

The algorithmic formulation of facial categorization based on oval map is shown in Table 2.

The algorithm signifies, the method first identifies the base facial image and adjusts the physical parameters of each test image respectively. These structured test images are mapped with a generated oval with specification of touch points at circumference distance of 30° each. The numbers of touch points are compared with threshold limit to categorize them as full face dataset and partial face test set. After this stage, now two different test sets are available on which recognition process can be applied.

Table 1
Algorithm for Face Identification in Multi-Person image.

```
Algorithm
        Input :
                MImg      // Multi-Person Image
        Process :  1.LayerR LayerG LayerB]=GetLayers(MImg)          //Generate Color Layers
        2.      Generate Layered Statistics for Min, Max and Average Illumination Average
        Intensity
        3.      Generate Average Aggregative  Intensity Image
        4.      Apply Variation Analysis Based Color Balancing for Each Colored Layer : LayerR,
                LayerG, LayerB
        5.      ReformedImg=GenerateImage(ReformedR,ReformedG,ReformedB) //Generate the
                balanced reformed Image
        6.      Generate YCbCr color Model Image and separate each layer
        7.      Apply range Threshold on LuminanceImg for Generating the Skin Region
        8.      Generate expected mean value computation SkinImage  9.        Apply
TImg=Transform(CbImg,CrImg) to generate transit feature image
                10.     Apply Gaussian Analysis on Mean Difference Analysis DImg=(Timg-TransitMean)2
                for Neighbor Analysis
                11.     Apply Mutplicative enhancement to highlight skin region Threshold*DImg*(Timg-
                        TransitMean)2
                12.     Apply Dynamic Threshold to identify the finer skin region
                13.     blks=GetBlocks(SkinRegionImg)
                14.     ForEach blk in Blks
                        start
                15.             if blk.length <Threshold
                                        blk.type=background
                16.             else
                                        blk.type=SkinForeground
                                end
                end
        17.     ResultImg=ReconstructImage(blk)
Output:
        ResultImg       //Skin Region Extracted Image for Group Images
```

4. Full face recognition

The framework described in this paper, divided into two main segments. In first segment, the recognition the full face image is performed and in second segment the partial face view images are processed. In this section, the feature extraction and recognition process applied for full face recognition is presented. To generate the features, the structural, directional and textured features are collected using three different methods. These methods are applied individually as well as under fusion process to provide solution in case of orientation, illumination, pose variations and nonlinearity in images. These extracted features are compared individually and collectively using distance based methods with kernel specification. This kernel controlled distance map is able to recognize the image by covering the recognition method. In this section, all the feature extraction and recognition methods are explained.

4.1. LBP feature method

LBP (Local Binary Pattern) generates the uniform patterns based on extensive texture features. This information descriptor is able to provide rotational ineffective features so that the robustness against pose and head position can be derived. This feature measure applied the circular analysis on intensity and contrast parameters and interpolates values as quantize measure. As the name depicts, the method applies the bitwise rotational transition in a circular form to generate a pattern. The region covered in circular region neighbors can be estimated to generate the signified feature. LBP featured form of centralized pixel C(cx, cy) is given in Eq. (1)

$$\text{FeaturePattern} = \sum_{i=1}^{N} S(Img_i - C)2^i \tag{1}$$

S = 0 or 1
Here N is Number of Neighbors
S status value to represent the coverage of the region
C Centralized pixel.

This local descriptor is applied to sample points segmented with radial interpretation applied to center C. This illumination robust and rotation robust texture method loses some information which signs to the non uniform patterns. The LBP information patterns are significantly defined uniformly with space effective form. The histogram indicators describe the featured notation. This featured notation representation in bar graph form is shown in Fig. 5 for identifying full view image. The figure here showing the complete raw image, LPB formed extracted texture form and relative histogram featured form. Algorithmic representation of this radial segmentation based feature extraction and histogram generation is shown in Table 3.

According to the method described in Table 3, individual full view facial image is divided in smaller segmented by applying circular region over it. Each region is identified here with center and radius specification. These segmented areas pixel is analyzed respective to centered pixel specific neighbor intensity analysis. LBP qualifier is applied here to generate the feature vector. These feature vectors are collected to form the result LBP image. Obtained featured image is applied by histogram processing to generate the intensity graph for the image.

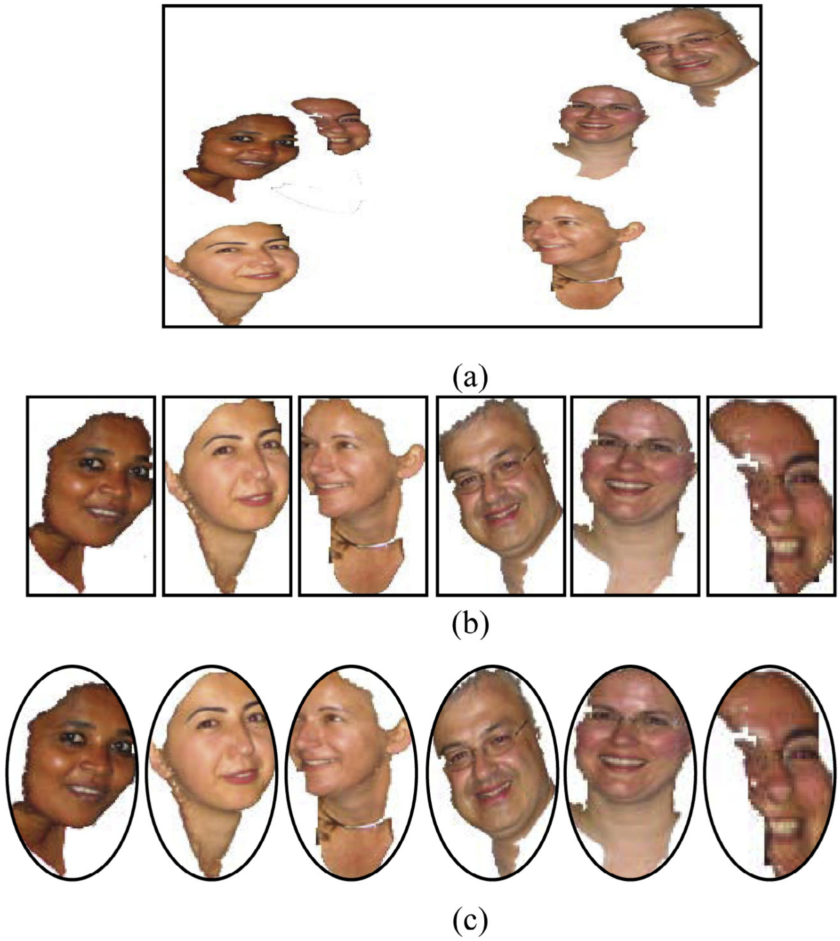


Fig. 4. Face Data Categorization based on Oval Map (a) Segmented Facial Images (b) Individually Extracted Face Images (c) Oval Mapped Faces.

Table 2
Oval map for face categorization.

```
Input:
        SegImgSet : Extracted Face Images Dataset
Process:
        1.      Analyze the Density of SegImgSet and Identify the index of Maximum Intensity Image
        2.      Identify the size of this index intensity image and considere as Base Estimator called BaseImg
        3.      ForEach segImg in SegImgSet
                begin
        4.              TsegImg=Transform(segImg,BaseImg.Size) //Normalize the physcial Attributes of Image
        5.              Generate the Center and radial characteristics for TsegImg for generation of Oval Structure
        6.              Apply Oval Map for TsegImg
        7.              Identify the Touch Points from the to oval Structured Image
        8.              if TouchCount>Thrshold
                        begin
        9.                      FullImageSet.Add(segImg)
                        else
        10.                     PartialImageSet.Add(segImg)
                        end
                end
Output:
        FullImageSet : Image set with full face Image
        PartialImageSet : Imageset with Partial Image Set
```

4.2. Gabor featured

Gabor filter is an orientation robust linear method that explores the edge features and shapes the visual representation of an object. In the spatial domain, this filter is applied to the specification of viewpoint and to identify the high intensity regions with kernel specification. The method is based on the low pass filtration, which generates the energy points over the image. The point exploration

Fig. 5. LBP Featured Results on TestFullImg Sample images (a) Left Pose Sample Raw Image 1, LBP Featured Image and Relative Histogram Featured Image (b) Left Pose Sample Raw Image 2, LBP Featured Image and Relative Histogram Featured Image (c) Right Pose Sample Raw Image 3, LBP Featured Image and Relative Histogram Featured Image (d) Left Pose Sample Raw Image 4, LBP Featured Image and Relative Histogram Featured Image.

