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ROBUST FACE DETECTION USING DELAUNAY TRIANGLE BASED GEOMETRICAL FACIAL FEATURES

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ABSTRACT: Facial features are classified or grouped to generate the unique identity of individual human faces. The quality of face images detected should be sufficient to guarantee an accurate detection response and reduced true positive rate to identify the original human face, which in turn provide high security in public gathering applications. Though efficient face detection was ensured, trade off occurred between true positive rate and computational complexity. To address the challenge of increasing the true positive rate and reduce the computational complexity, this paper proposes a novel technique named Robust Face Detection using Delaunay Triangle (RFD-DT). In this model, first apply Spectral Cluster for efficient face detection from images acquired using Faces94 dataset. Subsequently, gender detection for the detected face is performed by applying Delaunay Triangle to guess whether the given image is a male or female. Finally, age estimation is carried out by applying Wrinkle Textured Seed Point. Extensive experiments carried out on the Faces94 dataset have revealed the outstanding performance of the proposed RFD-DT technique when benchmarked with various well established high-tech schemes. The results obtained by RFD-DT witness a significant increase in accuracy by improving the true positive rate with minimized computational complexity when compared with the results produced by the other methods.

KEYWORDS: Face Recognition, Region of extraction, Spectral Cluster, Wrinkle Textured, Seed Point.

1 INTRODUCTION

Face detection along with gender and age identification is an active research area that determines the presence of human faces in color images. Given with the face images, robust face detection based on gender classification finds out whether the given facial image belongs to the gender male or female. Though significant strides have been made in tackling the problem and providing security in public gatherings, major challenges remain in solving it in the geometrical regional texture.

To improve the recognition performance and speed, Blur and Illumination Robust Face Recognition (B-IRFC) via Set Theoretic Characterization [1] algorithm was proposed. This algorithm solved challenges involved in blind image de-convolution. The blur information affected due to the probe image was easily detected and low dimensional face feature was extracted to handle the illumination variations for efficient face recognition. It works very well for small blurs. However, parameters related to blur kernels increase the computational complexity and therefore it affects the average face recognition rate.

The identification of exact face features, age and gender need to handle different facial expression and face views of the acquired face images. Another method called, Robust Face Recognition for Uncontrolled Pose and Illumination Changes (RFR-UPIC) [2] was presented to handle different facial expressions and views of an images. It was said to be robust and therefore addressed pose and illumination variations. This in turn enhances the overall accuracy of face recognition. But, the qualities of images were not sufficient to guarantee an accurate recognition response and the error rate of this is not being sufficient for high level security provisioning.

The aforementioned works and other analogue methods have clearly shown the necessity to propose and develop robust face detection model to improve the true positive rate and reduce the computational complexity for efficient face detection. The main contributions of this work are as follows: (1) it proposes a simple and reasonable way to simultaneously improve the true positive rate and reduce computational complexity in the training and test samples. (2) The designed algorithm can lead to robust face detection by properly integrating the distance measure and region of interest to be extracted in a significant manner.

The rest of the paper is organized as follows: In section 2 review works related to robust face detection model is presented and subsequently proposed technique for robust face detection based on geometrical facial features in section 3. In section 4 experiments to evaluate the efficacy of this technique using Faces94 dataset is presented. Finally 5 discusses on various parametric definition and analysis with state-of-the-art methods. Finally, concluding remarks is presented in Section 6.

2 RELATED WORKS

An obvious approach to provide novel face representation and detection approach would to decompose into different scale and orientation using multi scale and multi orientation Gabor filters [3]. However, it involves a challenging problem of uncontrolled illumination variation and it was addressed in [4] by applying hybrid fourier features.

Up to now, many face representation approaches have been introduced including multimodal palm print and hand geometry features [5] and image quality assessment [6]. However, pose variations remained unaddressed. In [7], Markov Random fields were applied to for pose-invariant face detection using an extension of Lucas-Kanade algorithm. However, none of these techniques explicitly perform human identity and gender detection. Therefore, these techniques may pose significant challenges when applied to real world applications. In [8], sparse reconstruction-based metric learning method was presented to exploit the detection and improve the rate of accuracy.

Over the recent years, a few researchers have developed face detection model using multi-scale image fusion [9] and face antispoofing [10]. Authors have achieved promising results for a large group of images. However, the performance of the approach heavily relies on accuracy of the pixel level and person specific, which can deteriorate under pixel differences and pose variations.

