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IMPROVEMENT OF FACE DETECTION INCORPORATING ILLUMINATION-BASED ROBUST SKIN COLOR MEASURE

by

Md. Asif Anjum Akash

Department of Computer Science and Engineering
Khulna University of Engineering & Technology
Khulna-9203, Bangladesh
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Improvement of Face Detection incorporating Illumination-based Robust Skin Color Measure

by

Md. Asif Anjum Akash
Roll: 1607559

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Computer Science and Engineering

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Khulna University of Engineering & Technology
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Declaration

This is to certify that the thesis work entitled "Improvement of Face Detection Incorporating Illumination-based Robust Skin Color Measure" has been carried out by Md. Asif Anjum Akash in the Department of Computer Science and Engineering, Khulna University of Engineering & Technology, Khulna, Bangladesh. The above thesis work or any part of this work has not been submitted anywhere for the award of any degree or diploma.

Aminul 23/6/19

Signature of Supervisor

Dr. Muhammad Aminul Haque Akhand
Professor,
Dept. of Computer Science and Engineering,
Khulna University of Engineering & Technology

Asif Anjum
23/06/2019

Signature of Candidate

Md. Asif Anjum Akash
Roll: 1607559
Dept. of Computer Science and Engineering,
Khulna University of Engineering & Technology

Approval

This is to certify that the thesis work submitted by Md. Asif Anjum Akash entitled "Improvement of Face Detection Incorporating Illumination-based Robust Skin Color Measure" has been approved by the board of examiners for the partial fulfillment of the requirements for the degree of Master of Science in Computer Science and Engineering in the Department of Computer Science and Engineering, Khulna University of Engineering & Technology, Khulna, Bangladesh in June, 2019.

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Abstract

Human vision system is amazing in detecting face easily but it is very challenging in computer vision and image processing as it depends on quality of image, illumination, lighting conditions, face sizes, occlusions, and face position etc. The existing face detection systems, including popular Haar feature based face detection (HFFD), very often detect a region as a face which is eventually not a face. To counteract such false detection, incorporation of human skin color property is considered a way of improving face detection accuracy in several recent studies. But these methods are found to be dependent on illumination conditions meaning that the performances of these methods degrade when applied to images with different illumination conditions. The aim of this study is to devise a robust face detection system integrating skin color matching that will perform well under different illumination conditions. In pursuit of this goal, a novel skin color matching method is proposed which is a composite of two rules to balance the high and low intensity facial images by individual rule. In the proposed method, illumination intensity of a given facial area is measured and then appropriate rule is applied based intensity value to verify the area as face or not. The proposed skin color matching is verified in face detection with HFFD on four benchmark face datasets (Put, Caltech, Bao and Muct) and a self-prepared dataset. Experimental results and analysis revealed the effectiveness of proposed composite skin color matching to improve face detection while compared with prominent existing skin color-based face detection methods.

Lists of Tables

Lists of Figures

Chapter 1

Introduction

Face detection is a very crucial part in the area of image procession and computer vision. Many studies are available which present different techniques of detecting human faces from images or video streams. As face detection is a very popular authentication system, accuracy is a severe concern here. This thesis will present a novel way to improve the accuracy of standard face detection system. This chapter will discuss about the basic problems of face detection and the ways to handle the challenges in a short. Finally, the objectives of this thesis and the organization of the rest of the chapters are also included in this chapter.

1.1 Background

Because of automation of system, non-contact authentication system is becoming popular day by day. Face detection and recognition is one of the non-contact authentication systems. Face detection authentication system has some benefits than other non-contact biometric identification system like Heartbeat sensing, Irish scanning, Human body presence sensing etc. because, for face detection only a camera is enough whereas others need various equipment. Face detection crucial part of computer vision and image processing [1]. Face detection from an image or any video stream is useful in various applications as well as in daily life. Online job application uses face detection for ensuring a human applicant. Air conditioner uses face detection sensors for smart air flow control [2]. Now-a-days, face detection system is embedded in every high-quality smartphone for the purpose of auto focusing. Smart home uses face detection for room temperature and lighting control. Moreover, face detection is the pre-step of face recognition which is the most widely used biometric system. Face recognition is used in various authentication applications including crime deterrent. Face recognition is used for smart payment system. Face unlock is provided in every high-quality smartphone now a days. Besides, face detection is also a pre-step of emotion analysis. Therefore, the accuracy of face detection system is a concern.

1.2 Motivation

A face detection method finds facial features from an image or a video stream ignoring other background images. Human vision can detect face easily but it is very challenging in the field of computer vision and image processing because there are various issues for detecting faces from images with different quality, size, lighting effect, face position, face rotation angle etc. Researchers have proposed different face detection techniques using artificial neural network [9-14, 61], support vector machine (SVM) [15], particle swarm optimization (PSO) [16], template matching [17,18], kernel probability map [19]. There exists also example based [20], component based [21] and many more [22-26] face detection system. But the most popular and used face detection system is feature matching based face detection system [1, 3, 27-31].

