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Race classification using gaussian-based weight K-nn algorithm for face recognition

Sasan Karamizadeh and Shahidan M Abdullah

Advanced Informatics School (AIS), Universiti Teknologi Malaysia(UTM), Kuala Lumpur,54100, Malaysia

Corresponding author: Ksasan2@live.utm.my

ABSTRACT

One of the greatest challenges in facial recognition systems is to recognize faces around different race and illuminations. Chromaticity is an essential factor in facial recognition and shows the intensity of the color in a pixel, it can greatly vary depending on the lighting conditions. The race classification scheme proposed which is Gaussian based-weighted K-Nearest Neighbor classifier in this paper, has very sensitive to illumination intensity. The main idea is first to identify the minority class instances in the training data and then generalize them to Gaussian function as concept for the minority class. By using combination of K-NN algorithm with Gaussian formula for race classification. In this paper, image processing is divided into two phases. The first is preprocessing phase. There are three preprocessing comprises of auto contrast balance, noise reduction and auto-color balancing. The second phase is face processing which contains six steps; face detection, illumination normalization, feature extraction, skin segmentation, race classification and face recognition. There are two type of dataset are being used; first FERET dataset where images inside this dataset involve of illumination variations. The second is Caltech dataset which images side this dataset contains noises.

Keywords: Face recognition, illumination, skin segmentation, Filters and FERET and Caltech datasets.

INTRODUCTION

The face recognition technology has grown rapidly in recent years, and it has been utilized in various areas. There are various obstacles in the multifaced recognition systems in real-time particularly in the populated regions; however, key challenges posed by this system is the issues with computation time, illumination conditions, and the increasing rates of misclassification due to low quality of face image streams (S. Karamizadeh, Abdullah, & Zamani, 2013). This paper addresses these issues but the multifaced recognition technology using the current real-time normally needs an environment that is controlled. In environments that cannot be controlled, the light changes in various locations and in short intervals are a prominent barrier to the system of face recognition. An even further challenge in the face recognition is illumination and in distinguishing the images of faces that look alike. An essential trait of the human face is skin segmentation, which is also distinguishable for many subjects; it is also quite dynamic and responds to the geometric changes of facial pattern (Gross & Brajovic, 2003) . A crucial hindrance in applications using real time is the face recognition utilizing various illuminations (Baker, Sim, & Bsat, 2003). The program known as the Face Recognition Technology or FERET was created to set up a massive facial images database that was independently collected from the developers of algorithms (Alexandre, 2010). Chromaticity is an essential factor in facial recognition and shows the intensity of the color in a pixel, it can greatly vary depending on the lighting conditions. Therefore people with different race can appear to have similar features. Variations in the conditions of lighting, a growing quantity of targets in an environment and streams of low-quality can have an adverse effect on the performance of the system. This paper proposes novel algorithm for multiface recognition system in real time. This algorithm establishes a technique of race classification utilized to filter out the dataset to reduce the rates of misclassification and used computation duration. The engine for face recognition utilized in this paper is built according to the Hidden Markov Model using the features of (Choudhary & Goel, 2013; S. Karamizadeh, Abdullah, Halimi, Shayan, & javad Rajabi, 2014). The next sections, will discuss about related work, methodology and experimental results discussion and comparative study.

Related Works

In this section, we have reviewed some papers related to our paper. Many current works have been carried out on the processing of illumination in face recognition (Baradarani, Wu, & Ahmadi, 2013; Kao, Hsu, & Yang, 2010; Lian & Er, 2012). (Land & McCann, 1971) proposed the Retinex approach to retrieve the reflectance element out of the image through the model of illumination reflectance (Jobson, Rahman, & Woodell, 1997). The Retinex approach (Jain & Learned-Miller, 2010; Jobson et al., 1997) presents the Single Scale Retinex (SSR) in processing the illumination variations. The Discrete Cosine Transform or DCT is an invertible linear transformation that can relate data points at a finite sequence based on the sum of cosine functions that oscillate at various frequencies (Najan & Phadke, 2012). The direct DCT transform is applied to convert the original signal to the frequency domain and it is able to convert back the signal that is transformed to the original domain by utilizing a DCT transform that is inverse. Following the transformation of the original signal, its DCT coefficients reveal the significance of the frequencies which are found within (Azam, Anjum, & Javed, 2010). At a specific angle of illumination, the face image contains a light area that is covered by two dark areas; the light area is known as the specialized light area. Likewise, a dark area is covered by two light areas known as the specialized dark area. There is a statistical machine learning technique known as the Gaussian mixture models (GMM) (Reynolds, 2015) . The GMM classifier is more accurate as it uses the estimation of maximum likelihood to train the classifier (Ng & Pun, 2012a). According to (Y. Wang & Yuan, 2001), face detection of humans is based on color images under complex situations involving arbitrary image backgrounds. They utilized an evolutionary computation method to group the color pixels that are skin-like and segment off every face-like area. Following the location of the face-like area, each area is applied with the wavelet decomposition to detect the potential facial elements and to identify if an eye is present in the area. When an eye is detected in an area or the facial elements reveal a face-like model, then it is identified as a human face. The study by Yao and Gao (Yao & Gao, 2001) implemented a form of transformation coordinate that enhances the lips and skin's chrominance. They proposed that using the coordinates it was possible to implement a face identification approach in terms of transformations of lip chrominance and skin chrominance to manage the changing object's pose and a complicated background (Kakumanu, Makrogiannis, & Bourbakis, 2007).In Table.1 related works are critically revered.

