AUTOMATIC FACE RECOGNITION SYSTEM

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ABSTRACT

The paper presents the implementation of algorithms to develop an automatic face recognition system. The system extracts the human face and then recognizing that face for a match of the desired people from face database. It consists of two major phase which are the face detection and face identification. In face detection, the face region is extracted from the original image using skin color techniques. Various techniques are used to handle bad illumination and face alignment problem. In face identification phase, Eigenfaces approach is used to overcome the problems of large sets of image and improper illuminating conditions. Experimental results are presented using images of students. The efficiency of the applied approaches is analyzed and compared with previous works.

Keywords: *Automatic Face Recognition, Eigenfaces, Face Detection*

1. INTRODUCTION

Since the beginning of time, humans have relied on facial recognition as a way to establish and verify another person's identity. Humans are very good at recognising faces and complex patterns. Even a passage of time, changes in appearance and partial occlusion doesn't affect this capability. Because of this remarkable ability to generate near-perfect positive identifications, considerable attention has been paid to methods by which effective face recognition can be replicated on an electronic level. Facial recognition technology isn't any different. If a computer become as robust as humans in face recognition, a computer is able to locate human faces in images and then match overall facial patterns to records stored in a database.

Automatic face detection and recognition has been a difficult problem in the field of pattern recognition and computer vision for several years. Although humans perform the task in an effortless manner, the underlying computations within the human visual system are of tremendous complexity. The seemingly trivial task of finding and recognising faces is the result of millions of years of evolution and we are far from fully understanding how the brain performs it. Furthermore, the ability to find faces visually in a scene and recognise them is critical for humans in their everyday activities. Consequently, the automation of this task would be useful for many applications, such as internet, personal identification, security works, login authentication, law enforcement, surveillance and human-machine interface.

Besides that, face recognition technology seems to be a difficult task to develop since the appearance of a face varies dramatically due to facial expressions, illumination, head pose, and image quality determine the recognition rate. However, to date, so many solutions have been proposed that allows the automatic recognition of faces in real images. A vision system which would permit automatic machine-based face detection and recognition in uncontrolled environments will be implemented. This paper describes the theoretical foundations of such a system, its implementations and also its evaluations.

In this paper, a novel method is proposed for recognition of frontal and different views of faces under roughly constant illumination. The proposed scheme for both face detection and recognition phase are based on the analysis of skin colour detection method and Eigenfaces approach respectively. In skin color detection, the range of skin color under a constant lighting illumination is obtained by projecting a set of correspond skin samples into a graph. Meanwhile, the Eigenfaces approach in [1,2] transforms face images into a small set of characteristic feature images, which are the principal components of the initial training set of face images. Recognition is performed by projecting a new image into the sub-space spanned by the Eigenfaces and then classifying the face by comparing its position in face space with the positions of known individuals. Experimental results are presented using images from a class of students. The efficiency and accuracy of the proposed approach is analysed according to the FAR and FRR determination. The recognitions are performed under different lighting conditions for comparison purposes.

1.1. BACKGROUND AND RELATED WORK

Usually, a generic face recognition system may consists of three major phase which are Face Detection, Face Normalisation and Face Identification or Verification (recognition). From report of Yang [3], one of the face detection approaches is knowledge-based method to extract human face based on the rules derived from the researcher's knowledge of human faces. For a given input images, its features are first extracted and the face is identified based on the coded rules. However, this method may fail to detect faces that do not pass all the rules. Moreover, it is difficult to extend its functionality to detect faces in different orientation.

Meanwhile, invariant feature approaches are more flexible than knowledge-based approach. It is based on the observation that humans can detect faces and objects in different posed and lighting conditions. The unique facial features such as eyebrows, eyes, nose, mouth and hair-line that are treated as the elements for recognition. However, due to the illumination, noise and occlusion, some feature especially nose and mouth may fail to be extracted correctly. The development of the feature-based approach can be further divided into three areas, which are the low-level analysis, feature analysis and active shape analysis.

Low-level analysis deals with the segmentation of visual feature using pixel properties such as edges [4], gray-scale [1, 5, 6], and colour [7–14]. In feature analysis, visual features are organised into a more global concept of face and facial features using information of face geometry. There are two general approaches in the application of face geometry. The first approach involved sequential feature searching strategies based on the relative positioning of individual facial features.

The facial feature extraction algorithm by De Silva *et al*. [15] is a good example of feature searching. The algorithm is reported to have an 82% accuracy in detecting all facial features from quasi-frontal (<±30°) head and shoulder faces on a plain background. However, it does not rely on gray and color information, and also it fails to detect features correctly if the face image contains eyeglasses and hair covering the forehead. The techniques in the second approach group features as flexible constellations using various face models. A probabilistic model usually used for the spatial arrangement of facial features enables higher detection flexibility. The algorithm is able to handle missing features and problems due to translation, rotation, and scale to a certain extent. Much successful detection using this techniques have been proposed [16, 11].

Active shape models depict the actual physical and hence higher-level appearance of features. Once released within a close proximity to a feature, an active shape model will interact with local image features (edges, brightness) and gradually deform to take the shape of the feature. There are generally three types of active shape models in the contemporary facial extraction research. Those types are snakes [17], deformable template techniques [18] and PDM model [19].