Since face detection is a complex task, many face detection methods fail to detect correct faces from images. Several studies [4-8] described research trends of face detection through analysis of different face detection systems and human skin color detection systems with pros and cons of standards. Among the feature-based face detection system, HAAR feature based face detection (HFFD) system is the most widely used method [1, 3]. Viola and Jones [3] proposed a classical face detection framework based on the boosting strategy. The popular tool OpenCV uses HFFD for the face detection purpose [1]. Chen et al. [29] found that facial landmarks usually used for face alignment are useful for face detection. A major problem of the existing face detection systems is that they very often identify a region as a face which is not a face actually. This false detection decreases the accuracy of a face detection system; the popular HFFD also suffers from the same problem.

Recently, incorporation of human skin color property in face detection methods is found to improve detection accuracy. A number of skin color properties are identified through different studies in [1, 32-47]. But in this study, it is found that the common problem of the detection methods is that each method performs well for the specific type of illumination condition. On the other hand, performances of those methods are not impressive when applied to an image having different illumination conditions in it. A hybrid technique may yield better skin color detection but will require careful selection.

1.3 Problem Statement

Existing face detection systems sometimes make wrong detections. Sometimes they detect some regions as faces which are not faces really. Those are called false positives. Those false positives decrease the accuracy of face detection. There are several face detection methods. Among them Haar feature based face detection system is the most popular. But this method also generates false positives. But for authentication those false positives are very much unwanted. For that reason, our goal is to minimize those false positives as much as possible resulting much higher accuracy. Recently, incorporation of human skin color property in face detection methods is found to improve detection accuracy. A number of skin color properties are identified through different studies in [1, 32-45]. But in this study, it is found that the common problem of the detection methods is that each method performs well for the specific type of illumination condition. A hybrid technique is proposed to handle that challenge.

1.4 Objectives

The aim of the study is to develop a robust face detection system which will perform well for different types of illumination conditions. It is very challenging to formulate a human skin color detection rule which is capable of detecting human skin color for wide domain of skin color and for wide domain of illumination condition. To reach the goal, a noble hybrid skin color matching system is developed after rigorous analyses of different skin color detection formulas which is capable of acting differently at different illumination intensity. The whole task is an integration of following objectives:

- Study on various face detection methods.
- Find out the strength and weakness of those face detection methods.
- Studying various human skin color detection methods.
- Finding out the result of incorporation of those human skin color detection methods with traditional face detection system.
- Investigate a robust face detection method introducing a new hybrid human skin color detection method which takes the complementary strengths from existing human skin color detection methods.

1.5 Scope of the Thesis

Image processing and computer vision is a large field in the era of computer science. Face detection is a very crucial part of computer vision because it has many days to day life applications. Among the many methods of face detections, we chose the most popular method to work with and to improve it. Incorporation of human skin color property in standard face detection system is a good way to improve accuracy. To design a face detection system which performs well in every illumination condition is a challenging task because, each of the existing human skin color detection method is found illumination dependent. Some methods work well in high illumination but suffer in low illumination condition. Some methods work well for dark skinned people when some methods work well on while skinned people. Those challenges are taken in this research.

1.6 Thesis Contribution

The novelty of proposed method is that its filtering process is according to illumination intensity. In this study it is found out that, every human skin color filtering method has some strength and weakness which is dependent on illumination intensity. Proposed method chose best two methods from existing established methods for face filtering purpose among them one is very good for bright scenario and for bright skinned face and another is very good for low light condition and for dark skinned people. Proposed method got the strengths from two of those methods which help to increase accuracy significantly and also capability of detecting faces of variety of races. From the experimental result it is found that proposed method is capable of detecting faces from images having illumination intensity from 2.5394 to above which is quite enough.

1.7 Organization of the Thesis

The rest of the thesis are organized as follows.

- **Chapter 2** presents literature review related to face detection. It will discuss different methods of face detection. Investigation on several existing popular standard and hybrid skin color detection methods are also provided here. A brief evaluation of the human skin color detection methods is also included.
- **Chapter 3** presents the proposed hybrid robust face detection method.
- **Chapter 4** presents experimental results to identify the proficiency of proposed robust face detection method comparing with standard human skin color matching systems.
- **Chapter 5** concludes the paper with a brief summary. Future research scope is also included.

