Virtual Image Representation and Adaptive Weighted Score Level Fusion for Genetic Face Recognition

S. Deepa, A. Bhagyalakshmi, V. Vijaya Chamundeeswari, and S. Godfrey Winster

Abstract Face recognition is the most interesting and wide area of research over the past few decades. This research work proposes the effective virtual image representation and adaptive weighted score level fusion face recognition-based algorithm to classify the genetic faces and non-genetic faces. The algorithm integrates the virtual image and original image, which is a nonlinear transformation of original image. This virtual representation improves moderate intensities pixels and changes the high or low intensities pixels. In face images, various pixels have distinctive significance. Subsequently, it is sensible to fix various weights to individual pixels. Then score level fusion is performed for recognizing the faces, which overcomes illumination due to lighting in the image. Genetic face recognition accuracy gets impacted by the variations in face due to age. The proposed score level fusion scheme gives the best optimal solution for genetic face recognition with respect to age variation. Using statistical measure, distance is calculated between the virtual image and original image for both test and training set of images. The performance results reveal that the proposed score level fusion is robust to different test conditions and performs well compared to existing algorithms.

Keywords Genetic face recognition · Score level fusion · Virtual image representation

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1 Introduction

Face recognition is an interesting specialization of pattern recognition, and at the same time, it is a complex issue considered in the field of computer vision. There are many challenges in the face recognition process. Significant efforts have been given to the development of exact and robust face recognition algorithms. It is yet, one of the greatest challenges to recognize the faces genetically irrespective of enormous appearance changes because of variations on illumination, expression, aging and poses. Genetic face recognition is identifying the person belonging to the same gene based on similar facial characteristics. Accuracy of genetic face recognition gets impacted by the variations in face due to age. Researchers have tried in the last few decades to develop a face recognition system to recognize the faces with different modalities, unfortunately, no approach present till now for recognizing the same faces with age variation. To overcome this, an algorithm has been developed using nonlinear transformation and adaptive weighted score level fusion method for genetic face recognition, to identify the faces irrespective of age variation with limitations. In spite of the variations, the algorithm can still extract particular highlights of the original face which improves the efficiency of the genetic face recognition and to find the group of similar faces with respect to age variations. In this method, adaptive weighted score level fusion technique is implemented for original image and virtual image to recognize the faces efficiently and to overcome the variations due to illumination, pose and expression. The proposed score level fusion algorithm recognizes the faces with respect to age difference for similar person in different background.

In paper [1], the algorithm has been proposed that joins weighted virtual images to understand a higher face recognition exactness. Image fusion incorporates highlights from numerous sources and can improve performance in the fields of face recognition. When all is said in done, fusion is implemented at three levels, decision level, feature level, and score level. In paper [2], the fusion of score level approach is broadly attributable to the great achievements and it has been arranged into four fusion rules: max rule, min rule, product rule, and sum rule. The paper [3] proposes another age assessment system which exploits different-stage highlights from a feature extractor of generic system, a proposed convolutional neural organization (CNN), and decisively consolidated these features with a determination of handcrafted feature with age-related. The papers [4–8] propose an another fusion scheme, implemented by feature and score level fusion to improve the accuracy of recognition which is referred to as the matcher performance-based (MPb) fusion scheme. In paper [9], a novel adaptive fusion and category-level dictionary learning approach (AFCDL) overcomes the limitations such as Hugh variations in background, speed of the object, motion in video surveillance which is implemented for Multiview action recognition. In paper [10], multi-biometric framework of human recognition is implemented by consolidating biometric hints from various sources (algorithms, numerous sensors, and modalities) at various levels. The scores acquired from various uni-biometric frameworks can be resolved by utilizing score standardization before fusion and afterward

proposes an effective score fusion procedure dependent on Dezert-Smarandache theory (DSmT). This paper [11] will propose cutting edge fusion of multimodal biometric procedures to increase acknowledgment execution of delicate biometrics. The key commitment of this paper is the investigation of the impact of separation on delicate biometric qualities and an investigation of the power of acknowledgment utilizing fusion at different distances. This paper [12] intends to examine the impact of fusion of multimodal biometric frameworks at fusion of feature and score level for gender orientation characterization. These papers [13, 14] used genetic algorithm for Monaural speech separation for better results, likewise it can be used for genetic face recognition for better performance.