Behavioral analysis of human faces has been a hot topic in the areas of computer vision and pattern detection due to the increasing need from real-world applications. Recently, optimal fusion algorithms [11] were introduced with the aid of virtual multi modal to improve the effectiveness of the false accept using log likelihood ratios. Another method based on Nuclear Norm Regularized Regression (NNRR) [12] method to improve the robustness and reduce the complexity of face detection.

Though several face detection methods have been introduced, face detection poses with significant difficulties. This is because of large intra-subject variations with changes in the same individual that make the face detection system to be more different to analyze. In [13], compressed sensing theory was introduced to improve the detection rate to certain types and levels of occlusion. In spite of over two decades of intense research, pose invariance remain significantly challenging aspects of face detection for most real time applications. A photometric model [14] was designed with a statistical model to improve the face detection rate using same identity likelihood ratio. In [15], Coupled Latent Space discriminant analysis was presented for invariant face detection.

In order to handle intra and interclass variations a novel detection approach was presented in [16] using robust auxiliary dictionary learning to improve the detection rate. For pattern classification problems, it is highly required to design a model for face detection to minimize the presence of noise and to enhance the robustness of the classifier. In [17], a new representation based classification method was introduced to reduce the classification error and therefore increase the face detection rate.

The recently proposed face detection model based on the representation of geometrical features has performed very well in high-dimensional pattern classification problems. However, the training images collected from different media posed serious issues. In [18], to present a robust face detection model obtained from different gamut of media. However, face images having low resolution captured at a distance degrades the face matching performance. In [19], to address this issue, linear prediction model and camera motion control was investigated to improve the identification accuracy. Low rank matrix decomposition [20] was investigated on different face databases for improved face detection performance.

With the aforesaid methods, in this paper, a Robust Face Detection using Delaunay Triangle (RFD-DT) technique to reduce the computational complexity for robust face detection by optimizing the true positive rate is presented. Further the discussion of the proposed work is stated in a detailed manner.

3 ROBUST FACE DETECTION USING DELAUNAY TRIANGLE

The facial detection of a person with gender and age identification helps in knowing the person's behavior and possible actions being produced. In addition, different facial expressional classes give a scope for identifying the appearance and age estimation, and hence for any detection algorithm to work in practice, it must account for these variations. First, a spectral cluster model for extracting exact facial portion is presented. Next, this model is used along with the Delaunay Triangle to classify the gender classes of the detected human face objects. Finally, Wrinkle Textured Seed Point is applied to the human face image to identify the age, maximizing the age identification rate from acquired input. Pursued by, each step of this technique is explained in briefly.

3.1 SPECTRAL CLUSTER-BASED FACE DETECTION

The first step in a face detection based application is the efficient detection of faces within an image. For detection of facial features, it is foremost step to detect face from the attained image. In the proposed work, the face and its characteristic points are located through the skin color features by determining whether the image pixel is a skin color or non skin color. With this differentiation, the non skin color regions are rejected whereas the image pixel possessing the skin color is used for further analysis. This is performed by applying Spectral Cluster to the acquired input images, improving accuracy of human face images being detected. Figure 1 shows the structure of Spectral Cluster-based Face Detection (SC-FD) model.