Chapter 2

Literature Review

There are two ways to improve accuracy of face detection. One is increasing true face detection rate (increasing true positive rate) and the another is decreasing false detection rate (reducing false positive). This study presents an efficient way to improve the accuracy of standard face detection reducing wrong detections incorporation of human skin color matching. There are several face detection methods. Many researchers proposed many human skin color detection rules also. However, standard human skin color detection method has limitations because skin color is highly subject to illumination condition and they work on a certain domain. Therefore, to overcome those limitations and for combining those strengths, a few hybrid skin color detection methods combining two or more standard methods have been reported in the literature. This section first describes several standard face detection methods. After it describes and analyses on different popular standard skin color detection methods and several hybrid skin color detection methods. In this study, all of those standard skin color detection methods were implemented and incorporated with standard HFFD to find out their strengths and limitations specifically. Detailed performance of each method will be found in the experimental result and analysis section.

2.1 Standard Face Detection Methods

All of the face detection methods can be classified into two major division. One is feature-based face detection and another is image-based face detection. Two division can be further classified into some subdivisions. Figure 2.1 depicts the classification of all the face detection methods. A brief discussion on those major division is presented in the following section.

2.1.1 Feature Based Face Detection

All of the objects have their own unique features. So that they can be detected by finding their corresponding features. Like other objects human face has its own features like nose, eye, mouth etc. All of the features of human face are found out form images. A suitable algorithm is designed to train machine with those features. After that machine can find out those features from images thus can detect faces from images. Among the feature based face detection technique haar feature based face detection is pioneer. In this study haar feature is also used

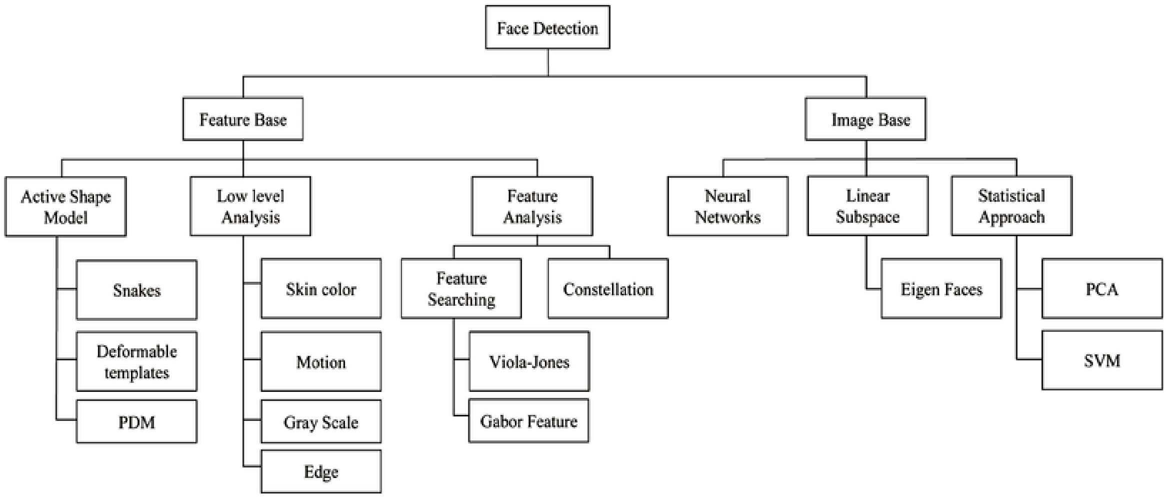


Figure 2.1: Classification of face detection system [62].

for its very good computational speed which will be discussed in details in the next chapter. Also, human skin color is a good facial feature. Usually human skin color feature-based face detection methods finds the human skin color among the whole image and the other pixels which do not hold skin color information are discarded. Then by edge detection technique it detects objects those hold human skin color properties. Among those faces are identified by geometric calculations. The advantage of feature-based face detection techniques is that it is a faster process than image-based face detection technique.

Active Shape Model

Active Shape Models concept for object detection was developed by Tim Cootes and Chris Taylor in 1995 [58]. They are statistical models of the shape of objects which iteratively deform to fit to an example of the object in an image. This method works with three steps.

Snakes

Snakes are used commonly to locate head boundary. For this purpose, a snake is first initialized at the proximity around a head boundary. Then edge detection is done and they are locked nearby the edge boundary of the head and thus assume the shape of human head. The evolution of a snake is achieved by minimizing an energy function, E_{snake} (analogy with physical systems), denoted as

$$E_{snake} = E_{internal} + E_{external} \tag{2.1}$$

where $E_{internal}$, $E_{external}$ are the internal and external energy functions, respectively. The internal energy defines the snake shape holding its basic properties. But the external energy counteracts the internal energy and thus it enables the edges to deviate from the hard line and eventually catches the shape of head boundary.