Face normalisation involved in standardising face image in aspects such as orientation and scaling. When normalise face, it is advantageous to detect eyes. The size, pose, and image-plane rotation of face in the image can be normalised by using the position of both eyes. Eyes detection is divided into eyes position detection and eyes contour detection. However, most algorithms for eye contour detection which use the deformable template proposed by Yuille [20] require the detection of eyes position to initialise the eye templates. Thus, eye position detection is important not only for face recognition but also eyes contour detection.

Brunelli [21] and Beymer [22] located eyes using template matching. In this method, an eye template of a person is moved in the input image and a path of the images that has best match to the eye template is selected as the eye region. Lam [23] detected eye corners using the corner detection algorithm proposed by Xie [24]. Lin [25] computes costs for all pixels in the face region using the properties of eyes that the intensity variation is large near eyes and eyes are darker region their surroundings and they selected a pair of pixels with the largest costs as eyes. However, since these algorithms estimate the searching windows for eyes in the face region by using anthropometrics standards, these algorithms require the face region detection to be complete.

Feng [26] proposed an eyes detection algorithm using three cues. The first cue is the intensity differences between the face skin region and eyes. When the face region is binaries by threshold, eyes appear as holes in the face region. The second cue is the direction of the line joining the centers of the eyes. The third cue is the response of the eye variances filters.

Eigenfaces Algorithms is one of the most successful techniques that have been used to recognise faces in images. This technique consists of extracting the eigenvectors and Eigenvalues of an image from a covariance matrix, which is constructed from an image database. These eigenvectors and Eigenvalues are used for image classification, obtaining nice results as far as face recognition is concerned.

Turk and Pentland [27] applied principal component analysis (PCA) to face recognition and detection. However, Sirovich and Kirby [28] were the first to apply PCA for representing face images. They suggested that any particular face can be economically represented along the Eigenpictures which span a subspace or the image space. Since Eigenpictures are good in representing face images, projections along them can be used as classification features to recognise faces. To detect the presence of a face in a scene, the distance between and image region and the face space is computed for all locations in the image. The distance from face space is used as a measure of "faceness", and the result of calculating the distance from face space is a "face map". A face can then be detected from the local minima of the face map.

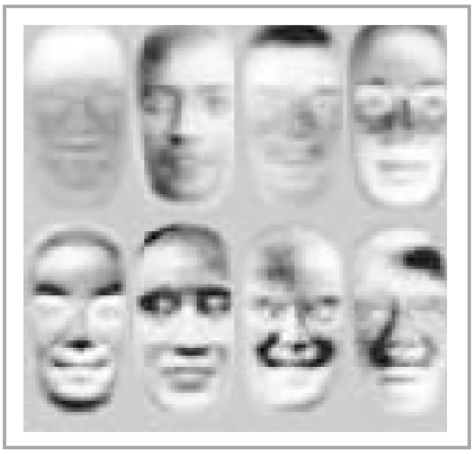


Figure 1: A set of perfect Eigenfaces [29]

This method transforms face images into a small set of characteristic feature images, called "Eigenfaces", which are the principal components of the initial training set of face images. Recognition is performed by projecting a new image into the subspace spanned by the Eigenfaces and then classifying the face by comparing its position in face space with the positions of known individuals.

2. SYSTEM DESIGN

Due to the complexity of the face recognition problem, a modular approach was taken whereby the system was separated into smaller individual stages. Focus was then placed upon making each stage a reliable section before integrating the modules into a complete system. The face recognition system includes three major tasks, they are the face detection, face normalisation and face recognition and each of these tasks are further broken down into separate stages.

2.1. PRE-PROCESSED STAGE

First and foremost, the image captured by using an USB web camera in RGB 24 bit format with resolution 320×240 pixels. This size is suitable for process speed and also retains image information. Person in the captured image should be in frontal view and also must include the head, neck and shoulder. Skin-like background should be avoided to prevent from any false detection.

2.2. LIGHTING NORMALISATION

Lighting normalization is involved to adjusting the illumination intensity of the image so that all images can be regarded as taken under the same lighting condition. Statistical equations are used in lighting normalisation:

$$\text{Mean Image, } A_{mean} = \frac{1}{\text{height} \times \text{width}} \sum_{i=1}^{\text{height}} \sum_{j=1}^{\text{width}} A_{ij} \qquad (1)$$

Standard Deviation Image,

$$\sigma^2_A = \frac{1}{\text{height} \times \text{width}} \sum_{i=1}^{\text{height}} \sum_{j=1}^{\text{width}} (A_{ij} - A_{mean})^2 \qquad (2)$$

$$\text{Normalized Image, } A_{normal} = \frac{(A - A_{mean}) \times c_1}{\sigma^2_A} + c_2 \qquad (3)$$

Where c_1 is user–defined standard deviation constant and c_2 is user-defined mean constant. Their value will influence the intensity of the normalised image.

2.3. FACE DETECTION

Face detection is a necessary first-step in a fully automatic face recognition system, with the purpose of localizing and extracting the face region from the background of a given arbitrary color and still image. Recent discoveries in skin biometrics are adding a new dimension to face detection and boosting accuracy by significant levels. Because the skin biometric uses the same facial images as traditional facial recognition systems, the face biometric and skin biometric can be easily fused together to yield exceptional levels of performance.