In this paper, an algorithm is proposed to recognize the similar faces with respect to age, with the help of virtual image representation and adaptive weighted score level fusion. The paper work is described as follows. Proposed score level fusion genetic face recognition algorithm is explained in Sect. 2. In Sect. 3, Implementation and results are carried out for different databases emphasizing that the algorithm works satisfactorily. Conclusion and References are discussed in Sect. 4.

2 Proposed Genetic Face Recognition System

Figure 1 demonstrates the architecture diagram of the proposed approach for score level fusion genetic face recognition. The original training and test face image from the dataset are pre-processed and converted into virtual image representation which is nonlinear transformation. The first distance is calculated between the pre-processed image from training and test database, and then second distance is calculated between virtual image from test and training database. Euclidean distance measure is used to calculate the distances between the two pre-processed and virtual images. These two distances are normalized to calculate the weight using the distance values. Then score level fusion is applied for calculated weight and distance values. Using this fusion values, genetic face images are classified with respect to age. Face images are taken from different perspectives and different age to prove the classification of genetic and non-genetic faces and with respect to age difference. Statistical measures of the classification results demonstrate that the proposed algorithm is very productive in recognizing the faces genetically and group similar faces with different age.

The following subsections briefly describe the stages of the proposed score level fusion face recognition system.

2.1 Pre-processing of Images

The aim of pre-processing is an improvement of the image data that enhances some image features or suppresses unwanted distortions important for further processing.
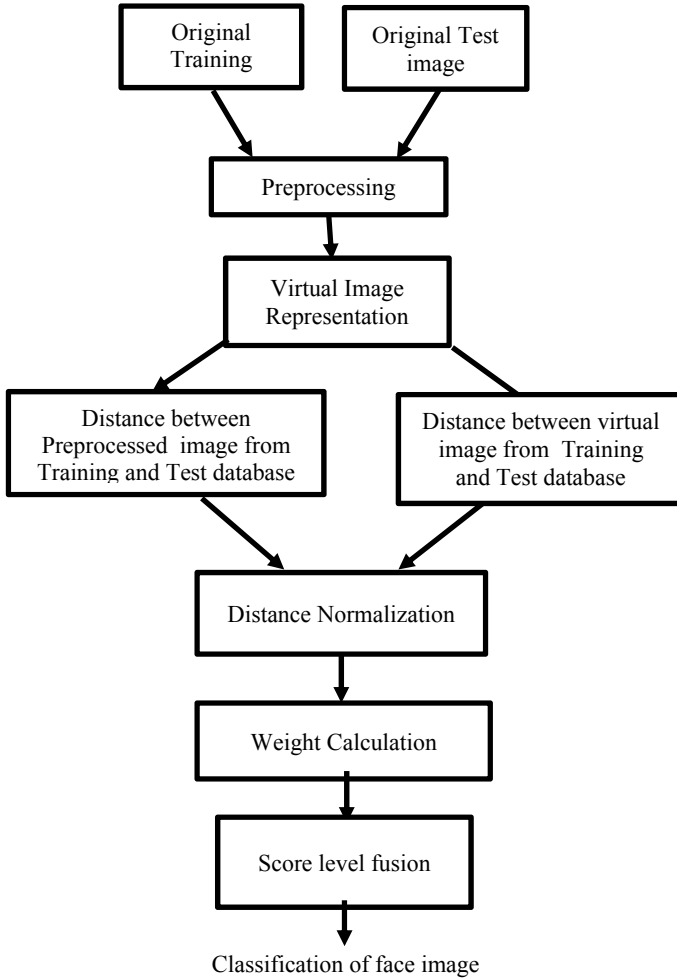
Fig. 1 Architecture diagram of the proposed system

Histogram equalization is used for pre-processing. Histogram equalization is a technique to enhance the contrast by adjusting image intensities. Figure 2 shows the original and pre-processed image.