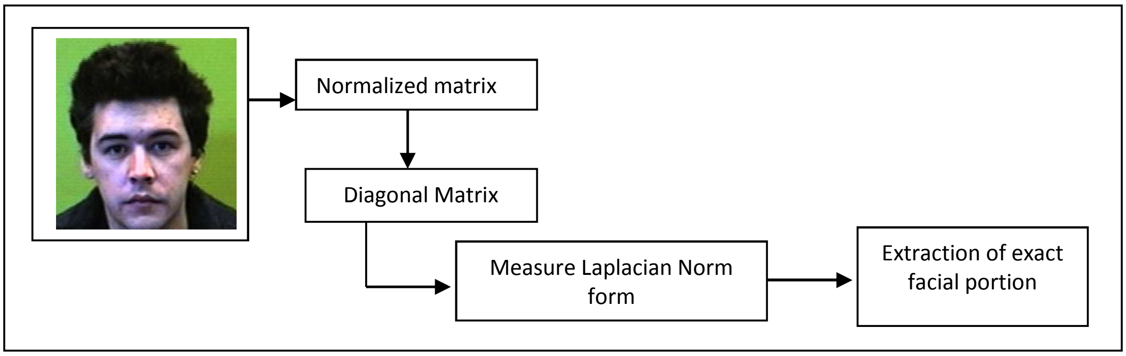

Figure 1 Structure of Spectral Cluster-based Face Detection

As shown in the Fig.1, the SC-FD model is introduced to evaluate the skin color features and generate spectral color featured clusters of the attained face. In SC-FD, a graph 'G' is assumed to be a weighted model, where each edge between two vertices 'v_1 and v_2' possess a non-negative weight '$W_{ij} > 0$'. The degree of vertex is as given below.

$$D_i = \sum_{i=1}^{n} W_{ij} \tag{1}$$

From (1), the similarity distance bound values are obtained and the spectral clusters are generated using Laplacian form. From (1), 'n' connected points are considered and represented in the form of a diagonal for the matrix 'M' as given below.

$$M = \begin{bmatrix} L_1 & L_{11} & L_{12} \\ L_{21} & L_2 & L_{22} \\ L_{31} & L_{32} & L_n \end{bmatrix} \tag{2}$$

$$D = \begin{bmatrix} L_1 & \dots & \dots \\ \dots & L_2 & \dots \\ \dots & \dots & L_n \end{bmatrix} \tag{3}$$

From (2) and (3), the Laplacian form is normalized into a diagonal matrix with the objective of evaluating the skin color features and therefore reducing the false positive rate. The Laplacian Normalized form 'Lap_{norm}' is then evolved using the normalized matrix 'M' and the diagonal matrix 'D' as given below.

$$Lap_{norm} = I - D^{-1/2} * MD^{-1/2} \tag{4}$$

Let us consider an image 'A', then by measuring the average value of 'R, G, B' for an image 'A' and identifying the greatest average value with respect to the '$ith\ jth$' coordinate, similarity distance bound are attributed to spectrum of skin color value. It is formulated as given below.

$$R_A = \frac{1}{ij} \sum_{i,j=1}^{n} R_{ij} \tag{5}$$

$$G_A = \frac{1}{ij} \sum_{i,j=1}^{n} G_{ij} \tag{6}$$

$$B_A = \frac{1}{ij} \sum_{i,j=1}^{n} B_{ij} \tag{7}$$

$$MAX(R_A, G_A, B_A) = MAX\ (MAX(MAX(R_A)\ G_A)B_A) \tag{8}$$

Now, the skin color features are extracted using a prior estimation likelihood threshold 'δ' arrived from the trained human faces. Therefore, the skin color and non-skin color features are obtained as given below.

$$If\ (MAX(R_A, G_A, B_A) > \delta)\ then\ EF = Skin\ color\ features \tag{9}$$

$$If\ (MAX(R_A, G_A, B_A) < \delta)\ then\ EF = Non - skin\ color\ features \tag{10}$$

From (9) and (10), by ignoring the non-skin color features and using the skin color features, the exact facial portion of the acquired human face image is obtained, therefore improving the spectral cluster accuracy. Next step is to categorize the face as male or female using Delaunay triangle technique and fully discussed in the further section.

3.2 Delaunay Triangle-based Gender Detection

Once the face is detected from the obtained image, Delaunay Triangles is applied to the detected face for gender identification. Let us consider a point 'PN' or the extracted features 'EF', then the Delaunay Triangles for gender detection either using the point 'PN' or extracted features 'EF' is given as below.

$$DT = \begin{cases} T\ (EF_l, EF_m, EF_n)\ , where EF_l\ \in PN, EF_m \in PN, EF_n\ \in PN, \\ \qquad \frac{C\ (EF_l, EF_m, EF_n)\ \cap EF}{(EF_l, EF_m, EF_n)} = \emptyset \end{cases} \tag{11}$$

Where '$C\ (EF_l, EF_m, EF_n)$' represents the circle circumscribed by vertices 'EF_l, EF_m, EF_n' forming a Delaunay Triangle '$T\ (EF_l, EF_m, EF_n)$'. Delaunay Triangulation is then calculated for the Euclidean distances as given below.

$$Dis\ (P, Q) = \sqrt{(Q_1 - P_1)^2 + (Q_2 - P_2)^2 + \ \ldots.. + (Q_n - P_n)^2} \tag{12}$$

Where '$P = (P_1, P_2, \ldots., P_n)$' and '$Q = (Q_1, Q_2, \ldots, Q_n)$' represents two points '$P\ , Q\ \in PN$'. The Euclidean distances obtained from (12) are then loaded into the database. Figure 2 shows the structure of Delaunay Triangles for input image. As seen in figure, features detected from face have been labeled in green boxes. Once all the features have been extracted, the next task is to decide whether these features represent female or male face.