Table 3
LBP featured form.

```
Input:
        FullFaceImgSet : Extracted imageset with full face view
        Rad : The radial size for segmentation size specification
Process:
        1.      ForEach img in FullFaceImgSet
                begin
        2.              Divide the img in radial blocks of size Rad and transit it horizontally and vertically
        3.              ForEach seg in RadialSegImage
                        begin
        4.                      Generate LBP feature pattern on seg using equation (1)
        5.                      LBPFeatureSet.Add(LBP_Pattern)          //Generate the segmented feature
pattern set
        6.                      Generate Histogram on LBP_Pattern called LBP_Hist
        7.                      LBPHistSet.Add(LBPHist)
                        end
                end
Output:
        LBPFeatureSet: The segmented LBP featured block set
        LBPHist: The segmented LBP Histogram Block set
```

or region exploration is done based on magnitude analysis as a response to the sinusoid measure. The phase and the magnitude estimation apply for the featured computation. The frequency domain observation applies to Fourier transformation along with proportional value observation. This filter generates a response mask with evaluation of high magnitude and phase robust points taken from different viewpoints. This mask is applied to complex sinusoid specification for the image and the featured region is collected from the image. The formulation of the Gabor kernel mask is defined in Eq. (2)

$$g_{f,\theta^{(Ix,Iy)}} = Exp\left(-\frac{1}{2}\left(\frac{Ix^2_{\theta_n}}{\sigma_x^2}+\frac{Iy^2_{\theta_n}}{\sigma_y^2}\right)\right)\mathrm{Exp}(2\Pi f x_{\theta_n}) \tag{2}$$

where, f for frequency
θ_n for orientation
σ_x and σ_y for standard deviation
observation for envelope analysis.

The angular robustness of the system is achieved by evaluating the plane specific observation from view point specification is obtained as

$$\begin{bmatrix} Ix_{\theta_n} \\ Iy_{\theta_n} \end{bmatrix} = \begin{bmatrix} \sin\theta_n & \cos\theta_n \\ -\cos\theta_n & \sin\theta_n \end{bmatrix}\begin{bmatrix} Ix \\ Iy \end{bmatrix} \tag{3}$$

The phase robust orientation points are evaluated to generate the featured transformation to the image. The orientation point is selected using Eq. (4)

$$\theta_n = \frac{\Pi}{p}(n-1) \tag{4}$$

Here, p represents number of particular orientation vector.
n for number of orientation points.
In this work, the Gabor filter is applied at the segmented window point with the specification of the orientation vector and the magnitude evaluation. The segmented window specific Gabor

featured segment is evaluated for the segment (Seg) is given in Eq. (5)

$$Seg_{f,\theta^{(Segx,Segy)}} = \mathrm{Seg}(\mathrm{x},\mathrm{y}) \otimes g_{f,\theta^{(lx,ly)}} \tag{5}$$

Here, $\otimes$represents the convolution operator specific window evaluation applied to the image segments.

The Gabor masking is applied to image in complex form. The generated mask and Gabor featured image obtained for testfullimageset is shown in Fig. 6.

Figure here includes the input image and the energy and frequency distribution obtained from different viewpoints to generate the Gabor form. The directional aspect of the complex form image is here identified as directional aspect. This Gabor feature map is mapped on image to generate frequency and direction robust feature image.

The algorithm, shown in Table 4 described the generation of the image into smaller segments. For each segment, the identification of the multiple viewpoints is done. From these viewpoints, the Gabor feature mask is generated which applies to image segments to obtain a feature image.

4.3. Structural feature

To acquire the structural information from facial image, an improved curvature generation approach is presented in this section. The method is divided into three sub stages. On first sub stage, the curvature information is extracted based thick edge point region detection. A window segmented method with constraint based analysis is applied to the internal structure formation. These constraints include high visibility, thick edge points, length of connected points and zero crossing. A real maxima is applied to identify the corner point to the segment and neighbor pixel analysis with kernel specification is applied to generate connected region. Contour measure with gap filling is applied to generate the primary curvature. A low scaled analysis of first degree curvature is applied to achieve the structural shape. The elimination of low width edge curves and short length edge curves is done. The length (l) evaluation of the plane is given in Eq. (6)

$$\mathrm{ExpCurve}(\mathrm{l}) = (\mathrm{x}(l,\sigma), \mathrm{y}(l,\sigma)) \tag{6}$$

The plane derived evaluation respective to standard deviation is obtained by applying the convolution operator on segmented window by Eqs. (7) and (8)

$$\mathrm{x}(l,\sigma) = \mathrm{x}(l) \otimes \mathrm{Gaussian}(l,\sigma) \tag{7}$$

$$\mathrm{y}(l,\sigma) = \mathrm{y}(\mathrm{l}) \otimes \mathrm{Gaussian}(l,\sigma) \tag{8}$$

Gaussian filter is here applied in segmented window form. This evaluation is based on the difference observation on standard deviation. This Gaussian vector is applied on both x and y plane selectively.

Along with the curvature generating process, three different constraints are applied collectively to identify the structure more subjectively. In this operation, smaller chunks, and thinner edges are cleaned. Above all, the curvature points with zero crossings are counted as part of the final construction. The curvature generation of test set images is presented in image 7. This figure includes the maxima feature points on face image as well as zero crossing curvature are also shown in the figure for each image. The algorithmic formulation of the method is shown in Table 5.

The algorithm shows that the work is applied separately to each facial segment with standard deviation base visibility analysis. As the initial curve is drawn, cleaning is applied to remove unrequired curves. This cleaning is based on the size, density and cross points count of the generated curvature. The results obtained in Fig. 7 shows that the algorithm provided an impressive structural form of extracting full view face image.

4.4. Facial fusion based on feature modality

After applying the promising experimentation of test images, three different types of images are obtained to represent the texture aspect, structural aspect and rotation robust contextual information aspect. Fusion process is about to understand these featured information and decompose them in an intrinsic mode. Based on the strength of knowledge aspects some weight is assigned to relative featured image. This mutation information inspection under the lights of weighting feature effects generated the resultant feature image. This probabilistic information emphasization based on mutual featured observation is given in Eq. (9). The equation here represents the fusion process applied on three extracted feature images under LBP, Gabor and Structural method described in Sections 4.1–4.3. These features are applied with extracted featured pixel with appropriate weight assignment. The log probabilistic multiplier is applied to avoid the zero value and to generate the real time feature data. The probabilistic magnitude analysis based result fusio image is formed. The equation impact is shown in figure (8)

$$\mathrm{ResImg}(\mathrm{x},\mathrm{y}) = \sum_{x,y\in LBP}\sum_{x,y\in GI}\sum_{x,y\in CI} w(i)Pt(x,y)log\left(\frac{Pt(x,y)}{Pt(x)xPt(y)}\right) \tag{9}$$

Here, LBP is LBP featured Image

GI is Gabor featured Image
CI is Curvature Extracted Featured Image
x, y is the plane derivation of the image
Pt is the magnitude value obtained from each featured form to apply fusion
w is the weight assigned each of the feature form.

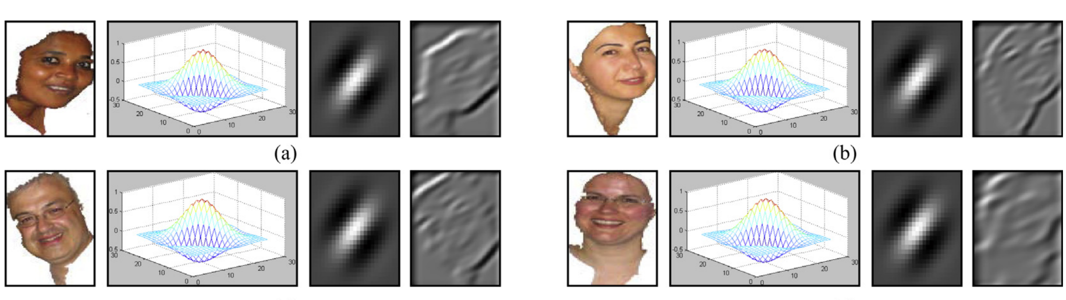


Fig. 6. Results of Gabor Filter on FullViewTestSet (a) Energy, Frequency Distribution and Gabor Feature for Sample Image 1 (b) Energy, Frequency Distribution and Gabor Feature for Sample Image 2 (c) Energy, Frequency Distribution and Gabor Feature for Sample Image 3 (d) Energy, Frequency Distribution and Gabor Feature for Sample Image 4.