The YCbCr color space is chosen because it will highlight the skin color region with respective color and then easily to detect the face region. YCbCr is a polar coordinate system with Y denoting illumination value and Cb and Cr denote the chrominance values. The YCbCr can be related to RGB by following equation:

$$\begin{aligned} Y &= 0.2989 \times R + 0.5866 \times G + 0.1145 \times B \\ Cb &= -0.1688 \times R - 0.3312 \times G + 0.5000 \times B \qquad (4) \\ Cr &= 0.5000 \times R - 0.4184 \times G - 0.0816 \times B \end{aligned}$$

Since Y is denoted as illumination of image which it is an unwanted aspect and can be ignored during skin colour segmentation.

The goal of skin color segmentation is to reject non-skin color regions from the input image, leaving only skin areas. Skin color segmentation can basically be performed using appropriate skin colour thresholds where skin colour is modeled through a range between minimum value and maximum value. Hence, to obtain the range which considered as skin color, a set of skin sample is taken from different image at different part, such as cheek and forehead. The range is obtained by searching for the highest probability of each component YCbCr that appears in each skin sample. The range is

$$59 < Y < 233, \ 108 < Cb < 126, \ 129 < Cr < 154 \qquad (5)$$

Morphological operations such as dilation and erosion are carried out to eliminate the unwanted "noise" inside a face image. Disc-shaped with size 20 of structuring element is used because human faces are known as circle-like shape. Erosion will makes the overall regions including the face region (the largest region) shrink, and then will remove the small non-face regions. In order to resize face region back to normal size, dilation process is required by using the same structuring element. After that, the image will be looked "clean" and it is ready for face normalisation and face recognition.

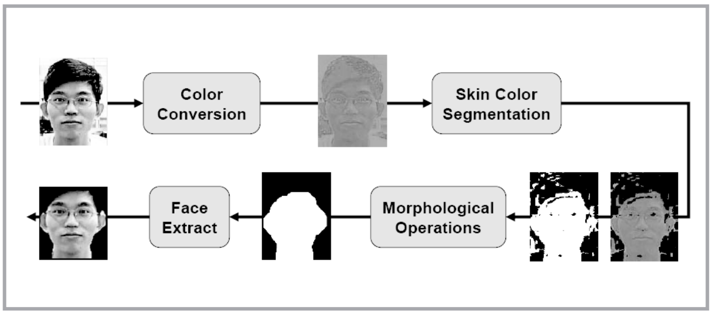


Figure 2: Face detection

2.4. FACE NORMALISATION

The face region extracted previously is not suitable to go directly for recognition yet. The face might be tilted and not vertical position and since in databases the images are all in vertical position, this will produce wrong identification. Therefore, a process of rotation needs to be done to overcome this problem. However, first the eyes should be detected as a guideline to rotate the head.

The techniques to be used for eyes location is by using edge techniques. There are a few methods available such as Sobel, Prewitt, Roberts, Laplacian of Gaussian, Zero cross and Canny method. Among these methods, Sobel is the most suitable because it is not too sensitive to edge existence in an image. Thus, only edges that are obviously and able to avoid any unnecessary edge exist in the image.

Since the main focus is to detect the eyes, the face is cut and remain the top half part of the original image. This is to prevent from detecting the mouth and nose region. The eyes region will consists the most edge and by applying dilation and erosion process as done previously will give a final result that consist only of two white regions, thus the eyes region. Here, the dilation and erosion process involve vertical and horizontal line to eliminate the head edge line. Hence, by searching for the largest white region, a rectangular is applied around the region.

The next step is to detect the center of the eye. We first made an assumption that the center of the eye locate at the center of the rectangular. With this assumption, both center point for respective rectangular is computed and draw a straight line connected these two points. The angle theta, made by this line regarding to horizontal base line is then computed.

Let the center point for left eye is (x_1, y_1) and for right eye is (x_2, y_2). The angle theta, θ as shown in Figure 1 is calculated as follow:

$$(6) \quad \theta = \left[\tan^{-1}\left(\frac{y_1 - y_2}{x_1 - x_2}\right) \right] \text{rad} = \left[\tan^{-1}\left(\frac{y_1 - y_2}{x_1 - x_2}\right) \times \frac{180}{\pi} \right] \text{deg}$$

The whole process of eyes detection and head rotation discussed are as shown in Figure 3.

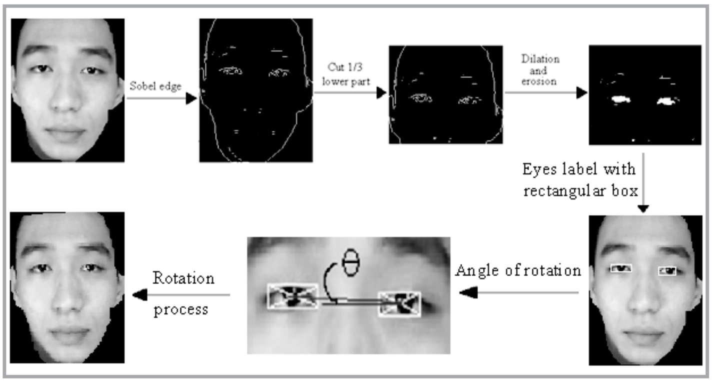


Figure 3: Eyes detection and head rotation process

2.5. FACE RECOGNITION

In this recognition phase, Eigenfaces approach was applied as the identification method. This approach considers training, where the face database is created and the projection matrix is obtained from all the database face images. Also the mean face is calculated and the reduced representation of each database image with respect to mean face. These representations are the ones to be used in the recognition process.