Let p be an image given as a m_r by m_c pixel matrix of intensities from 0 to M-1. M is the intensity value. Let f denote the histogram normalization of p. So

$$f_n = \frac{\text{number of pixels with intensity } n}{\text{total number of pixels}} \quad n = 0, 1, \ldots, M-1. \tag{1}$$
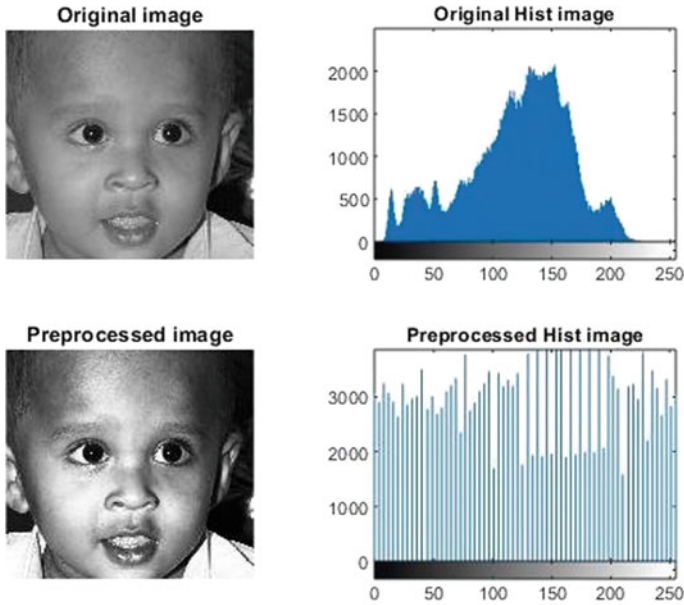
The image of the histogram g is defined by

Fig. 2 Pre-processed image

$$g_{i,j} = \text{floor}\left((M-1)\sum_{n=0}^{p_{i,j}} f_n\right) \tag{2}$$

where floor () rounds to the closest integer. This is equal to intensity of pixel transformation, k of p by the equation

$$T(k) = \text{floor}\left((M-1)\sum_{n=0}^{k} f_n\right). \tag{3}$$

2.2 Non-linear Transformation

In order to recognize face images successfully, however, much valuable data as could be expected are required. The original image pixel with high intensity relates to virtual image of low intensity pixels in nonlinear transformation, and the other way around. To direct face recognition, the inverse of the image is used as a supplement of the source image. Figure 3 shows source image and its relating virtual image. The virtual face images have a converse portrayal, yet look like human appearances. Also, in addition the pixels with high intensity speak to significant facial highlights in virtual
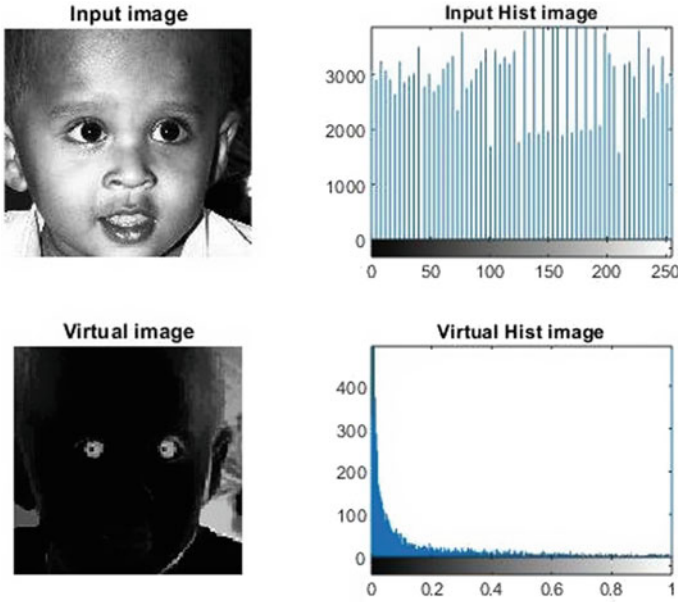
Input image