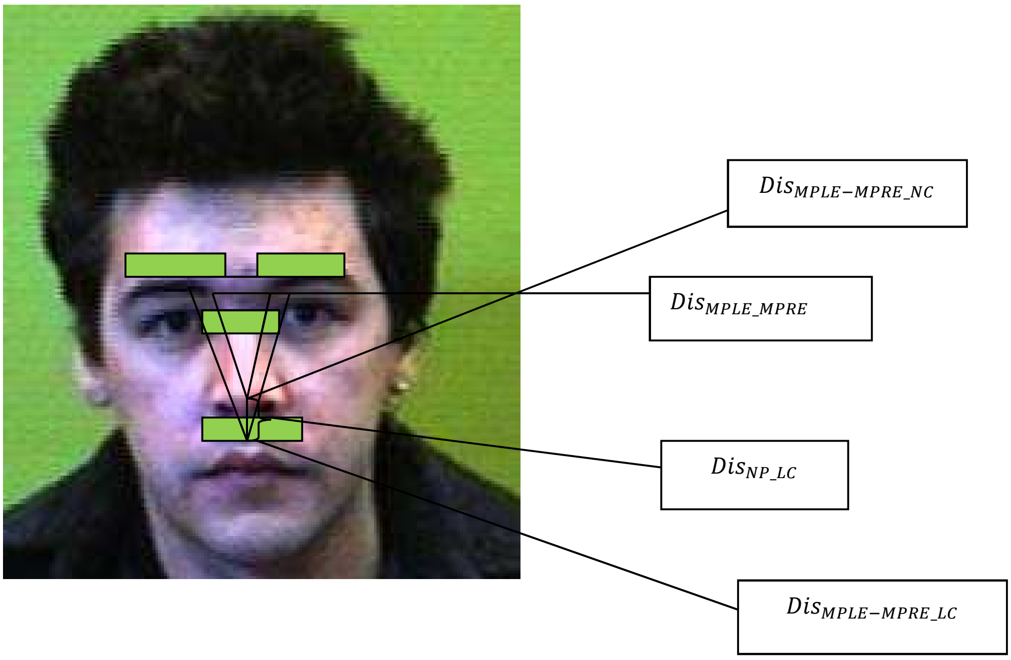

Figure 2 Structure of Delaunay triangles for gender detection

As shown in the Fig.2, the proposed work evaluates the correlation of male and female to obtain the threshold valued. Based on the four ratios threshold values, the decision regarding the male or female is made. The four ratios threshold values include the Distance between left eye midpoint to right eye midpoint and nose center ($Dis_{MPLE-MPRE\_NC}$), Distance between midpoint of left eye and midpoint of right eye (Dis_{MPLE_MPRE}), Distance between nose tip and lip center (Dis_{NP_LC}) and Distance between left eye midpoint to right eye midpoint and lip center ($Dis_{MPLE-MPRE\_LC}$). They are evaluated as given below.

$$Dis_{MPLE\_MPRE} = \frac{Dis\ (LE\_RE)}{Dis(E\_N)} \tag{13}$$

$$Dis_{MPLE-MPRE\_NC} = \frac{Dis(E\_N)}{Dis\ (E\_NC)} \tag{14}$$

$$Dis_{MPLE-MPRE\_LC} = \frac{Dis\ (LE\_RE)}{Dis(E\_LC)} \tag{15}$$

$$Dis_{NP\_LC} = \frac{Dis\ (N\_L)}{Dis\ (NC\_LC)} \tag{16}$$

From (13), (14), (15) and (16), four threshold values are obtained that serves to differentiate between male and female face. Fig.3 shows the algorithm steps for Delaunay Triangle-based Gender Detection.