Table1. Shows different algorithms are compared in term of advantage and disadvantage

Algorithms	ADVANTAGE	DISADVANTAGE
SSR	(i). The scale of an SSR increases, its color reliability features improve.	(i). Includes halo artifacts. (ii). SSRs have different dynamic range compression characteristics according to the scale. (iii). The SSR does not run good tonal execution.
MSR	(i). Works effectively with images that are grayscale.	(i). Histogram equalization is utilized to improve the color of the images. This may result in a change in the color scale causing the artifacts and having an imbalance in the color of the images.
ASR	(i). Restores the image faster while retaining the performance of comparable dazing.	(i). Extended significantly. (ii). Weak outcomes between pixels that contain small variations.
HOMO	(i). The features cause the link with the low frequency of the image with illumination and the high frequency with reflection.	(i). Discrete feature in attractive aspects between contiguous discrete scales that may not be found at the output.
DCT	(i). This filter advantages the decrease in the face space dimension while maintaining low, mid and high frequencies of coefficients.	(i). DCT does not have the time frequency localization because on average they are over the allotted time.
WAVELET	(i). This requires no training images. Nevertheless, they cannot get rid of casted shadows completely as they lack adaptability in preserving the discontinuities effectively.	(i). This cannot be implemented as there are more mature and faster algorithms for wavelet transformation.
ISO-TRO-PIC	(i). Is able to preserve edges of image and is able to reduce noise at the same time.	(i). It is insensitive to orientation and symmetric, resulting in blurred edges.
STEER-ABLE	(i). The dynamics in various frames for particular individuals can be learned to assist in subject recognition.	(i) .Requires a lot of features
NON –LOCAL	(i) . Operates at the level of preprocessing and reveals several critical advantages that make it the more preferred selection when designing a robust face recognition technique.	(i). It has poor de-noising ability in the constant areas.
ADAPTIVE NON-LOCA-ONL	(i) . The applications that include segmentation, Relaxometry, or Tractography might make use of the improved data that is created after applying the proposed filtering.	(i) . This technique does not reduce the difficulty of the algorithm significantly while only decreasing slightly the accuracy of filtering.
MODIFIED ANISOTRO-PIC	(i). Filtration technique can be categorized as a single scaled spatial filter and some multi scale approaches in other domains.	(i) . It is slower than the schemes of set theoretic morphology. (ii) . Has dissipative features including blurring of discontinuities.
DoG	(i). Does not require any prior information of the light sources or 3D shape, or a lot of samples for training. Thus, it can be applied directly to a single image for training per person.	(i) .Based on texture: utilizing spatial information (ii). Linking of edges: too much segmentation (iii).Based on image: only has a low-level characteristic

Research Methodology

The steps used in this paper can be classified into two steps: preprocessing and face processing in Figure 1. Auto contrast is designed to adjust the overall contrast in an image without adjusting its color. After auto contrast balancing is applied on the image, we need to reduce the noise on the input image, such as salt and pepper and speckle noises, can affect the algorithms› efficiency. Therefore, the Weiner filter is applied on the input image to reduce noises. Weiner filter used mean and variance statistical measure for filtering.

The preprocessing step is continued by the application of auto color balancing. Auto color balancing improve the colorcast in an image, in order to stretch out the intensity range. This method is useful when the image information is poor that is foreground and background both are dark or over exposed. The auto color balancing helps the proposed scheme improve the accuracy in the segmentation technique that adaptive thresholding technique method to extract skin pixels. The next step in the proposed scheme is the facial detection technique. The algorithm proposed is employed to detect multiple faces in an image frame. The method extracts the Haar-like features that are combined to form a classifier in the training images. After the training phase, the classifier can be used to detect faces.

The next step in our scheme is to recognize the faces detected by the scheme. To do so, there are two parts including the race classification and illumination normalization. Most of facial recognition methods use geometrical features, which are efficient, but there are still rooms to improve in misclassification. It is a common problem in facial recognition systems due to the similarity of the features between different people, especially when the face image lacks quality, this is the case when a detected face is far from the camera, or when the size of the subject in the dataset increases, both factors increasing the rate of misclassification. We handle these problems by introducing a race classification method. The results of this method are further used eliminate irrelevant samples from the dataset, in order to avoid misclassification of the images.

In the next step, the proposed face processing scheme adopts the Discrete Cosine Transform (DCT-II) normalization algorithm to enhance the image for the feature extraction method. DCT-II algorithm omits the effect of illumination variation, which is a common problem in current facial recognition algorithms. To extract facial features, we used a Singular Value Decomposition (SVD) feature extraction technique, and these extracted features will then be utilized to train a Hidden Markova Model (HMM) classifier.

The race classification scheme proposed in this paper, has very sensitive to illumination intensity. Hence low or high illumination density can affect the result dramatically and since the classification performance depends on the proposed method, an extra monitoring step is required to decrease misclassification rate. the FERET and Caltech databases is being used. FERET dataset contains images with illumination and minimum noise, and Caltech includes images with certain degree of noise. So, color images containing noise and different lightning conditions are required for extracting features.