To calculate the Eigenfaces, training image was obtained refers to the images in database in db1. These images can be consider as an N-by-N face I(x, y) as a vector of dimension N^2, so that the image can be thought of as a point in N^2-dimensional space. As for this study, N^2 was chosen to be 7600 (95 by 80 pixels). A database of M images can therefore map to a collection of points in this high dimensional "face space" as $\Gamma_1, \Gamma_2, \Gamma_3, K, \Gamma_M$. The average face of the set is

$$\psi = \frac{1}{M}\sum_{i=1}^{M}\Gamma_i \tag{7}$$

Each face can be mean normalised and be represented as deviations from the average face by $\Phi_i = \Gamma_i - \Psi$ for i = 1, K, M. Therefore, the training images have to be normalised using the formula shown below:

$$(\text{rnorm}, \text{gnorm}, \text{b norm}) = \left(\frac{Nr}{r_1 + r_2 + K + r_N}, \frac{Ng}{g_1 + g_2 + K + g_N}, \frac{Nb}{b_1 + b_2 + K + b_N}\right) \tag{8}$$

An example of a training set and normalised training images can be seen in Figure 4 and mean image in Figure 5.

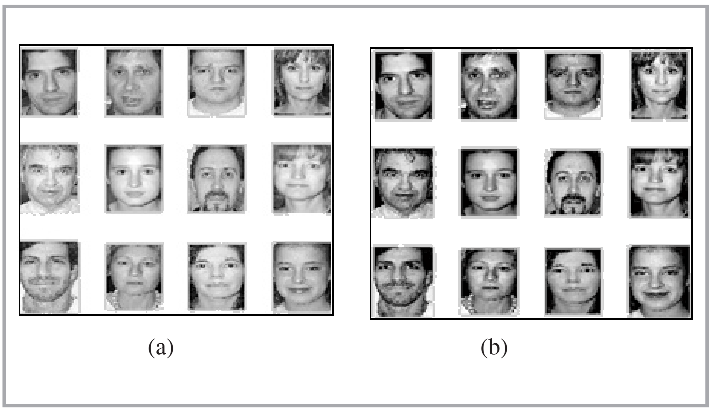


Figure 4: (a) Training set images; (b) Normalised training images

Figure 5: Mean image

The covariance matrix, defined as the expected value of $\Phi\Phi^T$ can be calculated by the equation:

$$C = \frac{1}{M}\sum_{i=1}^{M}\Phi_i\Phi_i^T \tag{9}$$

$$C \cong AA^T \quad \text{where } A = [\Phi_1, \Phi_2, \Phi_3, K, \Phi_M] \tag{10}$$

Since C is a dimension N^2 by N^2, solving for Eigenfaces is a computationally exhaustive task. Hence, for these Eigenvectors can be solved by taking the linear combinations of the Eigenvectors of a new M × M matrix L defined as

$$L = AA^T \tag{11}$$

Letting v_i denote the Eigenvectors of L, the Eigenvectors u_l of the covariance matrix C can be defined as

$$u_l = \sum_{k=1}^{M} v_{ik}\Phi_k \quad \text{where } l = 1, 2, K, M \tag{12}$$

Eigenfaces is then defined as the Eigenvectors which represent one of the dimensions of face image space. The Eigenfaces are a group of important characteristics that describe the variation in the group of face images. All Eigenvectors have and Eigenvalues associated to itself and the Eigenvectors with the largest Eigenvalues provide more information on the face variation than the ones with smaller Eigenvalues. Figure 6 shows the Eigenfaces projected from the training set images.

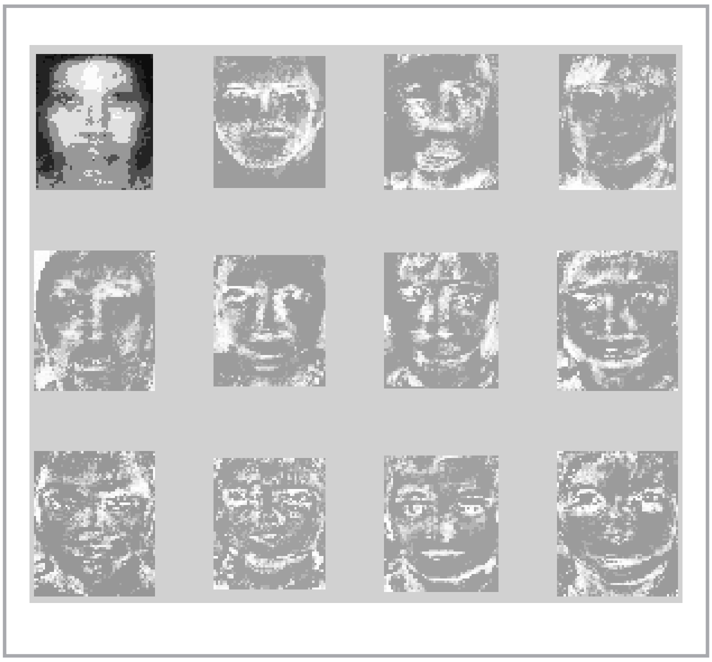


Figure 6: Eigenfaces

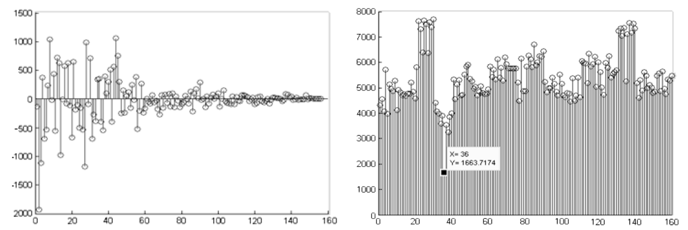
All the images from training set are projected to this Eigenspace. These can be represented by linear combination of the Eigenfaces that have a new descriptor as a point in a great dimensional space. This projection is constructed as follow:

$$\Omega_i = U^T(\Gamma_i - \Psi) \quad \text{where } i = 1, 2, K, M \qquad (13)$$