Input Hist image

Virtual image

Virtual Hist image

Fig. 3 Nonlinear transformation

images. The histogram of the original image and relating virtual image is represented in Fig. 3. The intensity of pixels average value in the source image is generally high. In actuality, intensity of the pixels of the virtual image is generally low. Additionally, the virtual image average gray level has been altogether diminished.

This virtual representation upgrades moderate intensities pixels and diminishes high- or low-intensity pixels. This virtual images show the particular highlights of the source face. The nonlinear transformation proposed in Eq. (4) can fulfill our prerequisite in light of the nonlinear characteristic. Subsequently, combination of integral virtual and source images gets best execution for recognition of faces.

$$V = \frac{255}{1 + e^{aX+b}} \tag{4}$$

where V is the virtual image, X is the original image, a and b are constants.

At the point when the data correlation gets stronger, the precision improvement will be decreased. Correlation coefficient is used to conduct the quantitative analysis between source images and virtual images. The meaning of coefficient of correlation is defined in Eq. (5)

$$\text{correlation} = \frac{\sum(x - \bar{x})(y - \bar{y})}{\sqrt{\sum(x - \bar{x})(y - \bar{y})}} \tag{5}$$

Fig. 4 Re-constructed image

The correlation coefficient should be determined to x and y which represents the two image vectors. The correlation factor varies for all the images, and there is a correlation of negative value between the source and the virtual data. The coefficient of correlation scope ranges from -1 to 1. On the off chance that the absolute estimation of the correlation coefficient is extremely near 1, at that point the virtual information to be sure doesn't give extra helpful data to fusion. Consequently, the algorithm can produce sensible additional information that also looks somewhat like faces. The moderately low relationship between source and virtual images demonstrates that they are integral to one another for face acknowledgment. It is also possible to re-construct the original image using the correlation factor. Figure 4 shows the re-constructed image by the following Eq. (6)

$$R = (V * C) + \text{Mean}(I) \tag{6}$$

where
    V—Virtual Image.
    C—Correlation factor.
    I—Original Image.
    R—Re-constructed image.

2.3 Euclidean Distance Calculation and Normalization

The database test image is pre-processed similar to that of training image and undergoes nonlinear transformation to get virtual images. The row vector of each original and virtual image class is shown in Eqs. (7) and (8)

$$X_i = \left[x_{(i-1)n+1}, \ldots, x_{in}\right] i = 1, 2, \ldots, Cl. \tag{7}$$

$$V_i = \left[v_{(i-1)n+1}, \ldots, v_{in} \right] i = 1, 2, \ldots, Cl. \tag{8}$$

Cl is the different classes of n training samples. The i-th class of training samples of n-th source and virtual data are denoted as x_{in} and v_{in}.

A linear function for each source image and virtual image from each class is defined by Eqs. (9) and (10)

$$\alpha_i = \left(X_i^T X_i + \lambda E \right) X_i y \quad i = 1, 2, \ldots, Cl. \tag{9}$$

$$\gamma_i = \left(V_i^T X_i + \lambda E \right) V_i y_v \quad i = 1, 2, \ldots, Cl. \tag{10}$$

Constant λ, identity matrix E, test image y, and virtual test image y_v is obtained by Eq. (4). Euclidean distance measure is used to calculate the distance $d1$ between test images and training images, and the distance $d2$ between the corresponding virtual test image and virtual training image. The closeness between the training image and the test image are calculated using the Euclidean distance.