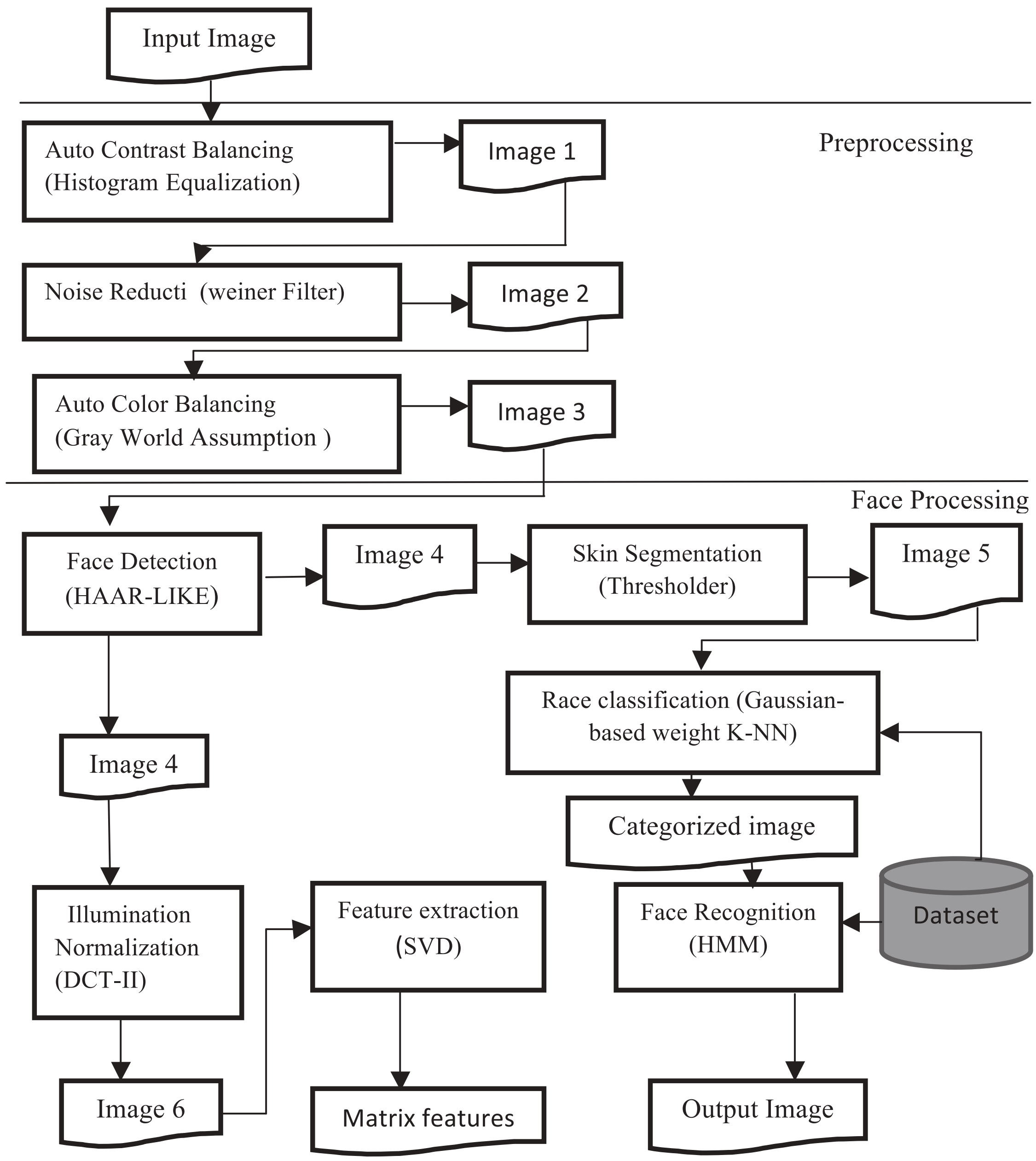

Fig 1. Research Framework

Auto Contrast Balancing

In this step, the proposed scheme tries to balance color channels using the Color Histogram Equalization method. The entire histogram is distributed with range of pixel intensity values which is balanced by histogram equalization. By modifying the histogram in such a way, it can distribute the intensities over the scale of values available and could possibly extend the histogram with zero as the lowest intensity and the highest intensity as the maximum value(S. Wang, Zhang, Deng, & Zhou, 2011).

Histogram equalization is a non-linear process. Channel splitting and equalizing each channel separately is incorrect. Equalization involves intensity values of the image, not the color components. So, for a simple RGB color image, histogram equalization cannot be applied directly on the channels (S. Wang et al., 2011). It needs to be applied in such a way that the intensity values are equalized without disturbing the color balance of the image. So, the first step is to convert the color space of the image from RGB into one of the color spaces that separates intensity values from color components. YCbCr is preferred as it is designed for digital images. Perform histogram equalization on the intensity plane Y. Now convert the resultant YCbCr image back to RGB (Bae, Jang, & Ra, 2010).

Noise Reduction

In second step, we discussed the method adopted to reduce ambient noise, especially noises created as an effect of Auto Contrast Balance mentioned in the previous section. After auto contrast balancing is applied on the image, in this paper we need to reduce the noise on the input image, such as salt and pepper and speckle noises, can affect the algorithms› efficiency. Therefore, the Weiner filter is applied on the input image to reduce noises (Kashyap & Shantaiya, 2011). Weiner filter used mean and variance statistical measure for filtering. The Wiener low pass filter is the best performance for image restoration. Its primitive assumption for all systems is the existence of speckle noise (Rogowska & Brezinski, 2002). As a matter of fact, the algorithm is useful for removing speckle noises. The Wiener filter uses a pixel-wise adaptive Wiener method based on the statistics estimated from a local neighborhood of each pixel.