The Ω is also known as the weight of respective image. As the projection on the Eigenfaces space describes the variation of face distribution, it is possible to use these new face descriptors to classify them.

Before going for recognition, the face image after detection and normalisation must be resize to be same dimension with those in database. Then the weight of the input image can be calculated using the equation (13). The vector Ω with dimension M×1 is compared with each vector Ω_i representing the weight of each training images. If the distance between Ω and Ω_i is inside a user-chosen threshold value and is the smallest distance, then there is a facial recognition of Ω belonging to class image i. This distance, known as Euclidean distance can be calculated using square minimal method given by the following equation.

$$\varepsilon_i^2 = \| \Omega - \Omega_i^2 \| \qquad (14)$$



(a) (b)

Figure 7: (a) Weight of input image
(b) Euclidean distance. The black square is the smallest distance.

2.6. OVERALL PROCESS FLOWCHART

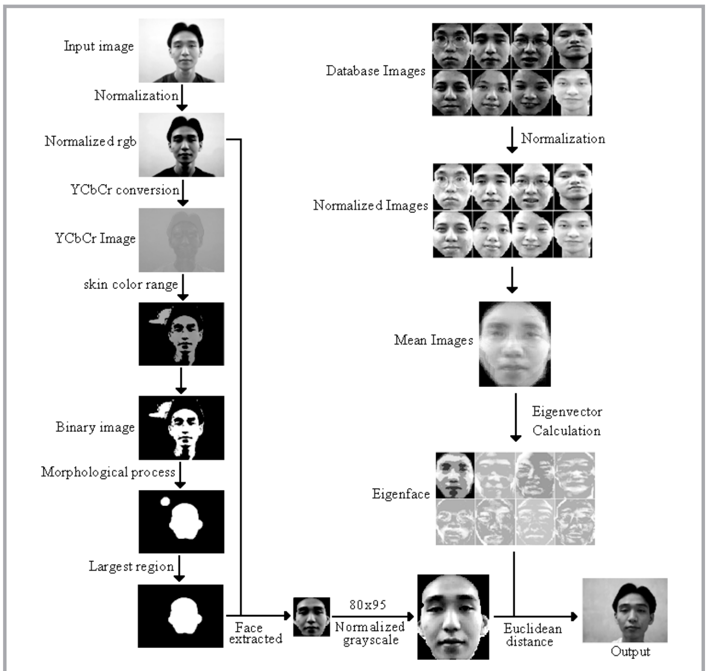
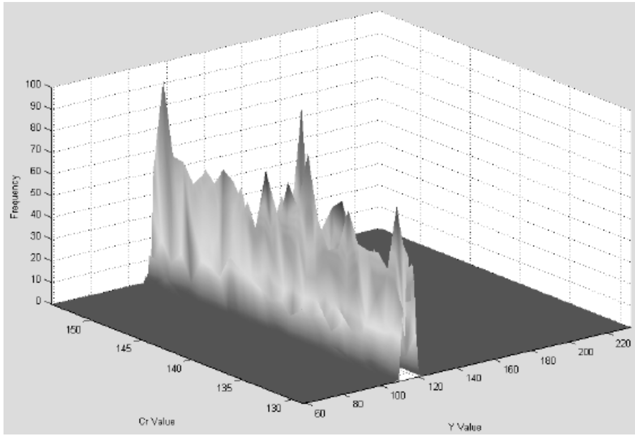