Table 4
Gabor feature image algorithm.

```
Input:
    Img : Full Facial View Image for Gabor Feature Generation
    win : The size of segmentation rectangular window
    N: Number of Radial Orientation observer
Process:
    1.    Divide Img in mxn blocks of size winxwin and for a segmentedSet
    2.    ForEach segimg in segmentedSet
          begin
    3.        For i=1 to N
              begin
    4.            θ=i*2*Π/N                 //Generate the featured viewpoint Angle
    5.            Apply Phase and Frequency Variation in segPixel from view point
    6.            Generate gabor mask for segimg under angular orientation specification using
              equation (2)
    7.            Apply Mask on segimg using MaskImg=SegImg Mask
    8.            GaborImage.Add(MaskImg)
              end
          end
Output:
    GaborImage : Generate the Gabor Image By applying the gabor mask on segmented image
```

Table 5
ZeroCrossed curvature generation algorithm.

```
Input:
    fullfaceImg: Is the extracted full face from group photo
    wsize: Size of rectangular segmentation window
Process:
    1.    Generate the n,m segBlks for fullfaceImg of wsize
    2.    ForEach blk in segBlks
          begin
    3.        Generate the Intial Phase Curvature called face curve using equation (6)
    4.        Get width and connected length statistics from facecurve
    5.        if width<Threshold1 Or Size<Threshold2     //Prune the smaller disconnected curve segments
              then
    6.        facecurve=0          // Filter the curvature by connectivity analysis
              else
    7.        Identify the crosspoints from face curve analysis
    8.            if facecurve.crosscount>0        //Remove the curve region with cross curves
                  then
    9.            facecurve=0
                  else
    10.           CurvatureFace.Add(facecurve)
                  end
              end
    11.   end
Output:
    CurvatureFace: Return the curvature frame curve as final structured image.
```

The outcome of this fusion process applied full face test image is shown in Fig. 8.

Here the figure is showing the fusion process applied using Eq. (9). The figure is showing the fusion process applied on sample

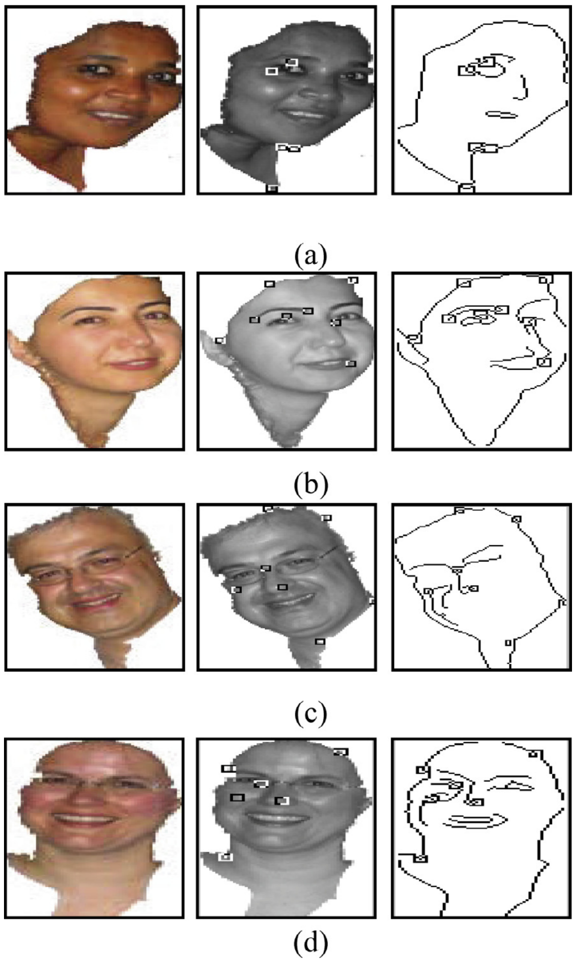


Fig. 7. Structural Feature based Curvature Results (a) Extracted Crosspoints and Structure for Sample Image 1 (b) Extracted Crosspoints and Structure for Sample Image 2 (c) Extracted Crosspoints and Structure for Sample Image 3 (d) Extracted Crosspoints and Structure for Sample Image 4.

image as well as showing the results on other test images. The first level of the figure is showing the generated featured image under three different methods. Each method is explored with result formulation already in Section 4.1–4.3. The log probabilistic weight driven fusion process is applied to generate the combined feature image shown at level two of algorithm. At level three, some of sample results obtained from three sample images is shown.

4.5. Kernel based distance adaptive recognition

To recognize the individual group face over the training set, it is required to apply the same feature model on the training set. These generated feature set is having the capabilities of illumination invariant and direction robustness. As the full facial view is visible, there is lack of chances of occlusion in facial features. Even then the structural map is able to handle such situations. To perform the recognition as expected pose based distance analysis map is applied. The expected pose direction is identified on query image which is later on applied with directional aspect with angular specification. To cover all pose position in the training set, multiple positions for each pixel are generated on that pose. Each directional view is then compared with training features under distance based mapping. A diagonal segmented method with density and geographical area analysis is applied to a pixel region on all three featured faces as shown in Fig. 9.

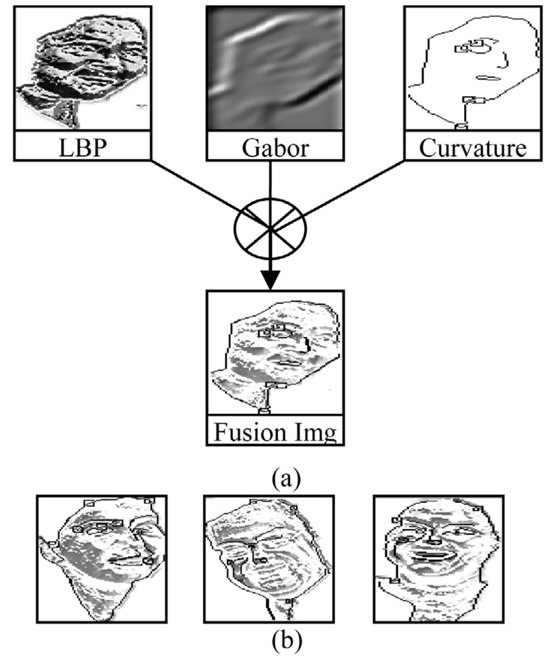


Fig. 8. Feature Fusion Results (a) fusion process with source feature image and fusion image (b) fusion results image for other test considered in Fig. 7.

To estimate the pose, the facial image is divided into three splitions applied on both diagonals of query as shown in Fig. 9 along with region number. Each diagonal difference area is analyzed in terms of pixel density and covered geographical region. The rule formulation obtained here in Table 6.

After estimating the pose, the base angle is obtained. Now the pixel positions on query image are updated with the angular range specification. The θ variation subjective facial generation applies to angular change called $d\theta$ to cover the range of 60°. Based on these angular facial updation, multiple query faces are generated and distance based observation is applied to training image. This nonlinear structured qualifier is applied to all individual featured faces and fusion faces. These N generated ordered for m structured faces for linear connected faces. This window point zi specific distance measure respectively to arbitrary point zp is given in Eq. (10)

$$\mathrm{d(zi, zp)} = ||\mathrm{zp} - \mathrm{zi}|| + \sum_{i=1}^{N} ||zp - zi|| \tag{10}$$

where zp, zi ε LBP, GI and CI.

The experimentation of different training sets applies to these query formed images is shown in Table 7.

The algorithm is showing the rule implementation described in Table 6 on each feature image as well as on fusion feature image. The Euclidian distance map with phase robustness is applied for effective face identification. The experimental results of this model are discussed in Section 6.

5. Partial face recognition

According to the framework described in Section 3, the group images can also have partial face images. In these facial images some part of facial information is hidden or not available because of overlapping by some other person or object. In this section, the recognition process for these partial faces is described. After extracting the partial facial region as separate image, the next work is to capture these features from the partial face images. To generate the feature form, two distinct methods are described in this

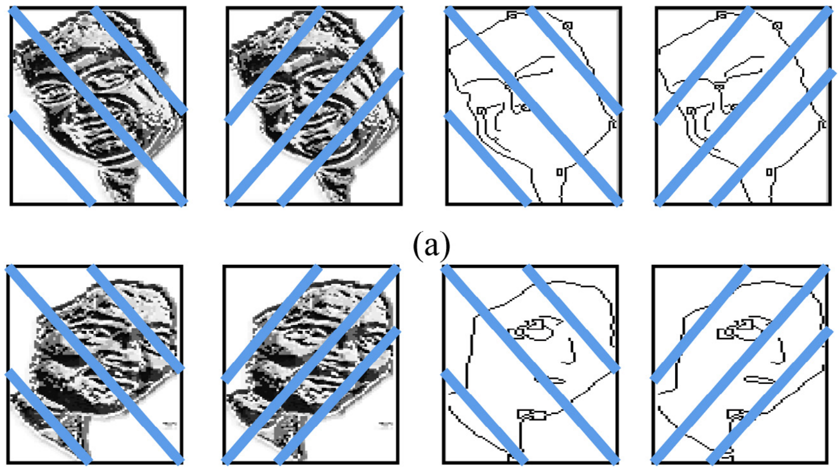


Fig. 9. Pose Estimation for structural change in query image (a) Diagonal Feature Extraction for Right Pose Estimation (b) Diagonal Feature Extraction for Left Pose Estimation.