Input: Image 'I', Extracted features 'EF', Threshold 'RT_1, RT_2, RT_3, RT_4'
Output: reduced true positive rate and computational complexity
Step 1: Begin Step 2: For each Image Step 3 : For each matrix 'M' Step 4: Obtain diagonal matrix 'D' Step 5: Obtain normalized form using (4) Step 6: Differentiate skin color and non-skin color features using (9) stored extracted features in 'EF' Step 7: Form Delaunay Triangles for the extracted features using (11) Step 8: Measure distance between midpoint of left eye and midpoint of right eye 'Dis_{MPLE_MPRE}' using (13) Step 9: Measure distance between left eye midpoint to right eye midpoint and nose center '$Dis_{MPLE-MPRE\_NC}$' using (14) Step 10: Measure distance between left eye midpoint to right eye midpoint and lip center '$Dis_{MPLE-MPRE\_LC}$' using (15) Step 11: Measure distance between nose tip and lip center 'Dis_{NP_LC}' using (16) Step 12: If '$Dis_{MPLE\_MPRE} > RT_1$' && '$Dis_{MPLE-MPRE\_NC} > RT_2$' || '$Dis_{MPLE-MPRE\_LC} < RT_3$' && '$Dis_{NP\_LC} > RT_4$' Step 13: Detected image is "Female" Step 14: Else Step 15: Detected image is "Male" Step 16: End if Step 17: End for Step 18: End for Step 19: End

Figure 3 Delaunay Triangle-based Gender Detection algorithm

As shown in the above figure, the Delaunay Triangle-based Gender Detection algorithm involves two parts. The first part extracts the face image using spectral cluster technique by differentiating skin color and non-skin color features. With the face image obtained, gender detection is performed using Delaunay Triangle in the second part. Once the necessary features are extracted for gender identification, then Euclidean distance is calculated among the features, next the ratios of male and female are evaluated and the threshold value is identified. Based on those threshold values, the given facial image is decided whether a male or female. Followed by, the explanation of age estimation based on wrinkle textured seed point technique in briefly.

3.3 WRINKLE TEXTURED SEED POINT-BASED AGE ESTIMATION

Once detecting the face and gender of an image, next tread is to calculate the age of an image based on Wrinkle Texture Seed Point technique. This model aims at improving the age identification rate using the ROI approach. Extraction of Region of Interest on the face is a good starting point to evaluate the unique feature based on the lines seen between midpoint of the nose to left and right end of the mouth.

The ROI approach proceeds with the principle that a seed point searches the seed point's neighbors to determine whether they belong to the same region. Finally, the seed point is obtained based on the line textured value of similar ranges that list down different wrinkles of the ROI portion of the face image.

The textured values of the ROI are measured from Eigen vectors that use the Euclidean distance of the regional pixels by calculating the distance between the testing image and already available training images. Then the minimum distance is observed from the set of values. The wrinkle texture seed point is trained for evaluating the age ranges from the training sample face images. Multiple trained wrinkle lines are generated and stored in template for testing the detect face image to identify the age ranges of the human face.

The Euclidean distance (ED) of the regional pixels is measured for each expression and is formulated as given below,

$$ED = \sqrt{\sum_{i,j=1}^{n}\left(x_i - x_j\right)^2} \qquad (17)$$

From eqn.(17), the distance between two pixels '$x_i - x_j$' is the Euclidean distance of their wrinkle feature vectors. As a result, by applying this model, the age identification rate is improved significantly.

4 EXPERIMENTAL RESULTS

In this paper, the aim is to improve the true positive rate and reduce the computational complexity during robust face detection. A dataset containing images obtained from 150 facial images composing of 20 female, 113 male and 20 male staff images. The image resolution was represented in 180 by 200 pixels portrait format in separate directories, each for male and female respectively is used to evaluate the performance of proposed technique.

By using Faces94 dataset and the defined testing method results are compared with existing method. RFD-DT technique is compared with the existing Blur and Illumination Robust Face Detection (B-IRFC) [1] and Robust Face Recognition for Uncontrolled Pose and Illumination Changes (RFR-UPIC) [2]. Experimental evaluation using RFD-DT technique is conducted on various factors such as true positive rate, computational complexity, age identification rate and accuracy rate of face image detected with respect to different face images.