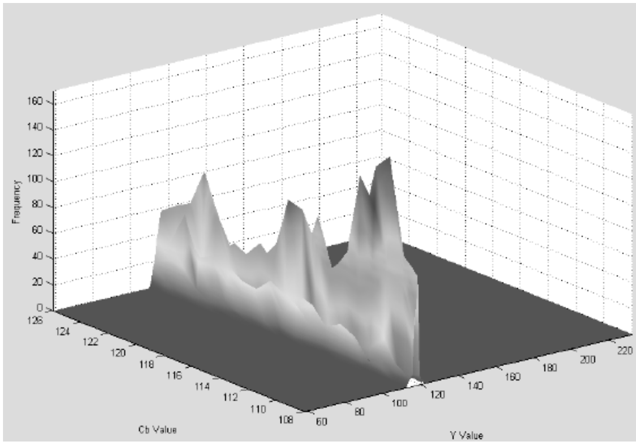
Figure 8: AFRS system flowchart

3. EXPERIMENTAL RESULTS

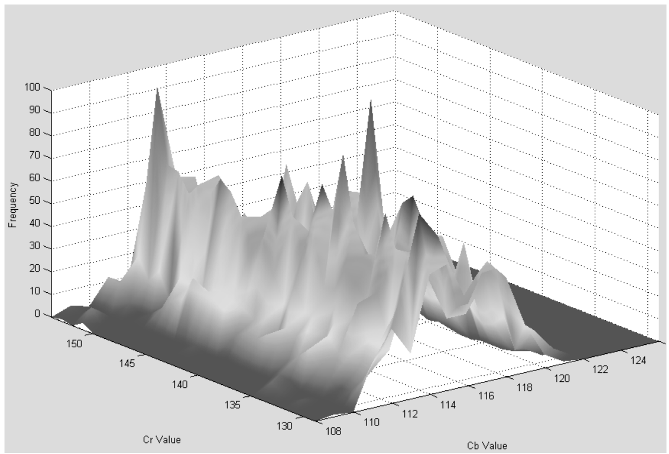
A set of 40 skin samples extracted from normalised images are projected into a graph corresponding to each component of YCbCr color space, as shown in Figure 9 below:



(a)Y-Cr



(b)Y-Cb



(c) Cb-Cr

Figure 9: YCbCr skin colour range 3-D plot

This skin colour range does vary depends on the lighting illumination during the image is captured. Thus, lighting normalisation is used to maintain the lighting intensity to ensure the range can be applied to all captured image.

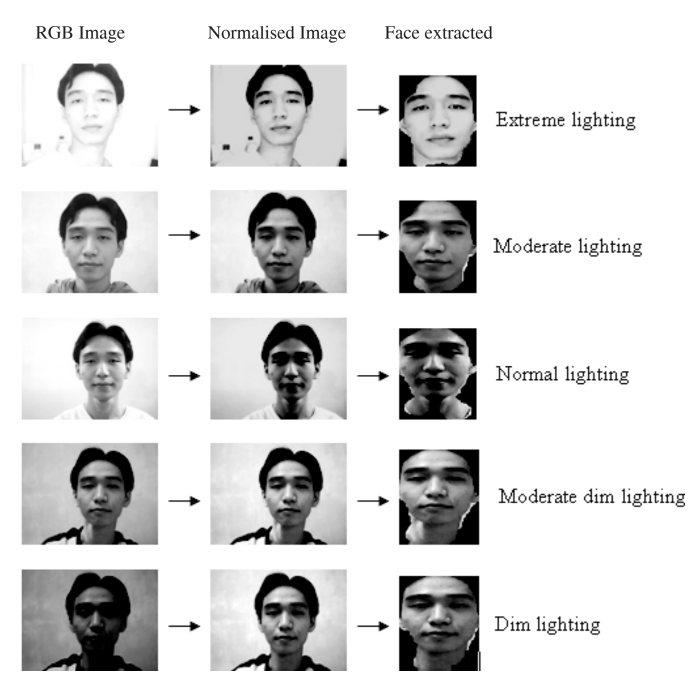


Figure 10: Lighting normalisation under different lighting condition

The threshold value is determined by initially recognising 20 people that exists in database and another 20 people that are not in the databases. The minimum Euclidean distances for each test performed are obtained. The average minimum Euclidean distances for those in database will be the minimum value for the threshold value and vice versa for those not in the database. These range is then applied to determine the FAR and FRR value for each corresponding threshold value. The FAR versus FRR plot is then obtained to determined the optimum value of threshold value for the system as well as the Equal Error Rate (ERR).

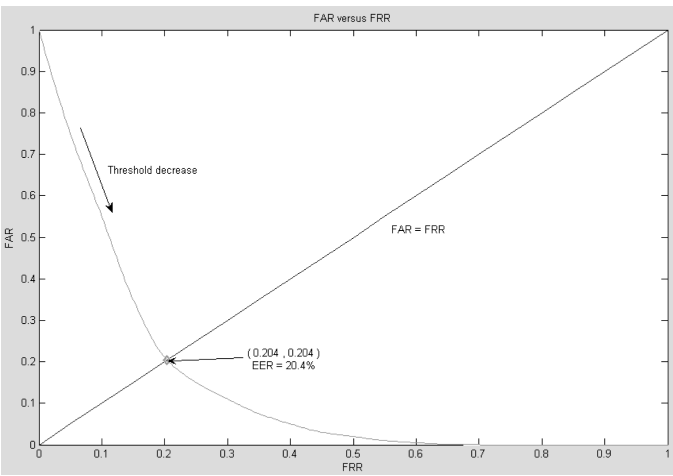


Figure 11: FAR versus FRR

False Acceptance Rate (FAR) is the percentage of unknown face that are accepted as known face and False Rejection Rate (FRR) is the percentage of known faces that are rejected as unknown face. The EER can be obtained by the intersection between the FAR-FRR curve and the FAR=FRR line. Thus the value obtained was 20.4%. This is an acceptable value for Eigenfaces approach although it is quite large. The corresponding threshold value can be obtained from threshold value versus either FAR or FRR, and the value obtained is 5.49×103. This eventually shows that the system accuracy and efficiency are optimised by applying this threshold value that gives the least error rate.

Prior to recognition process, the number of training images and the size of images should be chosen wisely. As shown in Figure 13 below, the accuracy increases exponentially as the number of training images per person increases. However, the selection of number of training images also depends on the size of the image. The effect of size of image to the system is shown in Figure 14.