Table 6
Rule formulation for pose estimation.

Rule	Decision
If (Density(region1)<DenThresh1 And CoverageArea(region1) <CovThresh1 (Density(region4)<DenThresh1 And CoverageArea (region4)<CovThresh1	Right Pose
If (Density(region5)<DenThresh1 And CoverageArea(region5) <CovThresh1 (Density(region8)<DenThresh1 And CoverageArea (region8)<CovThresh1	Left Pose
If Overlap(Density(region2), Density(region6)) and Overlap (Density(region3), Density(region7)) OR Overlap(Coverage (region2), Coverage (region6)) and Overlap(Coverage (region3), Coverage (region7))	Front Pose

section called Discriminative Point method and Structural Curve Method. Later on in the final stage, the number of points and curve map ratio is considered to identify the features of these partial faces to full image training set.

5.1. Discriminative point feature face

To explore the discriminative features and to absorb the missing region problem, the features are taken in the form of control points. To generate the control points, the facial region is divided into smaller quasi circular segments. The template is applied to explore the segment features. The segment is here designed to identify the margin difference along with rotational robustness. The rotation applied by considering the intensity difference observation respective to nuclear pixel. The method identifies the kernel adaptive high intensity pixel range in the each segment region. The limit applied for pixel selection is increased as the region is having the higher number of pixel points.

This feature point exploration method is limited to the quasi-circular segmentation described with two threshold limits. These limits are the radial size (rs) of applied template (tx) or segmented region (rg) and the (mx) maximum control points selected within the region. Each segmented window has applied the interpolation (fx) method to acquire the feature points. The third important vector to set the angular (θ) rotations on template while applying the template to gain robust feature points. This functional expression form to generate template qualified (qs) segment is given in Eq. (11)

$$\mathrm{qs}(\mathrm{x},\mathrm{y}) = \sum_{r=1}^{N} fx \cdot rg(x,y) \cdot Rt^{\theta_r} \cdot tx(x,y) \tag{11}$$

where N = Number of Rotational Transition
fx = Interpolation function to generate feature points
Rt = Rotational Transformation.

The selection of feature points based on pixel point analysis is given a fourier derived function expressed by Eq. (12)

$$\mathrm{fx}(\mathrm{rs},\theta) = \sum_{i=1}^{2rs} rg(i)e^{i.\theta} \tag{12}$$

The interpolation function is applied to each segmented region at different angular rotations to generate the feature points. Equation here signifies the equation for single angles extracted points. After applying the Eq. (11) integrated with Eq. (12) each circular segment will generate the feature points. A threshold limit is also applied to restrict the number of points so that the information representative points will be extracted. The sample results for two partial faces obtained from group photo processed in figure (4) is shown here in Fig. 10.

There the results are derived for rx = 8 and angular variation between 0 and 360° with a rotational difference of 5°. The figure shows that the method has identified the descriptive feature points that can even describe the structure of the facial image.

There the results are derived for rx = 8 and angular variation between 0 and 360° with a rotational difference of 5°. The figure shows that the method has identified the descriptive feature points that can even describe the structure of the facial image.

5.2. Structural curve generation

To explore the available information on a partial image, a more collaborative approach is required that can identify the textural features and present it as structural constraints. These geometric constraints are here generated on segmented facial image using a color model induced combined saliency and frequency measure analysis. To generate the textural information aspect, the information depth at each pixel position is applied. Based on this, the colorization is applied and shown in Fig. 11 on sample test set images.

To generate the discriminating textural and geometric features, RG-GB color planes are applied collectively for individual features. At first, the textural depth is estimated based gradient observation

Table 7
Pose robust distance adaptive mapping on individual feature and fusion feature images.

Input :
Img : Query Image
DBImg : FaceDB Image
bθ : Base Theta
θ1, θ2…. θN : Generate N Rotational Varience
dθ : Change in Theta

Process :
lbpImg=GenerateLBP(Img)
gaborImg=GenerateGabor(Img)
curveImg= GenerateCurvature (Img)
fuseImg=ApplyFusion(lbpImg,gaborImg,curveImg)
if(Pose(Img)=Frontal)
{
Minangle=-dθ*N/2
Maxangle=dθ*N/2
}
Else if(Pose(Img)=Left)
{
Minangle=0
Maxangle=dθ*N
}
Else
{
Minangle=-dθ*N
Maxangle=0
}
For i=1 to DB.Length /* Process DB Images*/
{
targetlbp=GenerateLBP(DB(i))
targetgabor=GenerateGabor(DB(i))
targetcurve=GenerateCurvature(DB(i))
targetfuse=ApplyFusion(targetlbp,targetgabor,targetcurve)
For θ=Minangle to Maxangle [step dθ]
{
dlbp(zi,zp)= ||zp-zi|| + $\sum_{i=1}^{N} ||zp - zi||$where zp,zi ε LBP
dgabor(zi,zp)= ||zp-zi|| + $\sum_{i=1}^{N} ||zp - zi||$where zp,zi ε gabor
dcurve(zi,zp)= ||zp-zi|| + $\sum_{i=1}^{N} ||zp - zi||$where zp,zi ε Curvature
dfusion(zi,zp)= ||zp-zi|| + $\sum_{i=1}^{N} ||zp - zi||$where zp,zi ε Fusion
mapscore=w1*dlbp+w2*dgabor+w3*dcurve+w4*dfusion
DB(i).score=mapscore
}
}
Index=Max(DB.score)

Output
Index /*Identify index of maximum map image*/

on both color planes. The obtained color gradient is shown in Fig. 11 by the second image of each sample. This color plane is applied by squaring segmented form to generate the textural observed geometric features. To measure the textural analysis, the saliency feature form is estimated for RG plane, whereas the frequency distance measure is applied to transform it to geometric

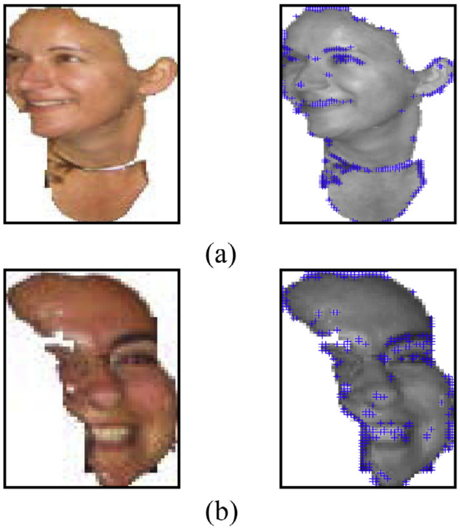


Fig. 10. Discriminative Feature Points for Partial Face Images (a) Extracted Feature Points for Right Pose Partial Face (b) Extracted Feature Points for Left Pose Partial Face.

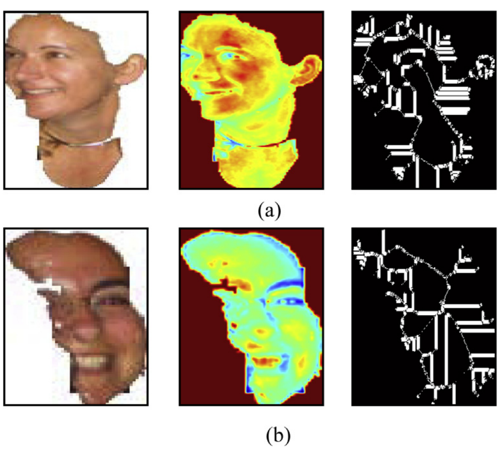


Fig. 11. Textural adopted Structural Feature Extraction on the partial test set images (a) Extracted Geometric Features for Right Pose Sample Image 1 (b) Extracted Geometric Features for Left Pose Sample Image 2.

features. To generate the frequency level observation, a probabilistic measure on each segment is applied under pixel magnitude repetition. This frequency observation based probabilistic estimation is given in Eq. (13)

$$\mathrm{fp(s)} = \frac{n_s}{Mx(n) \cdot Sz} \tag{13}$$

here, fp is the frequency probability
n is the number of neighbors
Mx is the maximum intensity in the region
Sz is the region size.