The true positive rate for gender classification is measured based on the number of face images taken as input for experimentation and the number of faces improperly classified are considered. The true positive rate for gender classification measures the ratio of difference between the number of face images provided as input and the number of faces improperly classified to the face images given as input. The True positive rate for gender classification is mathematically formulated as given below.

$$TPR = \frac{(n - No\ of\ faces\ improperly\ classified)}{n} * 100 \quad (18)$$

From (18), the true positive rate for gender classification 'TPR' is measured in terms of percentage (%). Higher the true positive rate for gender classification more efficient the method is said to be. The computational complexity involved during gender detection is the product of number of face images and the time taken for gender detection. The computational complexity is measured as given below.

$$CC = No.of\ face\ images * Time\ (gender\ detection) \quad (19)$$

The accuracy rate of face image being detected refers to the rate at which the number of face images (i.e. testing image) that accurately extracts the exact facial portion for further evaluation. With the exact facial portion, the face detection rate is also said to improve. The mathematical formulation for obtaining the accuracy rate is as given below.

$$A = \frac{No\ of\ face\ images\ extracting\ exact\ facial\ portion}{n} * 100 \quad (20)$$

From (20), the accuracy rate of face image being detected 'A' is evaluated and is measured in terms of percentage (%). Higher the accuracy more efficient the method is said to be.

5 DISCUSSION

The result analysis of Robust Face Detection using Delaunay Triangle (RFD-DT) technique is compared with existing Blur and Illumination Robust Face Detection (B-IRFC) [1] and Robust Face Recognition for Uncontrolled Pose and Illumination Changes (RFR-UPIC) [2] respectively.

5.1 IMPACT OF TRUE POSITIVE RATE FOR GENDER CLASSIFICATION

Table 1 represents the true positive rate for gender classification with different number of face images extracted (from male and female) using Matlab simulator. Out of 113 male and female facial images, 70 face images were used for experimentation and comparison is made with two other methods, namely B-IRFC [1] and RFR-UPIC [2].

Table 1 True positive rate for gender classification using RFD-DT, B-IRFC and RFR-UPIC

No. of face images	True positive rate for gender classification (%)		
	RFD-DT	B-IRFC	RFR-UPIC
10	79.39	69.48	60.21
20	82.32	72.45	65.15
30	85.56	75.36	66.18
40	80.18	70.29	61.14
50	82.24	72.35	64.19
60	86.42	76.17	66.11
70	89.47	79.60	69.40

In order to conduct experimentation, a total of seventy face images with background in plain green color where the subjects or male sit at fixed distance from the camera. With these images, the true positive rate is identified and tabulated in table 1.

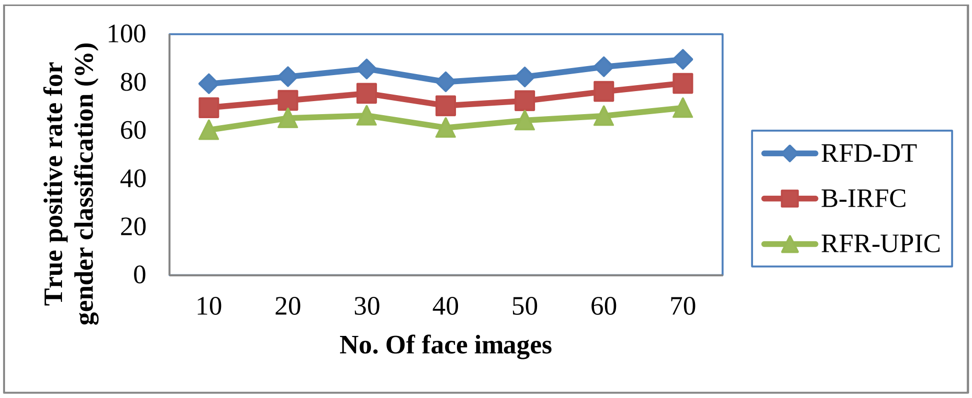

Figure 4 Measure of true positive rate for gender classification

Fig.4 illustrates the true positive rate comparisons for gender classification averaged over 70 random training of 153 images. It can be observed that the proposed measurement outperforms the others, indicating that it best describes the statistical distortion. The results reported above confirm that with the increase in the number of face images provided as input, the true positive rate also increases and comparatively observed to be higher using RFD-DT. The true positive rate for gender classification is improved with the application of Delaunay Triangle. The Delaunay Triangle considers circle circumscribed by vertices and evaluates the correlation of male and female to obtain the threshold value. Furthermore, the decision regarding the male or female is made based on the four ratios threshold values. As a result, the true positive rate for gender classification is improved by 11.94% compared to B-IRFC and 22.75% compared to RFR-UPIC.