$$d_1^i = ||y - X_i \alpha_i|| \quad i = 1, 2, \ldots, C. \tag{11}$$

$$d_2^i = ||y_v - V_i \gamma_i|| \quad i = 1, 2, \ldots, C. \tag{12}$$

The distance shows the commitment of a training image in order to distinguish a test image. A littler distance shows a higher recognition. Equation (13) is used to normalize the distance between the values 0 and 1

$$d_j^i = \frac{d_j^{\max} - d_j^i}{d_j^{\max} - d_j^{\min}}, (i = 1, 2, \ldots, Cl), (j = 1, 2). \tag{13}$$

where $d_j^{\max}$ and $d_j^{\min}$ are the maximum and minimum of d_j^i, respectively.

2.4   Weight Calculation

The main advantage of this proposed system is calculating the weight automatically. The distances $d1$ and $d2$ are sorted in ascending order, such that $P1, P2, P3 \ldots Pn$ are the sorted values of $d1$ and $V1, V2, V3 \ldots Vn$ are the sorted values of $d2$. The weights $w1$ and $w2$ for this proposed system are calculated by Eqs. (14) and (15)

$$w1 = \frac{P_2 - P_1}{(P_2 - P_1) + (V_2 - V_1)} \tag{14}$$

$$w2 = \frac{V_2 - V_1}{(P_2 - P_1) + (V_2 - V_1)} \tag{15}$$

The contrast value between the first score value and the second score value can decide a dependable weight for data fusion. The more noteworthy the contrast, the more certain the classification result.

2.5 Score Level Fusion

This work proposes an algorithm that joins virtual images weighted fusion to understand a face recognition exactness. Image fusion incorporates highlights from various sources and can improve performance in the fields of recognition of face, multibiometrics, and video retrieval. The fusion of score value approach is generally used attributable to its great performance, and it very well may be sorted into four combination rules: max rule, min rule, product rule, and sum rule. Most of past research studies prove that the best result arrives from the sum rule. The fusion result f_i is expressed in Eq. (16).

$$f_i = w_1 d_1 + w_2 d_2 \tag{16}$$

Despite the fact that score fusion has focal points over other approaches, deciding the best possible weights so as to realize optimization is a difficult assignment.

3 Implementation and Results

The score level fusion face recognition system shown in Fig. 1 is evaluated with face image databases with respect to genetic faces and non-genetic faces, faces of same person in different ages. Totally 200 face images of 20 persons with different ages are used for this algorithm. The proposed algorithm has been used to classify the genetic and non-genetic faces and similar person with respect to different ages such that images of different ages will be in different illumination, background and poses. So, this algorithm has overcome the complexities involved in face recognition. There are four database of sample face images are used in different analysis. Genetic and non-genetic faces of different families are gathered for databases. In the person 1 database, there are 13 images of same person with different ages and persons from same family descent and different family with different background setup and different illumination.