Based on this probabilistic estimation, the feature region characterization is made to obtain the textural adaptation for the block. This textural adaptation (ta) is shown in Eq. (14) for Block (Blk).

$$\mathrm{ta(Blk)} = \sum_{i=1}^{n} fp(blk) \cdot \log(fp(blk)) \tag{14}$$

After gaining the textural map, the saliency feature adaptation is also applied in the GB plane to capture the structural features. To highlight the structural information, a self similarity assisted peak value observation is applied. This mutual information observation with absolute difference is here applied to relative pattern matrix (pm). The histogram frequency based highlighted points (hp) are analyzed with respect to a weight matrix(wm). The observations are here applied under orientation vector so that multiple instance analysis will be obtained. The generated pattern matrix is shown in Eq. (15)

$$\mathrm{pn(pos,}\theta) = \mathrm{hp(pos,}\theta\mathrm{)xwm} \tag{15}$$

here, pos is the arbitrary high frequency point within the block
θ is the view point representation to generate multiple feature vectors.

The histogram points (hp) are generated through the logarithmic integral observation with frequency and the intensity domain. The generation of this structural window for the block(blk) with frequency variation is shown in Eq. (16).

$$\mathrm{hp(pos,}\theta) = \int_{x=1}^{n} blk(x,\theta)\mathrm{log}blk(x,\theta)\mathrm{dx} \tag{16}$$

According to the equation, each of block point is observed for highlighting a feature point with orientation specification respective to the given point. The descriptor points over the block can be obtained with weight window (wm) derivation is shown here below in Eq. (17)

$$\mathrm{wd(pos,}\theta) = \int_{x=1}^{n} \left|\frac{\partial}{\partial x} blk(x,\theta))\mathrm{dx}\right. \tag{17}$$

The peak value observations are taken and the structural points are obtained. In Fig. 11, 3rd image of each sample image is showing the structural information. These connected points collectively form a curve shape so that the discriminating information is obtained in a representative information form.

One the discriminative structural information is obtained in the form of points and curve, the final work is to generate the recognition method. Here a ratio driven point formulation method is applied for recognition process described in the next subsection.

5.3. Ratio based recognition

The partial extracted face is having the problem of missing and discriminative features of facial image. In Sections 5.1 and 5.2, more illustrative and indicatory methods are carried through the internal and the superficial construction of partial face database. Because of anonymous missing regions, these partial faces cannot be mapped directly to the full face database. For effective facial matching one-to-all multi-structural ratio map is provided in this subsection. This structured-ratio based recognition method is shown in Table 8.

The algorithm presented in Table 8 showing positional robust algorithm point and curve based map to locate discriminative points. The internal and external structural elements are analyzed with window based region map. The algorithm is individually applied on discriminative points and internal curve points based mapping. The region map with rotational and positional variation analysis is applied to achieve more accurate map. The ratio map obtained from discriminative and structural curve are combined by assigning the equal weights. For the recognition, this weighted ratio records for each database image. The maximum ratio map image is considered as the recognized result image. The experimentation applied on different scene images are given in the next section.

Table 8
One-to-all multi-strual ratio map.

```
Input :
Img : Partial Query Image
DBImg : FullFaceDB Image
dispV : Displacement Variant Threshold
angVMin:Expected Minimum angle variation
angVMax:Expected Maximum angle variation
Process :
DisFeature=GenerateDiscriminativePoints(Img)
CurveFeature=GenerateStructuralCurve(Img)
ForEach dbimg in DBImg
dbDisFeature=GenerateDiscriminativePoints(dbimg)
dbCurveFeature=GenerateStructuralCurve(dbimg)
        count=0
        ForEach inDpoint in DisFeature
        Status=0
                ForEach dbimgDpoint in dbDisFeature
                        For th=angVMin to angVMax
                                Pt.x= dbimgDpoint.x* cos(th)
                                Pt.y= dbimgDpoint.y* sin(th)
                                If Pt= inDpoint And status=0
                                        Status=1
                                        Count=count+1
                                End
                                If Pt.x>== inDpoint.x- dispV And Pt.x<== inDpoint.x+
        dispV And Pt.y>== inDpoint.y- dispV And Pt.y>==      inDpoint.y+ dispV And status=0
                                Status=1
                                Count=count+1
                                end
                        end
                end
        end
        DRatio=Count/Max(dbimgDpoint, inDpoint)
        count=0
        ForEach inCpoint in CurveFeature
        Status=0
                ForEach dbimgCpoint in dbCurveFeature
                        For th=angVMin to angVMax
                                Pt.x= dbimgCpoint.x* cos(th)
                                Pt.y= dbimgCpoint.y* sin(th)
                                If Pt= inCpoint And status=0
                                        Status=1
                                        Count=count+1
                                End
                                If Pt.x>== inCpoint.x- dispV And Pt.x<== inCpoint.x+
        dispV And Pt.y>== inCpoint.y- dispV And Pt.y>==      inCpoint.y+ dispV And status=0
                                Status=1
                                Count=count+1
                                end
                        end
                end
        end
        CRatio=Count/Max(dbimgCpoint, inCpoint)
        MapRatio(i)=CRatio*.5+DRatio*.5
end
[index ratio]=Max(MapRatio)
Output :
DBImg(index) : Ratio Mapped Image
```

6. Experimental results

To prove the validity of the proposed work model, a large range of facial images are evaluated taken from different datasets. The evaluation is here performed overall on 8 different datasets taken from web as well as collected in real time. These datasets are having the complexities in different aspects including the backgrounds, number of individuals, facial appearance etc. The images are of different smooth as well as complex backgrounds. Different real time environment such as wall background, offices, home, roadside etc. are considered to perform the evaluation. The numbers of individuals in the images are one, two or multiple. These facial images are having the complexities in terms of pose variation, partial occlusion etc. The illumination and the lighting problem are also common because of real time capturing of faces. The experimentation is here divided in two main stages. In first stage, the facial region extraction for both full and partial faces. The separate face representation is provided in this stage for both the single and multi-face images. The facial region extraction is here done using color model analysis with dynamic thresholding, Gaussian distribution and the color difference analysis. The hole filling and Oval fitting based on physical characterization is also applied to extract the facial region. After extracting the facial region, different feature models are applied on full and partial faces separately along with feature fusion implementation. These multiple features of input images are mapped to the dataset images using ratio based and distance based method. In second stage of this model, the facial recognition is performed. In this section, the separate results for facial segmentation and recognition are evaluated and presented. Before evaluating the results, the description of each of the dataset is required. The sample images taken from each of the dataset is shown here in Fig. 12.

Table 9 is showing different datasets taken here for defined model implementation. The single and multiple face images datasets are taken for both the segmentation and recognition. The datasets are having the front face as well as partial face images. These images are taken in real time scenario with contrast, brightness and illumination variation. The complex background scenes are also observed to verify the reliability. Different sets of training and testing samplesets are considered to identify the accuracy of different processes. The sample images with all these variations and complexities are shown here in Fig. 12. The individual analysis of both the segmentation and recognition process is provided to observe the accuracy.

Fig. 12 is showing the sample images taken from eight of the considered dataset in this experimentation. The model implementation is applied on multiple samplesets taken from each of the dataset and performs the facial region extraction and facial recognition. In this section, experimentation results and the comparative assessment with other methods is provided in different scenarios, parameters and constraints.

6.1. Analysis measures

The model outcome is here divided in two main stages called facial region localization and the recognition of facial image from group photos. As discussed earlier in Section 3, the facial localization is provided by using the color model, Gaussian filter, dynamic thresholding and mathematical operators. The oval based mapping is also applied geographically to identify the partial and full faces. Finally, the algorithmic model for structural and feature based methods is applied separately for partial and full face inputs. The quantitative results are here obtained for both the facial segmentation and facial recognition. The facial region segmentation is applied for each of eight datasets. The evaluation of facial localization is here done using False Acceptance Rate (FAR) and False Rejection Rate (FRR). FAR defines the ratio of mapping of negative example of any falsely detected face or the positive example does not overlap the ground truth area. The FRR is shown here in Eq. (18).

$$FAR = \frac{1}{m^-}\sum_{j=1}^{m^-} FN(FaceImg_j) \tag{18}$$

where, m^- defines the number of images negatively mapped to the ground truth.

$FaceImg_j$ are particular Face Image.

FN is the False Negative function that maps the input face image to the ground truth images. The overlapping is here identified relative to the mean value as well as the standard deviation observation of the generated extracted points.

In same way, the FRR is also the measure to identify the accuracy of recognition and provides the rate that identifies the particular positive example is falsely rejected. The FRR is shown in Eq. (19)

$$FFR = \frac{1}{m^+}\sum_{j=1}^{m^+} FP(FaceImg_j) \tag{19}$$

where, m^+ defines the number of images positively mapped to the ground truth.

$FaceImg_j$ are particular Face Image.