Auto Color Balancing

In third step, the proposed scheme tries to balance the color channels using the Gray World balancing method. Low computation is one of the advantages of the GW method. It provides a good image performance if the image is equally balanced with high color variation. However, the suitability is limited and is no longer efficient when the image comes with a large range of uniform color and heavy colorcast (Kwok et al., 2011). This process can be looped to try to force the average color to a neutral gray. Usually, this is too extreme, and is an indication that the gray world assumption is generally incorrect. A photo of the ocean can be used to illustrate this phenomenon. However, despite this problem, it is still capable of providing a rough estimate of the illumination (Adams Jr, Hamilton Jr, Gindele, & Pillman, 2003).

Face Detection

This paper utilizes the Haar Cascades face detection technique. The Haar characteristics are the key portion of the Haar Cascade classifiers in a face detection (Whitehill & Omlin, 2006). The Haar characteristics are utilized to detect the existence of these features in an image. Each feature is appointed a single value that is measured by subtracting the total amount of pixels in the white rectangle out of the total amount of pixels in the black rectangle. The features that resemble Haar are the rectangle features used to for fast detection of the face (Wilson & Fernandez, 2006).

Illumination Normalization

In this paper, we utilized the DCT-II normalization approach in this paper to remove the effects of illumination variations. The DCT-based approach for normalization sets up the quantity of DCT-II coefficients that corresponds to the low frequencies until zero and following these, it aims to achieve the illumination invariance (S. Karamizadeh, Abdullah, Zamani, & Kherikhah, 2015). DCT-II is utilized for a pre-process of features extraction techniques in various studies on face recognition (Najan & Phadke, 2012). The features of the DCT-II are adopted in a holistic local appearance-based or like appearance-based approach, which does not consider the spatial information when performing the classification. The DCT-II is recognized as a strong method of transformation in applications including face recognition, coding of images, and others. The DCT-II is based on the data as the entire sum of the cosine function for decreased size of data. The key idea for using DCT-II is that illumination variations can be significantly reduced by truncating low-frequency discrete cosine transform (DCT-II) coefficients in the logarithm DCT-II domain (Podilchuk & Zhang, 1996).

Skin Color Segmentation

An essential criterion of the human faces is the skin segmentation. There are several benefits to utilizing skin segmentation as a feature in detecting faces. There is a consistent color on the human skin that is distinguishable from most other materials and it is highly dynamic to the face pattern's geometric variations. Color permits quick processing and is impartial to scale, face orientation, maintains stability during occlusions, and not dependent of a person. It has been proven that skin color is a beneficial and dynamic feature for face detection, tracking, and localization. The two methods of building the model for skin segmentation model include the non-parametric skin modeling technique (the histogram model)(Gross & Brajovic, 2003) and the parametric approach (single Gaussian and a combination of Gaussians models)(Khan, Hanbury, Stöttinger, & Bais, 2012). The non-parametric techniques are quick in classification and training, and independent of the shape of distribution. The parametric techniques can also be quick as they possess the capability of interpolating and generalizing a non-completed training data. Nevertheless, they can also be rather slow (as in the combination of Gaussians) in both work and training, and their performance is strongly dependent on the shape of the skin distribution (Phung, Bouzerdoum, & Chai, 2005).

This paper aims to detect the facial skin and extracting skin pixels. Firstly, in order to do this, the frame of face image is transformed into: YCbCr,

$$Y= (0.299\times R) +(0.587\times G) +(0.114\times B)$$
$$C_b= (B-Y) \times 0.564+128.$$
$$C_r=(R-Y) \times 0.713+128.0$$

The image of the transformed $YC_b C_r$ is carried on to the following step to extract the skin pixels. The following equation is used to extract the skin pixels:

$$\{(77\leq C_b\leq 127$$
$$133\leq C_r\leq 173)\}$$

The skin pixels are extracted as pixels.

Race Classifier

In this step race classifier, which is an enhanced combination of Gaussian based-KNN algorithm is a non-parametric method employed in many papers for classifications and regressions. K-NN algorithm involves estimating the similarity between the input instance and the K-nearest available instances in the featured space. Each feature has a class label; therefore, the algorithm counts the number of instances belonging to each class. The classification result is the class with the maximum number of assigned instances. It should also be pointed out that all "K" encountered instances have equal votes. The weighted K-NN algorithm employs a similarity method to estimate the value of each instance›s vote to improve the classification performance in the following manner,

$$\mathbf{class}(\mathbf{x}) = \mathbf{argmax} \sum_{i=1}^{k} \mathbf{f}\big(\mathbf{x}, \mathbf{NN_i}(\mathbf{x})\big)\boldsymbol{\delta}\big(\mathbf{class}(\mathbf{NN_i}(\mathbf{x}), \mathbf{j})\big)$$

f (x,y) Function estimates the value of every feature vote and δ(i,j) function represents the Kronecker Delta functionality which is described as shown in the following:

$$(\mathbf{i}, \mathbf{j}) = \begin{Bmatrix} \mathbf{1}, \mathbf{i} = \mathbf{j} \\ \mathbf{0}, \mathbf{otherwise} \end{Bmatrix}$$

f (x,y) is described as shown in the following:

$$\mathbf{f}(\mathbf{x}, \boldsymbol{\mu} = \mathbf{y}, \boldsymbol{\Sigma}) = \frac{\mathbf{1}}{\sqrt{(2\pi)^2|\Sigma|}} \mathbf{exp}\left(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu})\right)$$