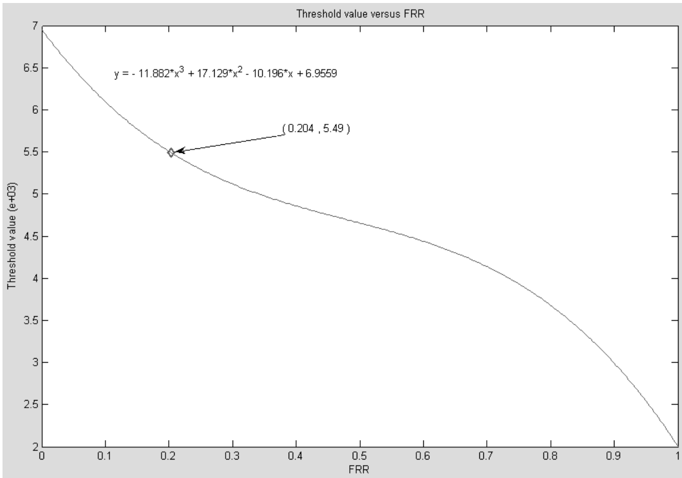


Figure 12: Threshold value

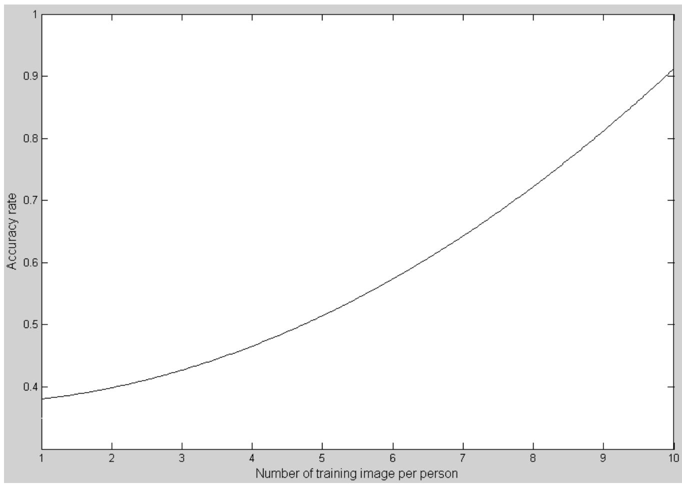


Figure 13: Accuracy and number of training image

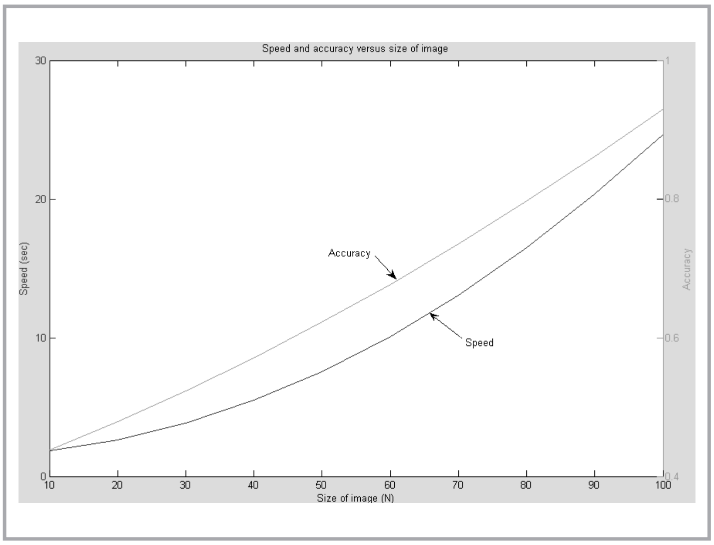


Figure 14: Effect of size of images

Larger size of image will tend to increase the accuracy of the system but delay the time of the recognition process due to eigenvector calculation. Thus for a system that provide high accuracy at high speed, we have chosen the size of image to be 95x80 and only 10 training images is obtained for each person. Finally, by applying all this conditions and value determined initially, the system accuracy can be ontained under different lighting condition for both front view and different view recognition for comparison purposes.

Table 1: Accuracy for different test

Test	Lighting Intensity		
	Normal	Extreme	Dim
Frontal view	90.00%	73.33%	48.33%
Multiple view	93.33%	65.00%	35.00%
With eyes detection and face rotation	75.00%	35.00%	11.67%

From table 1, it can be concluded that the lighting variation greatly affect the system's accuracy. The accuracies are worse under extreme and dim lighting due to failure in masking out the face region using the skin colour range determined previously even with lighting normalization included. Thus, the lighting condition must be controlled properly to ensure the intensity does not vary too much.

Under normal lighting, the accuracy is the highest for multiple views followed by frontal view recognition and the least for addition of eyes detection and face rotation. Both frontal and multiple views accuracy are acceptable, which is around 90%. The drastic drop of accuracy down to 75% with addition of eyes detection and face rotation is because of failure in eyes location that will eventually leads to error in head rotation. Thus the comparison with the Eigenfaces cannot be made perfectly. Therefore, both the eyes detection and head orientation modules are not included in our main system because of its poor accuracy.

3.1. COMPARISON WITH AVAILABLE METHODS

Skin colour had been our first choice as the main techniques to be applied in face detection module. Since the colour composition of human skin differs little across individuals, hence the different human skin color gives rise to a tight cluster in colour spaces even when faces of difference races are considered.