FP is the False Positive function that maps the input face image to the ground truth images. The overlapping is here identified relative to the mean value as well as the standard deviation observation of the generated extracted points.

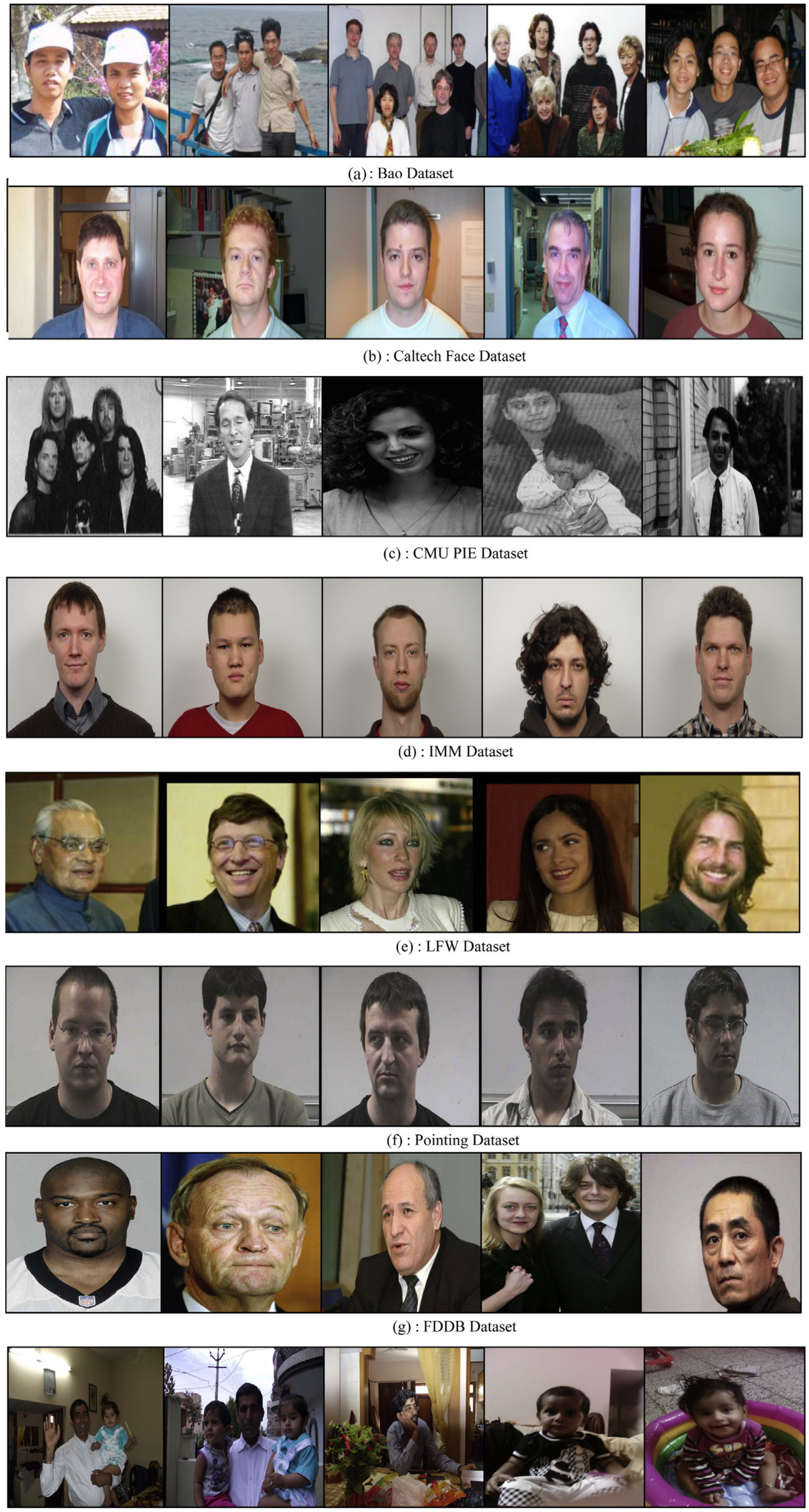
While performing the recognition, the accuracy of the recognition rate is identified and the formula for the recognition is shown in Eq. (20).

$$Accuracy = \frac{(TP + TN)}{Total} \tag{20}$$

6.2. Facial localization results

The accuracy of the facial recognition depends on the correctly extraction of facial region. For this a dynamic and multiple features and operator based method is defined in this work. The facial localization is more challenging because of the complex backgrounds as well as multiple faces in an image. Once the facial region is identified, it is required to represent the face image separately from the group and categorize it as the full or the partial face image. The facial region extraction is applied on all the available facial datasets. For each dataset three random sample test set of 100 images is taken and obtain the accuracy analysis based on mapping to the groundtruth images. The region extraction results obtained for different available datasets is shown here in Fig. 13.

Fig. 13 shows that segmentation and facial extraction results obtained for each dataset. A sample of 5 images is taken from each dataset to show the outcome. The results are here shown as the segmented facial region from the image as well as the extracted face region from the image. Once the region is extracted, the mapping of this region is done over the ground truth region with specification of mean and standard deviation measures. Based on these measures, the FRR and FAR parameters are evaluated for the considered sampleset. First six datasets from this dataset pool were also analyzed under facial localization by Ban et al. (2014). The localization results were obtained by the author against same measures. The comparative observation against the results derived by Ban et al. (2014) is here provided hereunder.



(a) : Bao Dataset

(b) : Caltech Face Dataset

(c) : CMU PIE Dataset

(d) : IMM Dataset

(e) : LFW Dataset

(f) : Pointing Dataset

(g) : FDDB Dataset

(h) : Self Collected Dataset

Fig. 12. Sample Images from Test Datasets.

Fig. 14 is showing the comparative evaluation of facial localization under FAR parameter. The error rate observation is here taken for acceptance rate analysis by applying the Mean value and STD value based quantization. The Measures are applied on six different datasets. Here Fig. 14(a) is showing the mean value based evaluation and the results shows for most of the datasets, the error in the

Table 9
Datasets description.

Dataset	Type	Number of images	Background	Used for
Bao Dataset (Frischholz, 2016)	Single and Multiple Person and Face Datasets, Real Time Full and Partial Face Images	370	Indoor And Outdoor Complex	Facial Segmentation and Facial Separation and Recognition
Caltech (http://www.vision.caltech.edu/html-files/archive.html)	Single Face Images with different Illumination and Lighting, Frontal Face Images	452	Complex Indoor and Outdoor	Facial Segmentation and Recognition
CMU PIE (Sim et al., 2003)	Grayscale Images with Single and Multiple Persons. Different Poses and Include Partial View. Different Illumination and Lighting	100	Complex Indoor and Outdoor Images	Facial Segmentation
IMM (Stegmann et al., 2003)	Color Single Frontal Face Images with Illumination Variation	120	Fix Wall Background	Facial Segmentation and Recognition
LFW Dataset (Learned-Miller et al., 2016) with Random Web Images	Celebrities Facial Images with Frontal and Partial Face Images	12,000/200	Complex Indoor and Outdoor Images	Facial Segmentation and Recognition
Pointing Dataset (Gourier et al., 2004)	Single Face Images with Different Poses	300	Fix Wall Background	Face Segmentation and Recognition
FDDB Dataset (Jain and Learned-Miller, 2010) With Random Web Images	Celebrities Dataset with single and multiple person images. Combined with Random Web Images for Facial Recognition	28,235/500	Complex Indoor and Outdoor Images	Facial Segmentation, Separation and Recognition
Self Collected Dataset of Single and Multiple Faces	The images of 30 Family Members, Friends and Relatives are analyzed for 100 Group Images. Single and Multiple images considered	30/100	Indoor and Outdoor Complex Background Images	Facial Segmentation, Separation and Recognition

acceptance rate is reduced. Only the CMU and Bao dataset provided the least significant facial extraction. For all other datasets, the mean value based FAR evaluation is more accurate. Fig. 14(b) is showing the FAR evaluation using STD parameter. The results show that the proposed provided more accurate localization for all datasets except.

Pointing dataset. Overall observations signify that the proposed multi featured model provided more effective facial localization for group as well as single face images with complex background. The method can be used as integrated stage for facial recognition to improve the recognition rate. Another evaluation is here taken using FRR (False Rejection Rate) parameter. The comparative evaluation results are shown in Fig. 15.

Fig. 15 is showing the comparative evaluation of Facial Localization under FRR (False Recognition Rate) parameter. The evaluation is here provided using Mean based FRR and STD based FRR parameters. The evaluation is here applied for six different projects and observations are taken against the localization method provided by Ban et al. Fig. 15(a) shows that the proposed model reduced the false rejection rate for almost projects except Bao and IMM. Fig. 15(b) shows the evaluation of using STD based FRR method. The results shows that the error rate for Bao and Caltech is increased and for rest of the dataset more effective localization is achieved.