Whereby x represents the input instance, and y represents the feature instance. Thus, x and y are RGB vectors (R, G, B). Thus, the formula for the weighted K-NN is improved as shown in the following

$$\mathbf{class}(\mathbf{x}) = \mathbf{argmax} \sum_{i=1}^{k} \frac{\mathbf{1}}{\sqrt{(2\pi)^2|\Sigma|}} \mathbf{exp}\left(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu})\right) \boldsymbol{\delta}\big(\mathbf{class}(\mathbf{NN_i}(\mathbf{x}), \mathbf{j})\big)$$

In this system, skin data will be detected using a thresholding procedure in YCbCr color system, so first we convert the photo to this color system then omits all pixels that are out of a predefined range of data. The mean of the extracted pixels is calculated (the result is a vector (R, G, B)). This color vector is later passed to k-NN classifier. In this paper weight K-NN was selected because weight K-NN is a very efficient classifier for small datasets since it does not need to be trained. Also, it is simple and reliable, the K-NN classifier calculate Euclidean distance of the color vector and all samples inside the database, where K is set to 10, the K determined based on trial-and-error. Then it sorts the distances ascending order. Further, it chooses the k nearest distances. The Gaussian-based scoring system calculate a Gaussian value based on the sample distance from the vector, the scheme calculates all the scores for each class label separately. The class label with highest score is chosen to be the sample›s label. The outcome of this step is categorized image which represent one of the race category Negroid, Mongoloid or Caucasoid.

Feature Extraction

The singular value decomposition (SVD) is adapted for the extraction of features utilized to identify the wide range of dataset faces. Three main perspectives are available in dealing with the features of the SVD (i)SVD assumed as to be a technique used to transform the correlating variables into a set of non-correlating ones thus more efficiently exposing the different relations among the original data items.(ii)SVD is a technique to recognize and order the dimensions of the data where the data points display the maximum number of variations.(iii)After identifying the location of the most variations, the best possible approximation of the original data points can be found. Thus, the SVD is viewed as an approach to reduce data (F. Karamizadeh, 2015).

Face Recognition

The Hidden Markov Model (HMM) is utilized in this paper, to perform the face recognition. A Hidden Markov model (HMM) (Assadi & Behrad, 2010; Tolba, El-Baz, & El-Harby, 2006) represents a statistical Markov model where the system that is modelled is assumed to be a Markov process with unobserved or hidden states. The observer can view the state directly in a normal Markov model; hence, the probabilities of the state transition are the only parameters. The state is not visible directly however the output that depends on the state is visible in the hidden Markov model. Every state contains a distribution probability over the possible sequence output. Thus, the output sequence that is generated by the HMM provide certain information regarding the states' sequence. Therefore, the objective of the HMM as a learning tool is to locate the best set of output probabilities and state transition for the set sequence output. The term ‹hidden› here, describes the sequence state where the model passes through, and not the model's parameters. The HMM needs the sequence of the 1D observation hence a 2D image is changed into either a sequence of 1D temporal or 1D spatial. The HMM estimates the parameters' maximum likelihood per a set of sequences output. Following the trained HMM, the probability output of an observation decides on the class that it belongs to. An effective approach to gaining the vector of observation for face extraction is through the utilization of the Karhunen-Loave transform (Haig, 1986) employed using lightening differences.

Experimental Results and Discussion

In our technique of verification of the FERET and Caltech datasets. The color images in these datasets involve of illumination variations and noise, ten people in 64 different lighting situations for nine poses are utilized in the databases. As we are only focusing on the problem of illumination and noise in this paper, the frontal face images under differing security lighting conditions are employed. We adopted the F-measure performance indicators; it can be adopted as a unique measurement for characterizing the level of the biometric system.

Different amounts of training data are used to test the algorithm to examine the algorithm's convergence. The algorithm is examined using five variations of training data rate as displayed in Table 2. The algorithm reveals enhancements when the training data rate increases to 70% and the rate of the testing data increases to 30%. Nevertheless, the rate of accuracy is reduced when the rate of training data is more than 70%. In addition, it reveals only a small change when the rate of training goes beyond 50%. For this experiment, the optimum training rate is established at 70% revealing approximately 84% F-measure rate.

Table2. Shows result of illumination normalization algorithms

Illumination variation	F-measure rate With 70% training rate	Running time per each sample
Discrete Cosine Transformation (II)	0.8492	0.032
Multi Scale Retinex (MSR)	0.83	0.048
Wavelet-based (WA)	0.7905	0.053
Single Scale Retinex (SSR)	0.81	0.031
Difference of Gaussian (GOG)	0.8274	0.051

As previously mentioned, the algorithm possesses the illumination normalization to avoid illumination variations. These next illumination normalization algorithms are examining to determine the technique with the highest performance using this algorithm namely, (i) MSR, (ii) DCT, (iii) SSR, (iv) WA, and (v) DOG. The rates of the F-measure are calculated with the entire algorithms for illumination variation as shown in Table 1. DCT (II) and MSR reveal results that are better compared to the others as observed in Table 1. The SSR and DCT(II) possess the minimum time for computation in comparison with the other techniques as observed in Table1, however, since the DCT(II) algorithm reveals a better performance, we utilized the DCT as the illumination normalization.