Figure 5 shows the database of different faces in which 7 faces belongs to the same person of different age (1–6 yrs, 2–5 yrs, 3–7 yrs, 4–2 yrs, 11–1 yr, 12–3 yrs, 13–4 yrs) and 5th image belong to same family and faces 6–10 belong to different family members. Figure 6 shows the pre-processed image of original face database of person 1. Pre-processing using histogram equalization enhances the contrast of the image which will be very useful for old images taken long back ago with less contrast and brightness. Figure 7 shows the nonlinear transformation of Person 1 database.
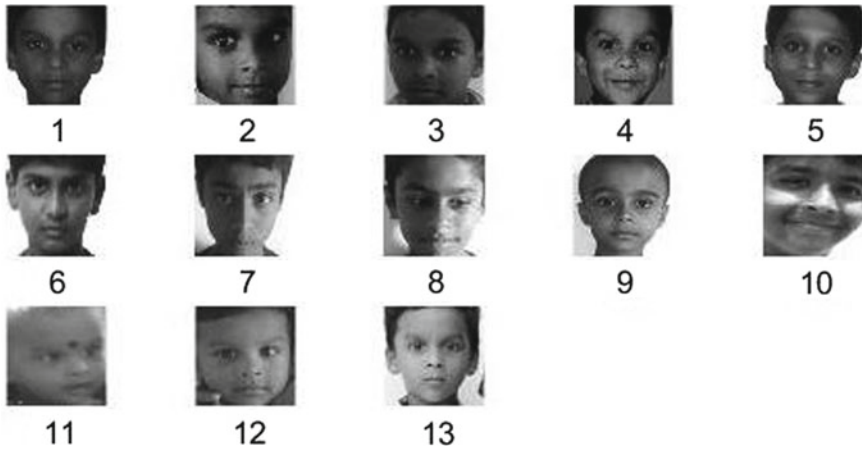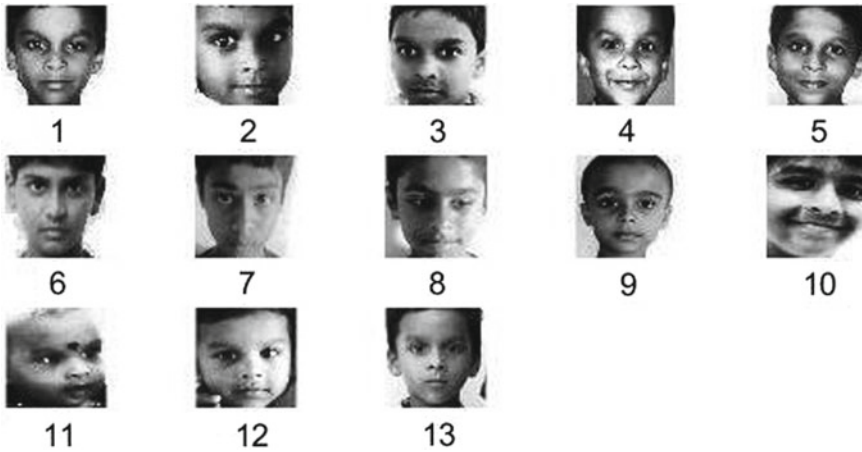
Fig. 5 Person 1 database

Fig. 6 Pre-processed image of Person 1 database

The virtual image representation, which is the complement of original image, can still show particular highlights of the original face which improves the efficiency of the genetic face recognition and finds the group of similar faces with respect to age variations.

From this output image, it is concluded that the main features have been extracted using these proposed algorithm and classified. For the classification purpose, distance values are calculated between the input image and database image for comparison. In this paper, Euclidean distance measure is used for calculating the difference error values for all the images. In Person 1 Database, 3rd face image is the input image
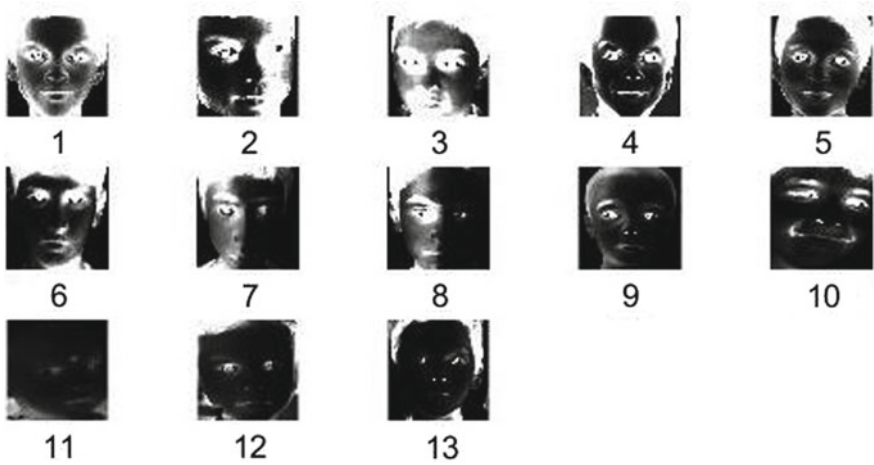
Fig. 7 Virtual image of Person 1 database

which is compared with all the remaining face images. The classification of similar, genetic and non-genetic faces for Person 1 Database is shown in Fig. 8.