6.3. Facial recognition results

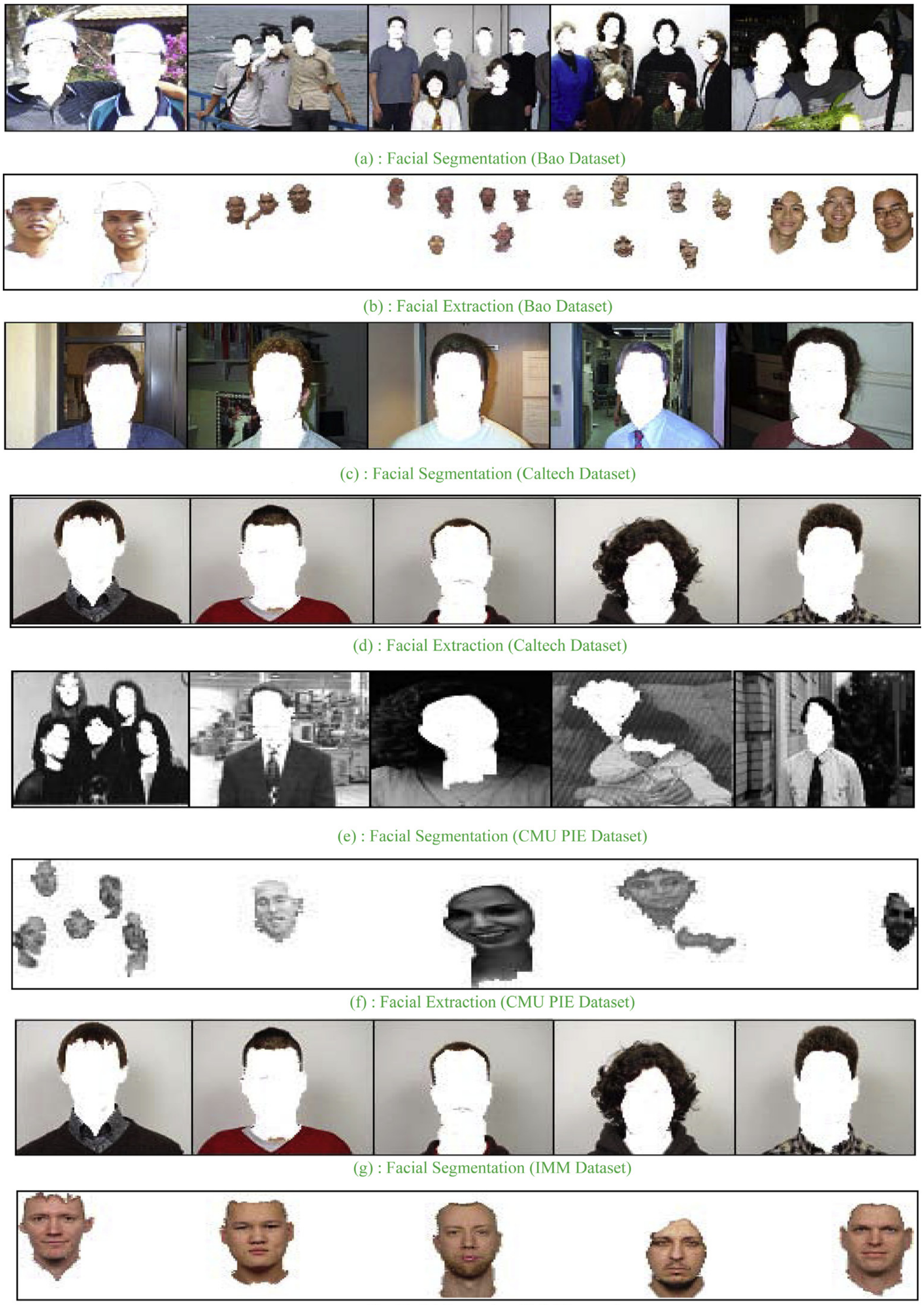
After extracting the facial region accurately, the final task of this work model is to perform the facial recognition based on structure based and feature based mapping. Separate algorithms are defined to generate the features and the dataset mapping for both the full and partial face images. The facial recognition is here applied on three main datasets. To perform the training and testing sets are generated for two types of images. The first set is generated of individual faces and second set is generated for group facial images. The properties of the samplesets used for group photo recognition is shown in Table 10.

Table 10 is showing the different dataset pairs considered for applying the facial recognition. Each sample set is having two groups of images. The first set is having the individual face images. This set worked as the training set. The group images are considered as the real time images and the complete work model is applied on these group images. At the earlier stage of this model, the facial region extraction and the identification of full and partial face images is done. Now, the separate feature generation and dataset mapping is applied using different algorithmic approaches already discussed in Section 3 of this paper. In this sub section, the evaluation of the recognition result under accuracy parameter is defined. To perform the accuracy evaluation the complexity of facial recognition is identified in terms of associated complex background and number of individual in group image. In this sub section, both these aspects are considered to generate the more accurate and adaptive evaluation.

Extensive experimentation is conducted on group images captured in different scenes and scenarios. These group images are taken from the web and mapped over the LFW and FDDB datasets as discussed earlier in Table 10. Some scene specific features are also collected in family, friends and functions. The group images are of different indoor and outdoor scenes with multiple persons. The scene specific sample sets of group photos are described in Table 11.

Each of the scenes is having individuals with full and partial face view. Each of the group image is taken as input image and applied to frontal full view facial training set. The experimental analysis here divided into two aspects. This observation is taken to identify the number of extracted individuals and second observation is taken here in recognition of individuals among the available training set. The error rate in the correct count of individuals for different scenes is shown in Table 12. The accuracy in individual count is here identified by figuring out the difference in the actual and identified number of individuals. Individual count with 0 differences is considered as most accurate extracted individuals. The recognition with difference individual map by more than 2 is considered as the worst individual extraction rate. The results show that the maximum accuracy for individual identification is obtained in case of indoor scenes, whereas the outdoor scenes are comparatively less accurate.

After extracting the individuals, the separate set of partial and full view individuals is done using oval shape map described in Section 3.2. To perform the facial recognition separate algorithmic approaches are applied on both full and partial extracted faces.



(a) : Facial Segmentation (Bao Dataset)

(b) : Facial Extraction (Bao Dataset)

(c) : Facial Segmentation (Caltech Dataset)

(d) : Facial Extraction (Caltech Dataset)

(e) : Facial Segmentation (CMU PIE Dataset)

(f) : Facial Extraction (CMU PIE Dataset)

(g) : Facial Segmentation (IMM Dataset)

(h) : Facial Extraction (IMM Dataset)

Fig. 13. Segmentation and Facial Region Extraction on All Datasets.

6.3.1. Full face recognition

To perform the full face recognition, weighted multi-featured based distance adaptive method is applied. The comparative analysis of this model is done against PCA (Principal Component Analysis), ICA and LDA-PCA methods. The comparative results are taken on different sample sets taken from different scenes. The comparative results obtained for full face recognition is shown in Fig. 16.

Fig. 16 shows the comparative accuracy results for full face recognition. The results show that the proposed multi featured based weighted analysis model improved the accuracy for all scenes. The results of the PCA are worst among all other approaches. The recognition accuracy also depends on the clarity of facial extraction. Because of this the accuracy of indoor scene extracted faces is higher than outdoor scenes extracted faces. The full view faces extracted from the classroom scene provided more accurate results among all approaches.