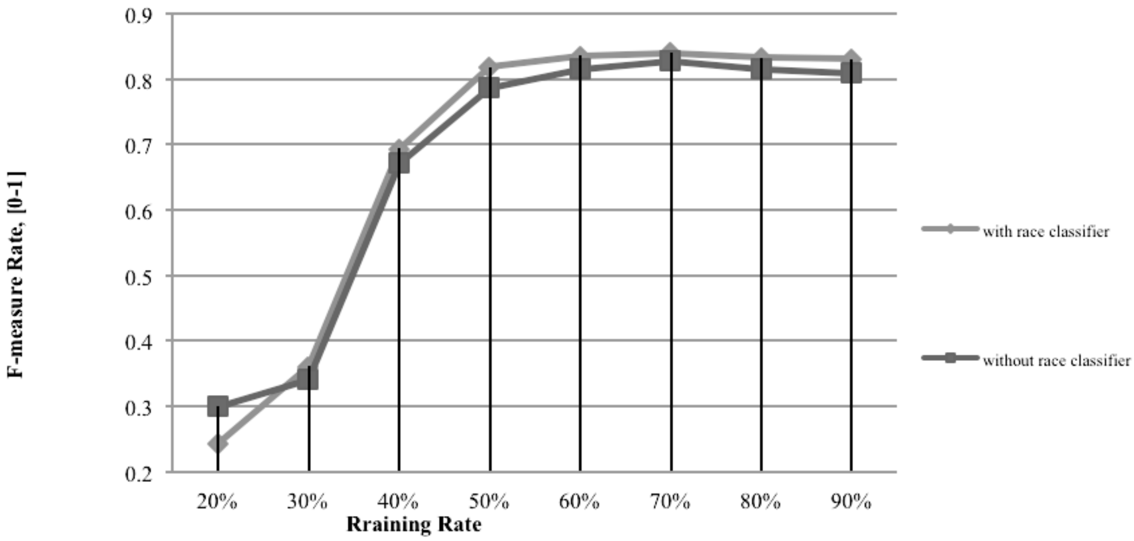

Fig 2. Performance is evaluated with and without race classifier

As previously mentioned, the algorithm uses a novel race classifier to improve the algorithm's rate of F-measure and to decrease the computation time. Figure 2 shows the performance of the algorithm being assessed using with and without race classifiers.

As it is shown in Figure.2, the best training mark is achieved by 70% which shows the highest F-measure rate reached best possible result with race classifier and misclassification is minimum in 70% rate. Among all training values, experiment for classifier shows the worst result with 20% training rate. In 20 percent dataset training, the result was not conclusive. Based on our experiments, training datasets should be 30% or higher to get conclusive and reliable results. If we have more training, testing data is not sufficient or not reliable in 20% or lower percentage of dataset training, in different tests, the variance of results is very high due to insufficient training dataset, so the results of 20% and lower are not reliable. Data for testing is not enough for testing. Due to inadequate on training data, the latter shows wide fluctuation. In addition, it can be caused by low number of training cases per race classifier. Since, systems select training images randomly, might be another contributing factor for less accurate classifier. In other words, it might be caused by less available training images per race classifier in experiments. After 20 times experiments, the results prove that 70% training rate is achieved the best results consistently.

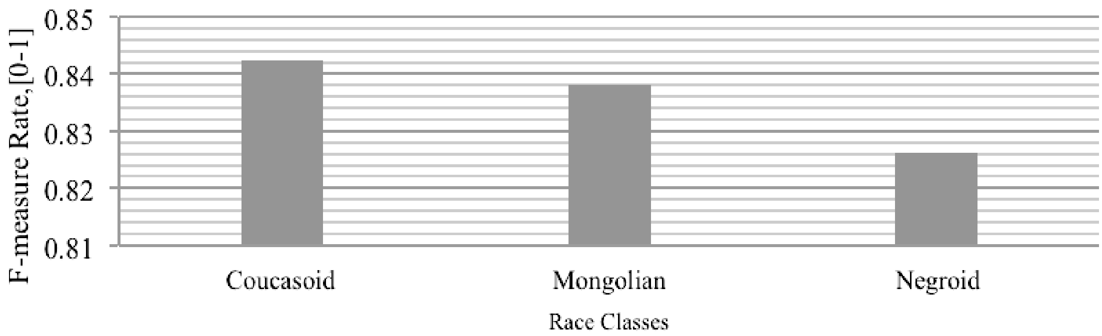

Fig 3. Shows the F-measure rate for each race class

Classification of skin segmentation is another component of this algorithm that influences the rate of the F-measure. Three skin colors are established as skin classes in this paper. After that, the three different classifiers are separately trained for the three skin classes. Every face image input is handed over to the classifier with the same skin class to be identified. The rate of accuracy for every skin class is observed in Figure 3. Table 3. the confusion matrix for the test data in three classes' skin color are shown. Each subject in the test has 100 images.

Table 3. Confusion matrix for face data

Gaussian-based K-NN	**yellow**	**white**	**Black**
Yellow	83	7	10
White	6	84	10
Black	15	3	82

In Table 3, a row represents the number of times a subject is recognized as one of the other subjects. As may be seen, the diagonal entries are the largest values with some confusion due to the extreme lighting and skin color. We can observe that white color skin can be recognized with high accuracy around 84 percent, but black color skin is easily confused with others.

Comparative of Experiment Step by Step in Caltech Dataset

Table 4 shows the result of experiment step by step, before and after applying the filters on Caltech dataset.