From Table 1, it is proved that the difference error value of the Images 1–5, 11, 12, 13 (genetic faces and similar faces) is less than the error value of the Images 6–10 (non-genetic faces). Specifically, the analysis of similar person with respect to age is proved. First three image from Table 1 is having less value compared to the 4th image.
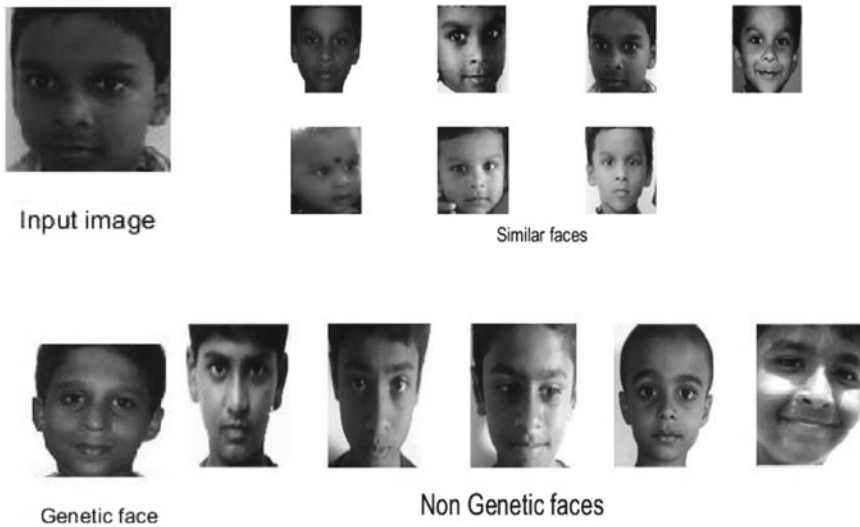

Fig. 8 Classification of similar, genetic and non-genetic faces

Table 1 Score-based fusion values for Person 1 database

| Proposed algorithm | Face database 1 | | | | | | | | | | | | |
	Image 1	Image 2	Image 3	Image 4	Image 5	Image 6	Image 7	Image 8	Image 9	Image 10	Image 11	Image 12	Image 13
Score level fusion	123.71	139.1	0	208	170.28	275.3	284.03	288.89	356.78	234.35	187.96	224.87	194.21

The classification graph has been plotted using these values, and the classification has been done for similar and genetic faces with non-genetic faces. From Fig. 9, it is proved that the genetic and similar faces are very clearly classified compared to non-genetic faces. This experimental results dependent on statistical measure acquired for genetically similar and non-similar faces lead to a road of genetic and age-wise similarity-based face recognition. Inverse transform score level fusion algorithm is the proposed approach, and it has demonstrated as a successful tool in removing the remarkable features belonging to the genetic resemblance and similar faces with respect to ages.

Table 2 shows the distance values of persons with respect to their ages. From these values, it is proved that there are more or less similar distance values for the same age of all the persons.