The luminance, Y component of YCbCr colour space has little influence on the distribution in the CbCr plane and that sample skin colours form a small and very compact cluster in the CbCr plane[30]. Skin colours classification is performed directly in the chrominance plane (CbCr) without taking the intensity value Y into account [31]. Same with our test and result, applying YCbCr with a range of skin colour can masked out the face region successfully. Similar approach is also performed for face detection [32] and obtained an accuracy of 89.40% for frontal faces, 90.74% for near-frontal faces and 74.67% for half-profile faces.

Compare with the detection module, using images downloaded from internet for testing, we obtained an accuracy of 85.67% (257 from 300 images). From those 42 images that failed in face detection, about 35.7% of it are due to the existence of moustache that cause part of the faces being omitted. The rest are due to invariant lighting.

Despite, using the database subject developed in this study, 90% (18 out of 20 people) accuracy was obtained. The 10% failures are due to difference in skin color for different races and face characteristics such as moustache. This shows that face detection module can perform well if and only if the face images are clear and under a suitable lighting.

Eigenfaces approach had been previously done by many researchers as one of the technique used in recognition system. The best image processing technique for several recognition methods has been investigated [33], where Eigenfaces is one of them. Hence, with intensity normalisation, Eigenfaces approach achieved and EER of 20.4%, which is the same rate with our current system. However, its verification of EER is computed under 258,840 verification operations while ours are computed under 20 verification operations only. Nevertheless, this system gives acceptable and satisfactory results over the recognition process.

In other study[34], with 50 pictures tested 48 recorded correct identification and claimed an accuracy of 96%. Under 20 recognitions each for 5 individuals [35], the system was capable to achieve an accuracy of 94%. In this current system can only provide a maximum accuracy of 93.33% with 3 recognitions for each 20 individuals. The low accuracy compared to theirs is mostly due to imperfection in face detection module or slight orientation of head during image captured.

As comparison for whole AFRS system, there is yet a same approach done previously. However, there is a similar approach done by a group of student to detect face for class attendance applications. They used HSV color space instead of YCbCr to mask out face region and apply Eigenfaces for recognition process. Their system accuracy is 75% (6 successful matches out of 8). This system, however manage to obtain 93.33% of accuracy due to successful developed normalisation module compare to theirs, although the lighting variation still have some effect on the accuracy.

Several techniques had been developed for graph matching [36], which are the Kohonen self-graph organising neural-network, a graph matching technique and K-nearest neighbor technique. Hence, graph matching technique is found out to be the best technique that gives 95% of recognition for the complete view of the face. However, the computational cost is relatively high. Due to this complexity, this technique is not favorable among the researchers although providing a relatively high accuracy.

A frontal face recognition system had been developed using neural network method [2, 37]. Their algorithm can detect between 77.9% and 90.3% of faces in a set of 130 test images, with and acceptable number of false detections. Similarly, a statistically based method for face detection is presented [38]. Their system builds probabilistic models of the sets of faces and non-faces, and compare how well each input window compares with these two categories. Under test set 1, their accuracy can achieve 86.8% and 98% while under test set 2 gives 90.9% and 92.1%.

Both the neural network and graph matching method as done by previous researchers manage to perform well and give as high as 95% and 98%. This is better than our system accuracy, 93.33%. Nevertheless, the complexity of graph matching that needs lots of computations and the needs of few hundreds of windows for neural networks method that ensure the high accuracy makes them not a preferable choice of method to be used in our system. Thus, using Eigenfaces method can also provide an acceptable accuracy rate.

4. CONCLUSIONS

The experiment done shows that the system performance is greatly affects by the lighting illuminations. Thus using predefined skin color range and threshold value, under normal lighting the system are able to provide an accuracy of 93.33% for multiple view recognition and 90% for frontal view recognition. Eigenfaces provide the theoretically way of determining underlying variations responsible for some high-dimensional observation by appropriate pre-processing steps and the accuracy of the Eigenfaces technique is superb. However, it is very sensitive to scale and rotation.

The failure in eyes detection can be cause by some factors. Firstly, the eye detection algorithm was being no means perfect and although an attempt was made to manually correct any misaligned images, it is clear that some images are not aligned well. It would be relatively simple to implement a system in which several small translation and scales of the original image were projected into face space for each recognition attempt, hence compensating for any inaccuracies in the alignment procedure.

Face recognition offer significant potential for future research and development. An analysis of the strengths and weaknesses of the automatic face recognition system has been presented and discussed for future references. With the implemented system serving as an extendable foundation for future research, extensions to the current system have been proposed.

5. RECOMMENDATIONS

As and extension of this work, it would be interesting to further enhance the performance of facial extraction instead of eyes detection only, especially to tackle the problem of non-frontal views recognition. However, detecting precisely facial features is a difficult and time consuming process that increases the time for recognition. Therefore, future studies should focus on a fast and efficient algorithm for precise facial feature detection.

Moreover, improvements of recognition on face changes in expression as well as disguise and occlusion can be done by combining both the global facial and localised feature in determining the weight of image for Eigenfaces comparison. A 3D image instead of 2D image should be further investigate and explore since it provides more information for comparison. The functionality of the system can as well be enhanced further to recognise multiple faces in an image. Face tracking can as well be implemented in the system to ensure the face can be reliably normalised before captured for recognition. ■

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