5.2 IMPACT OF COMPUTATIONAL COMPLEXITY DURING GENDER DETECTION

The results are conducted to measure the Computational complexity during gender detection are listed in Table 2. In the experimental setup, the number of face images ranges from 10 to 70, out of which 15 female samples and 25 male samples were considered.

Table 2 Computational complexity measured using RFD-DT, B-IRFC and RFR-UPIC

No. of face images	Computational complexity during gender detection (ms)		
	RFD-DT	B-IRFC	RFR-UPIC
10	0.37	0.49	0.56
20	0.64	0.75	0.82
30	0.78	0.90	0.99
40	1.00	1.07	1.16
50	1.07	1.22	1.28
60	1.19	1.34	1.39
70	1.33	1.48	1.54

As listed in Table 2, the RFD-DT technique measures the computational complexity during gender detection which is measured in terms of milliseconds (ms). The computational complexity during gender detection obtained using this technique RFD-DT offer comparable value than the modern methods. The time taken for gender identification for single face image using RFD-DT technique was 0.03ms, 0.049ms using B-IRFC and 0.056ms using RFR-UPIC.

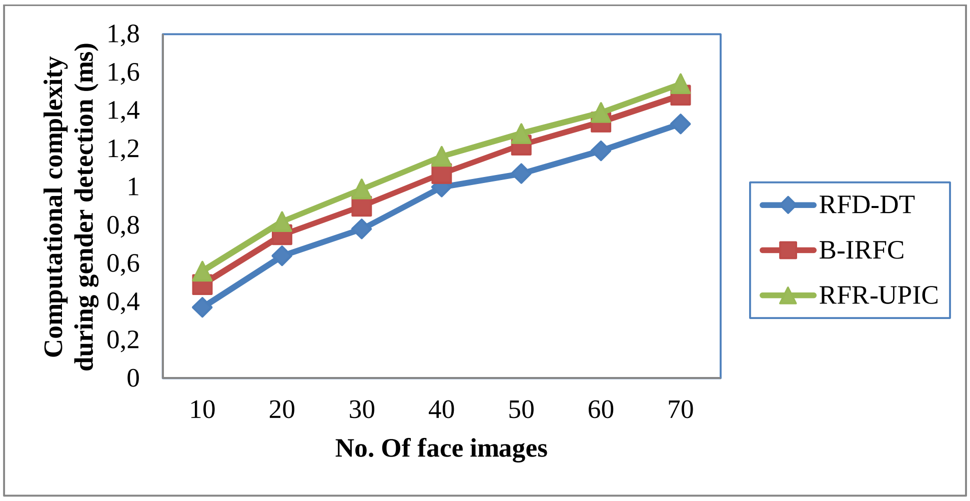

Figure 5 Measure of computational complexity

As illustrated in figure 5, when 10 face images were used as input, the computational complexity using RFD-DT was 0.37ms compared to B-IRFC and RFR-UPIC that showed 0.49ms and 0.56ms respectively. The advantage of applying Delaunay Triangle-based Gender Detection algorithm in RFD -DT technique where Euclidean distances are evaluated with the correlation of male and female to obtain the threshold value. This threshold value is then used for arriving at the decision whether the given face image is male or female. This in turn reduces the computational complexity by 15.70% compared to B-IRFC and 24.94% compared to RFR-UPIC.

5.3 IMPACT OF ACCURACY RATE OF FACE IMAGE DETECTED

In table 3, compare the rate of Accuracy rate of face image detected obtained by different number of face images for robust face detection. The experiments were conducted using seventy face images with background in pale green color and minor variations observed in head turn, tilt and slant respectively and the accuracy rate of face image detected is measured in terms of Percentage (%).