Table 4. Result of the experiment step by step

Number of experiments	Phase 1 (Preprocessing)			Phase 2(Face Processing)		
	Auto Contrast Balancing	Noise Reduction	Auto Color Balancing	Illumination normalization	Race classification	F-measure
1	✗	✓	✓	✓	✓	84.301
2	✓	✗	✓	✓	✓	64.501
3	✓	✓	✗	✓	✓	84.698
4	✗	✗	✗	✓	✓	63.598
5	✓	✓	✓	✓	✗	83.708
6	✓	✓	✓	✗	✓	84.616
7	✓	✓	✗	✗	✓	83.901
8	✓	✓	✓	✓	✓	84.798

As it is shown in first row of the Table 4, F-measure before applying auto contrast was 84.301, while after applying the function, F-measure has improved by 0.497%. In the next row, we avoid to apply the noise reduction algorithm. As it is shown in the table noise reduction algorithm improves our F-measure significantly by around 20 percent from 64.501 to 84.798. Third row shows that when we do not apply auto color balancing the performance of F-measure is 84.698. Auto color balancing has the lowest F-measure improvement rate among all filters. In the next experiment, we removed all the preprocessing steps. The outcome shows preprocessing steps can improve the F-measure by 21.2%. In the next round of experiment, we removed race classification, which is a face recognition step. The result show 1.09% decline in F-measure performance. Including illumination normalization this step alone improves the F-measure performance by 0.182%. On the seventh round of our experiment, we examined the role of auto color balancing combined with illumination normalization. Including these steps improve our F-measure by 0.897%. On the final round of our experiment we applied all the filters. All filters combined give the highest F-measure improvement. Our final result show 84.798 percent improvement on F-measure.

Comparative of Experiment Step by Step in FERET Dataset

Table 5. shows the experimental results of combination of preprocessing and face recognitions in step by step manner. It helps to compare and release their impact in overall.

Table 5. Result of experiment step by step

Number of experiments	Phase 1 (Preprocessing)			Phase 2 (Face processing)		F-measure
	Auto Contrast Balancing	Noise Reduction	Auto Color Balancing	Illumination normalization	Race classifica-tion	
1	✘	✓	✓	✓	✓	84.368
2	✓	✘	✓	✓	✓	84.591
3	✓	✓	✘	✓	✓	84.804
4	✘	✘	✘	✓	✓	83.789
5	✓	✓	✓	✓	✘	83.716
6	✓	✓	✓	✘	✓	84.628
7	✓	✓	✘	✘	✓	82.912
8	✓	✓	✓	✓	✓	84.996

Table 5. shows the Auto contrast is designed to adjust the overall contrast in an image without adjusting its color. As it is shown in the table, F-measure before applying auto contrast was 84.368, while after applying the function, F-measurehas improved by 0.628%. In the next row, we avoid to apply the noise reduction algorithm. As it can be seen in the table noise reduction algorithm improves our F-measurefrom 84.591 to 84.996 by 0.405%. The third row shows that when we did not apply auto color balancing the performance of F-measureis 84.804 because this preprocessing function remove colorcasts and color spectrum of the image. In our proposed scheme we apply all these three preprocessing including auto color balancing with outcome of F-measure 84.996 which is equivalent to 0.19% improvement. Auto color balancing has the lowest F-measure improvement rate among all filters. In the next experiment, we removed all the preprocessing steps. The outcome shows preprocessing steps can improve the F-measureby 1.207%. In the next round of experiment, we removed race classification, which is a face recognition step. The result show 1.28% decline in F-measure performance. This outcome acknowledges a common misclassification problem in face recognition systems. Low quality samples and images with different size increase the feature similarity, as a result feature extraction become inaccurate. Illumination normalization illumination normalization methods extracts the information which may disturb by low or high illumination intensity. Adding this step alone improves the F-measure performance by 0.368%. On the seventh round of our experiment, we examined the role of auto color balancing combined with illumination normalization. The outcome shows the largest proportion of improvement by this two steps. Adding these steps improve our F-measure by 2.084%. On the final round of our experiment we applied all the filters. All filters combined give the highest F-measure improvement. Our final result show 84.996 percent improvement on F-measure.

Comparative Study

We have compared the proposed scheme with most other popular schemes to find out its competitiveness. The (56x46) Lena test images were utilized for assessing the schemes to find out their performance. A comparison of the outcomes among the nine face recognition schemes with the improvements of the F-measure is presented in Table 6 below.

Table 6. Comparative study

	Auto contrast balance	Normalization	Race	illumination	Noise reduction	Auto color balancing
(Tanaka & Pierce, 2009)	✓	×	✓	×	×	×
(Chen & Chiang, 2010)	×	✓	×	✓	×	×
(Roomi, Virasundarii, Selvamegala, Jeevanandham, & Hariharasudhan, 2011)	✓	×	✓	×	×	✓
(Łukańko, Orzechowski, Dziech, & Wassermann, 2011)	✓	×	✓	×	×	×
(Ng & Pun, 2012b)	✓	×	✓	✓	✓	×
(Orzechowski, Dziech, Lukanko, & Rusc, 2012)	✓	✓	×	✓	×	×
(Khan et al., 2012)	✓	✓	✓	✓	×	×
(See, Noor, & Lai, 2013)	✓	×	✓	×	✓	✓
(Khan et al., 2014)	✓	✓	✓	✓	×	×
proposed scheme	✓	✓	✓	✓	✓	✓

Table.6 presents a comparison results between nine available enhancements of F-measure of face recognition schemes We have compared the proposed scheme with most other popular schemes to find out its competitiveness. The 56X46 Lena test images were utilized for assessing the schemes to find out their performance. A comparison of the outcomes among the nine face recognition schemes with the improvements of the F-measure is presented in Table 4 below; our proposed scheme along with (Chen & Chiang, 2010; Khan et al., 2012; Khan et al., 2014; Łukańko et al., 2011; Ng & Pun, 2012a; Orzechowski et al., 2012; Roomi et al., 2011; See et al., 2013; Tanaka & Pierce, 2009).