6.3.2. Partial face recognition

Some of the extracted faces from group photo are not complete with missing and discriminative features. In this work, structural point and curve based features are used to describe the facial interior and exterior aspects. These extracted features applied using

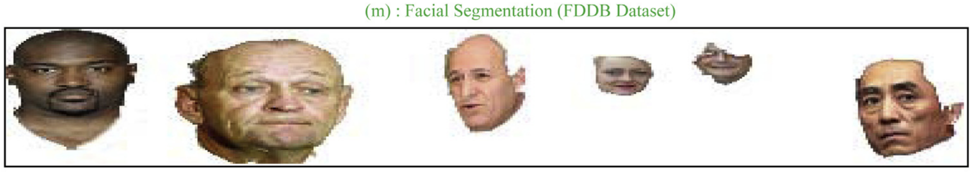
(i) : Facial Segmentation (LFW Dataset)

(j) : Facial Extraction (LFW Dataset)

(k) : Facial Segmentation (Pointing Dataset)

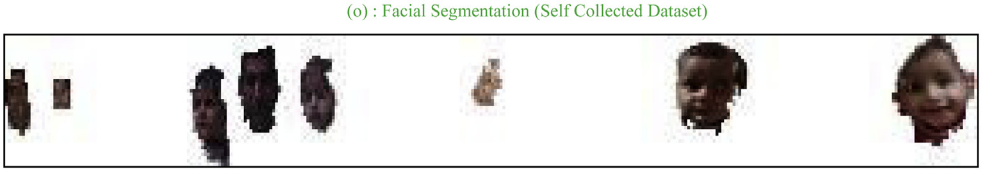
(l) : Facial Extraction (Pointing Dataset)

(m) : Facial Segmentation (FDDB Dataset)



(n) : Facial Extraction (FDDB Dataset)

(o) : Facial Segmentation (Self Collected Dataset)

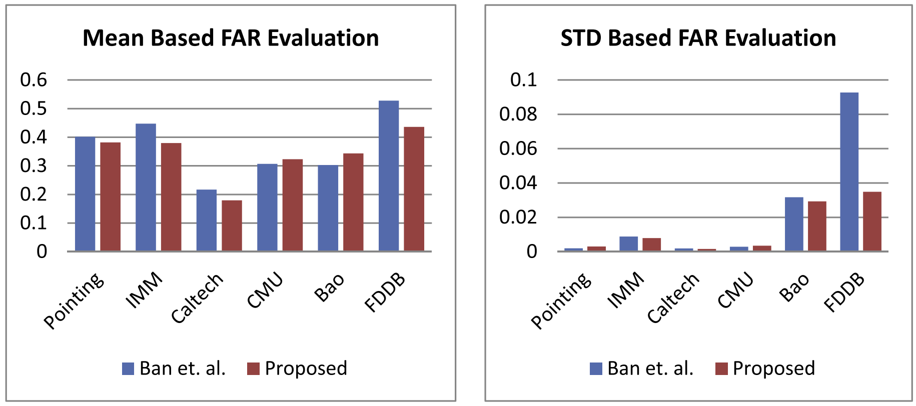


(p) : Facial Extraction (Self Collected Dataset)

Fig. 13 (*continued*)

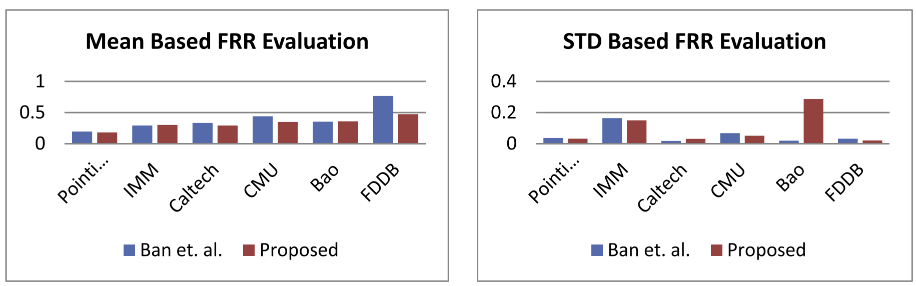
one-to-all based weighted method using direct mapping to the full face database. The accuracy of the method along with comparative results is shown in Fig. 17. The comparative observations are taken on distance based methods. As the work was applied on real time self captured and web collected images. Because of the accuracy results of approaches can be taken from the paper. PCA, LDA and LDAPCA are the approaches that I have already implemented on other databases. Same implemented approaches are applied on this real time group image database to generate the accuracy results. As the methods are not based on discriminative features, lower accuracy is obtained from these algorithms.

The results show that the proposed model provided the accurate results in comparison with existing approaches. The results of PCA and ICA methods are less effective. In some scenes, these methods provided the results below 55%, which can be considered as worst results. The proposed model provided the accuracy over 70% for partial to full facial map which can be considered as effective for group photos. According to the scene, the accuracy of



(a) : Mean Based FAR Evaluation (b) : STD Based FAR Evaluation

Fig. 14. Comparative Analysis of Facial Localization (FAR Evaluation).



(a) : Mean Based FRR Evaluation (b) : STD Based FRR Evaluation

Fig. 15. Comparative Analysis of Facial Localization (FRR Evaluation).

Table 10
Recognition dataset properties.

Sample sets	Individual image dataset source	Group image dataset source	Number of sample sets
Sample Set 1	LFW	LFW and Random Web Images of Celebrities	3
Sample Set 2	FDDB	FDDB and Random Web Images of Celebrities	3
Sample Set 3	Self Collected Family/ Friend Images of 30 Individuals	Select Collected Group Images taken at Home/ Roadside/Office 100 Images	2

indoor scenes is comparatively high as compared to the partial face images. The comparative observation of partial and full face recognition for different scenes is shown in Table 13.

The Table 13 shows that the model provided the effective recognition rate for both full and partial face images. The maximum accuracy obtained for full face is 92.68%, whereas the highest accuracy of the partial face image is 75.69%. The method recognition rate for the full face image is higher. The accuracy of recognition of faces in indoor scenes is comparatively higher than facial recognition in outdoor scenes.

Table 12
Accuracy of individual count.

Scene type	Number of images	Diff. individual	Accurate identification
Home	10	0	5
		±1	3
		±2	1
		Other	1
Office	10	0	6
		±1	3
		±2	1
		Other	0
Market	20	0	10
		±1	6
		±2	3
		Other	1
Park	10	0	6
		±1	2
		±1	1
		Other	1
Classroom	20	0	11
		±1	5
		±2	2
		Other	2

Table 11
Group photo database description.

	Scene type	Number of images	Number of individuals	Training set size
1	Home: Indoor	10	4–7	40
2	Office: Indoor	10	2–8	40
3	Market: Outdoor	20	2–7	60
4	Park: Outdoor	10	4–8	60
5	Classroom: Indoor	20	6–12	60

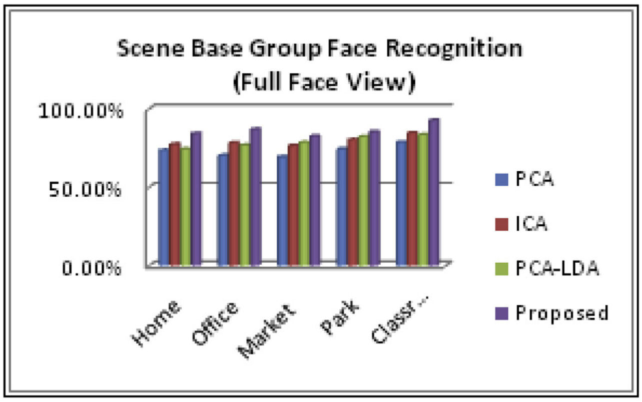


Fig. 16. Scene Based Group Face Recognition (Full Face View).

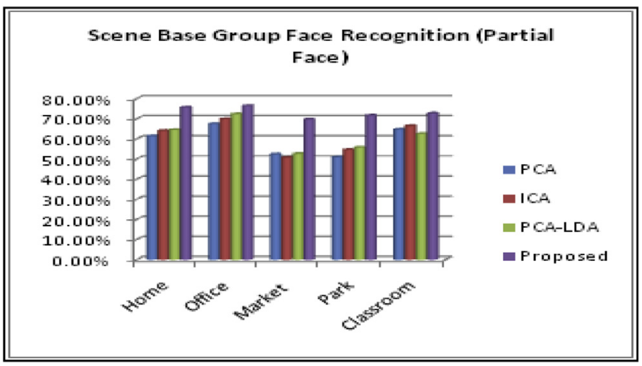


Fig. 17. Scene Based Group Face Recognition (Partial Face View).

Table 13
Partial vs. full face recognition.

	Partial face recognition	Full face recognition
Home	75.69%	84.36%
Office	76.41%	86.97%
Market	69.76%	82.69%
Park	71.71%	85.36%
Classroom	72.69%	92.69%

7. Conclusion

In this paper, a multi-featured and multiple algorithms based framework is provided for recognition of individuals in a group photo. The framework described the method to separate the faces as a facial test set for a group photo. These faces can be full or partial view faces. Based on the face category, separate feature methods and algorithms are applied. The full face recognition is provided using the distance based recognition method, whereas the partial face recognition is provided using a ratio based structural point and curve map. The evaluation of the work model is defined for two separate work stages called facial localization and the facial recognition. The facial localization is applied on eight datasets and the comparative observations shows that the proposed method has reduced the FRR and FAR. The work is experimented with real time captured and web extracted group images. The comparative analysis is applied against PCA, LDA-PCA and ICA methods. The analysis results are taken against different real time scenes. The results show that the proposed framework improved the recognition accuracy for extracted both full faces and partial faces. The observations also show that the accuracy of indoor captured scenes is higher than outdoor captured photos.

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