Table 3 Accuracy rate using RFD-DT, B-IRFC and RFR-UPIC

No. of face images	Accuracy rate of face image detected (%)		
	RFD-DT	B-IRFC	RFR-UPIC
10	91.37	80.52	70.25
20	93.34	85.45	75.26
30	95.18	89.29	79.10
40	92.29	83.40	73.21
50	94.50	85.61	75.72
60	96.81	87.92	77.73
70	97.25	88.36	78.17

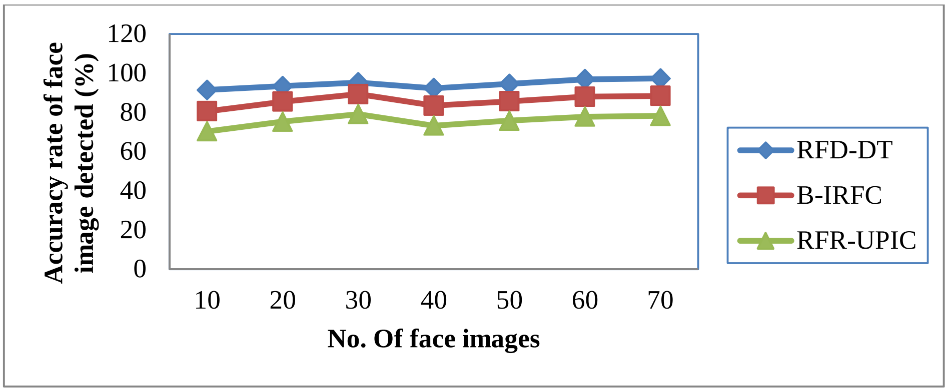

Fig. 6 Measure of accuracy rate of face image detected

From Fig. 6, it is illustrative that the accuracy rate of throughput for face image detection is improved using the proposed RFD-DT technique. This is because with the application of spectral cluster and Delaunay Triangle, the accuracy rate is increased where face detection is made by ignoring the non-skin color features and using the skin color features. Then, from the extracted skin color features, gender identification is made. This results in the improvement of accuracy of face image detected using RFD-DT technique by 9.12% compared to B-IRFC and 19.89% compared to RFR-UPIC.

5.4 Impact of Age identification rate

In order to increase the age identification rate with respect to different number of face images, the age identification rate using the RFD-DT technique and two methods, B-IRFC and RFR-UPIC with visual comparison is presented in table 4.

Table 4 Comparison of age identification rate

Methods	Age identification rate (%)
RFD-DT	95.17
B-IRFC	88.47
RFR-UPIC	82.27

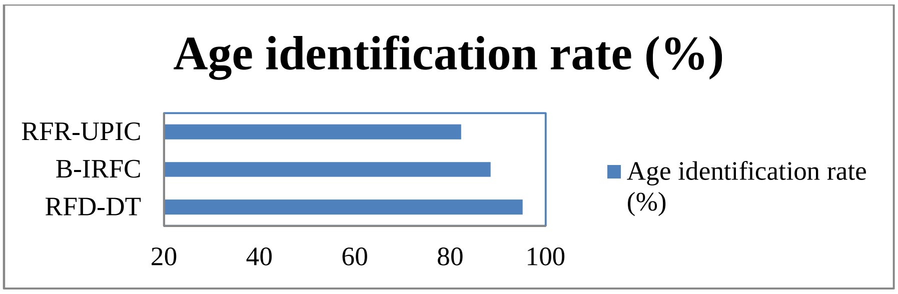

Fig. 7 Measure of age identification rate

From the Fig.7, the age identification rate is higher by applying the proposed RFD-DT technique than when compared to the existing methods respectively. This is because of the application of Delaunay Triangles and The Wrinkle Textured Seed Point-based Age Estimation model that attains 7.04% improvement when compared to B-IRFC [1] method and 7.00% compared to RFR-UPIC [2] method which shows that there is a significant gain using the proposed RFR-DT technique.

6 Conclusion

This paper proposes three novel face representations. First formulate Spectral Cluster model for face detection and then apply Delaunay Triangles on extracted faces, and finally Wrinkle Textured Seed Point for age estimation. In order to improve the true positive rate and reduce the computational complexity, Delaunay Triangles-based Wrinkle Textured Seed Point with distance measure and region of interest extraction is further proposed to represent a robust face detection technique. The correlation of male and female is evaluated and based on the threshold values, the decision regarding the male and female is made to reduce the computational complexity and robustness of the proposed representations. In robust age estimation phase for, Delaunay Triangles and Wrinkle Textured Seed Point are utilized to improve the age estimation rate and make the representation more compact and, thus, to improve the efficiency of the algorithm. Experimental results validate the efficacy of the proposed technique.

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