(Tanaka & Pierce, 2009) used a RGB-CoCr model for human face detection. This model utilizes the additional hue and chrominance information of the image on top of standard RGB properties to improve the discriminately between skin pixels and non-skin pixels. In this method, they do not have any prepressing in their research. However, they cannot check images with illumination. Additionally, other researchers such as (Roomi et al., 2011) used the Face region extracted from the input image using Viola Jones Appearance based method to tackle this issue.(Chen & Chiang, 2010) introduced new algorithms for dynamic face recognition using illumination impartiality in the domain of non-sub-sampled contour let transform (NSCT). (Ng & Pun, 2012a) Face detection module is the local Successive Mean Quantization Transform (SMQT) features and split up sparse network of winnows classifier. This method performs a face detection in order to measure the face position and amount on image, and then analyze each face's illumination feature. According these parameters, these methods classify the skin pixel and generate skin probability map, and finally fetch out a prefect skin mask for skin segmentation.(Łukańko et al., 2011; Orzechowski et al., 2012), used fusion algorithms PCA and LDA for face recognition. (PCA) is based on general features of face, whereas Linear Discriminant Analysis (LDA) focuses on unique features of image. Therefore, the fusion of these two algorithms may give better results than these methods used separately drawback of this research is High order dependencies still exist in PCA analysis and it is very time consuming. (Khan et al., 2012; Khan et al., 2014) examined and analyzed i) the impact of transformation of color space on the performance of skin detection and discovered the right skin detection color space, ii) a color space's illuminance component role, iii) the right skin color modelling technique based on pixel, and lastly, iv) the impact of algorithms of color constancy on classification of color-based skin. They merged various color space channels linearly revealing it as a process of fusion. The objective of fusing the various color space channels was to gain impartiality over the differing conditions of illumination and imaging. (See et al., 2013) Introduced the hybrid technique for face detection with images of low quality and various face positions which is a complicated function to perform.

In this paper image processing is divided into two phases in this paper. In the phase of pre-processing, auto contrast balance is used on the image to balance out the image's brightness, continuing after that with auto color balancing. The image normalization is used on the image when it enters the phase for face detection to carry out feature extraction. Moreover, skin segmentation and after that classification of race is carried out in tandem to optimize the algorithm's running time.

CONCLUSIONS

This paper aimed to enhance the accuracy of the illumination variation face recognition. In pre-proceeding stage, the gary world assumption was utilized for auto color balancing to separate the colors from 0 to 255 and reduction of noise was used to lower the images' noise in addition to the technique of histogram equalization that was utilized for the auto contrast balancing. The Haar Cascades approach was utilized face detection; the DCT-II was utilized for illumination normalization of the face. In the face recognition stage, in this paper, we proposed a new formula for race classification using a Gaussian-based weight K-NN algorithm and lastly the HMM was utilized for face recognition. The face recognition experiment used a large face database of 1035 images of 100 people taken from the FERET and Caltech datasets. F-measure is 84.9 percent and 84.7 percent for proposed algorithm. The excrement results show that the best result is achieved for Caucasoid while the lowest F-measure is achieved for Negroid skin color.

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تصنيف السلالات باستخدام خوارزمية الجار الأقرب (K–NN) المرتكزة على وزن جاوسين (Gaussian) للتعرف على الوجوه

ساسان كاراميزاده وشاهيدان محمد عبد الله

كلية المعلومات المتقدمة، جامعة التكنولوجيا بماليزيا، كوالا لمبور، 54100، ماليزيا

الخلاصة

أحد أكبر التحديات في أنظمة التعرف على الوجه هو التعرف على الوجوه من أعراق وألوان مختلفة. تعتبر اللونية عامل أساسي في التعرف على الوجه وتُظهر كثافة اللون في البكسل، ويمكن أن تختلف اختلافاً كبيراً حسب ظروف الإضاءة. في هذا البحث، إن مخطط تصنيف الأعراق المقترح وهو K-NN المرتكز على وزن Gaussian لديه كثافة شديدة الحساسية نحو الضوء. والفكرة الرئيسية هنا هي أولاً تحديد حالات الأقليات في بيانات التدريب ومن ثم تعميمها على دالة Gaussian كمدلول لفئة الأقلية، باستخدام مزيج من خوارزمية K-NN مع صيغة Gaussian لتصنيف العرق. في هذا البحث، تنقسم معالجة الصور إلى مرحلتين. الأولى هي مرحلة ما قبل المعالجة حيث توجد ثلاثة عمليات معالجة مسبقة تتألف من الموازنة التلقائية للتباين، وتقليل الضوضاء والموازنة التلقائية للألوان. أما المرحلة الثانية فهي معالجة الوجه والتي تشمل ست خطوات هي؛ كشف الوجه، ومعايرة الإضاءة، واستخلاص المميزات، وتجزئة الجلد، وتصنيف العرق والتعرف على الوجه. وتم استخدام نوعان من مجموعة البيانات؛ الأولى مجموعة بيانات FERET حيث تتضمن الصور داخل هذه المجموعة تفاوت الإضاءة. والثانية مجموعة بيانات Caltech والتي تتضمن الأصوات.