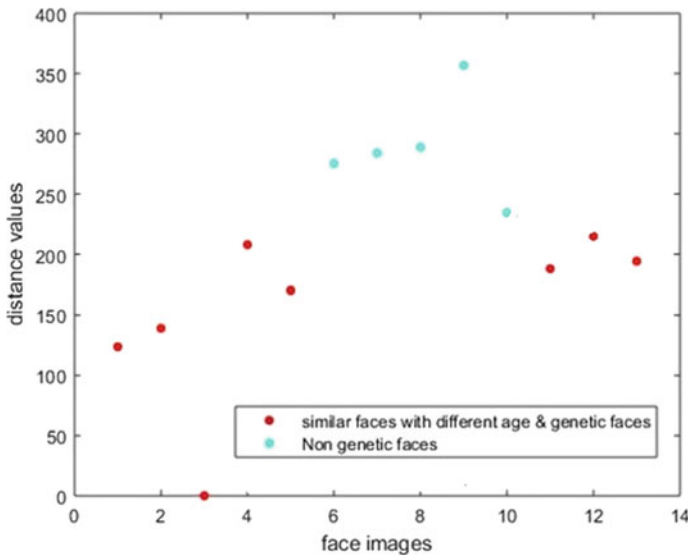Figure 10 shows the graph for the age group similarity values of all the persons.

Fig. 9 Classification graph of Person 1 database

Table 2 Distance values for all the persons related to ages

Ages	1	2	3	4	5	6	7	8	9	10
Person 1	188.0	224.9	208	194.2	139.1	123.7	136.2	172.5	185.1	230
Person 2	262.3	202.2	199.6	191.3	151.1	178.5	126.2	153.4	223.5	220.2
Person 3	250.6	186.8	226.8	183.6	170.6	135.9	147.7	164.8	174.6	246.3
Person 4	208.2	178.5	194.2	188.0	172.5	174.6	145.1	151.1	214.6	237.9
Person 5	196.4	195.6	218.5	179.8	146.8	165.9	139.6	163.6	204.7	225.1
Person 6	218.3	222.5	219.3	201.8	163.9	128.6	123.8	153.3	195.2	263.6

Fig. 10 Graph of distance values (w.r.t reference images) versus age group for person 1–6
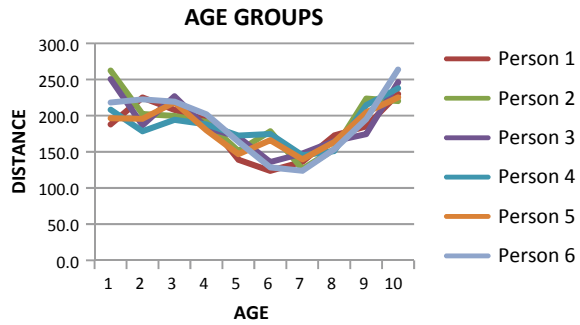
This analysis has been experimentally done based on statistical measure obtained by using the proposed algorithm. From this analysis, it is proved that inverse transform and score level fusion is a successful tool for extracting the significant features for classifying genetically similar and non-similar faces.

The proposed work implementation is done in MATLAB. Face image databases are gathered with respect to genetic faces and non-genetic faces, faces of the same person in different ages, faces of the same person with the same age at different locations and faces of different family members. Totally 100 face images are used for this algorithm.

The proposed algorithm has been used to classify the genetic and non-genetic faces. Sample faces have been illustrated in this paper. There are four database of images used in different analysis.

4 Conclusion

This research work represents the virtual image representation and adaptive weighted score level fusion for genetic face recognition. For recognizing the similar faces with respect to age, virtual image representation and adaptive weighted score level fusion is proposed in this research work. The algorithm integrates the original image and virtual image, which is a nonlinear transformation of original image. This virtual representation upgrades pixels with moderate intensities and changes the pixels with high or low intensities. Using statistical measure, distance is determined between the original image and virtual image for both test and training set of images. Additionally, various pixels have distinctive significance in representing face images. Subsequently, it is sensible to set various weights to individual pixels. Then the weight is calculated by the two least distance values, so the adaptive weight varies for all the images. Then score level fusion is performed for recognizing the faces, which overcomes illumination due to lighting in the image. According to the experimental results, the proposed algorithm performs well compared to the previous work in

recognizing accuracy. The proposed score level fusion scheme gives the best optimal solution for genetic face recognition with respect to age variation.

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