Deformable Template

In the head area some deformable template matching is performed such as eye template, nose template etc. Those templates are deformable and thus makes the process of template matching more reliable. Once a template such as eye template is initialized near eye boundary it is deformed by itself and moved toward to the optimal feature boundary. This deformation mechanism is a steepest gradient decent way and thus involves the combination of the external energy due to edge, peak, valley and brightness. (E_e, E_v, E_p, E_b) given by

$$E = E_e + E_v + E_p + E_b + E_{internal} \tag{2.2}$$

Point Distribution Model (PDM)

This is a filtering method. PDM confirm whether it is really a face or not. PDM is a compact parameterized description of contour of a shape. Contour of a shape is discretized into many level points. Variation of the point’s locations are first included into training set and then by PCA a linear flexible model is generated.

Low Level Analysis

This technique involves finding four features to human face. After computation with edge feature, gray scale feature, color feature and motion feature a face location is identified.

Edge

First the head outline edges are found out. After that the edges of other features in head boundary are found out. Edge feature detection for identify face is the oldest technique which was inspired from drawing of human faces in photograph. This method is introduced by Anila and Devarajan [59]. This approach has three steps i.e.

- Firstly, images are enhanced by median filter for noise removal that makes the further process easier and more accurate.
- In the second step, the edge images are constructed by enhanced images.

- Finally, a tracking algorithm is applied on the edge based enhanced images which finds the sub windows containing faces.

Gray Scale

Gray scale information of human face is a vital feature and very easy to work with. After a conversion to gray scale it is seen that some region such as eyebrows, pupils, and lips appear generally darker than other region of human face. Images are enhanced by the low-level gray scale threshold and thus makes the darker feature finding process easier.

Skin Color

Color information is also very crucial feature of human face. Color processing is much faster than finding other features. There are several color models such as RGB color model, YCbCr color model, HSV color model etc. by which human skin color can be found. There are several rules for skin color detection for those color model which will be described in later section. Several conversions are needed sometimes such as RGB to CyBC conversion, RGB to HSV conversion etc. A Sample skin color detection algorithm is presented in Fig. 2.2.

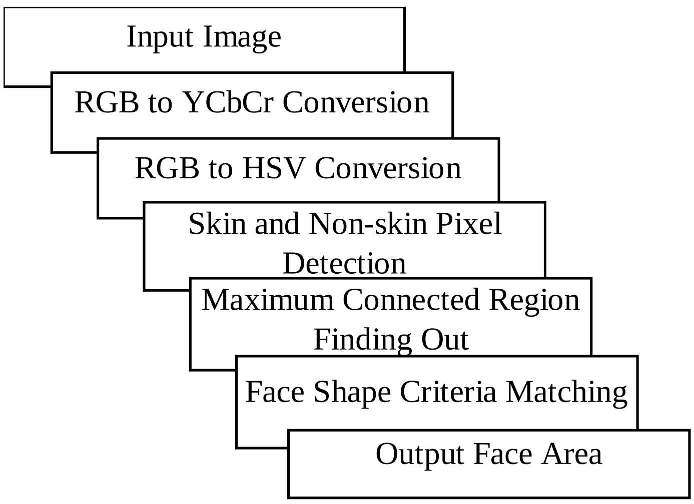


Figure 2.2: Sample of skin color-based face detection algorithm.

Motion

Motion information is applicable for a video sequence. Moving objects can be tracked by motion tracking algorithm. Going silhouettes like face and body parts can be extracted by simply threading accumulated frame differences. Besides face regions, facial features can be located by frame differences.

Feature Analysis

This thesis work is feature analysis based. Therefore, Feature analysis is found in the Chapter 3 in details. Feature analysis based face detection has main four steps i.e.
Haar Feature Identifying, Integral Image Calculation, Adaboost Algorithm to Bring Efficiency and Cascaded Classifier for Detection Haar Feature.

2.1.2 Image Based Face Detection

In image-based face detection system, a learning algorithm like artificial neural network, support vector machine and other algorithms use whole image for learning. Sometimes for rotation of a face feature of faces cannot be found. Although some feature-based face detection system also considers rotational calculation still they suffer from rotation of faces. For that reason, image based attracts some researchers. This approach eliminates some modeling errors. It is more generalized method. For training purpose many images including having different rotational faces is used. Template matching is the simplest image-based face detection method. But the method doesn't perform well as some complex computational systems like neural network based face detection system. Neural network based face detection system got good accuracy but it sacrifices computational time.

Neural Networks

This process is done by two steps. Firstly, lot of images are used for training the networks. Then trained network works as a face filter. Usually the network is trained with fixed size images; usually 20×20-pixel resolution. To detect faces from anywhere of the input image the filter is applied to every location of the input image. To detect faces different sizes the filter is scaled up and scaled down different multiple such as 5×5-pixel, 10×10-pixel, 20×20-pixels, 30×30-pixel etc. This computation generates much time complexity; thus, neural network based face detection need higher time complexity. The detection process is shown in the Fig. 2.3.

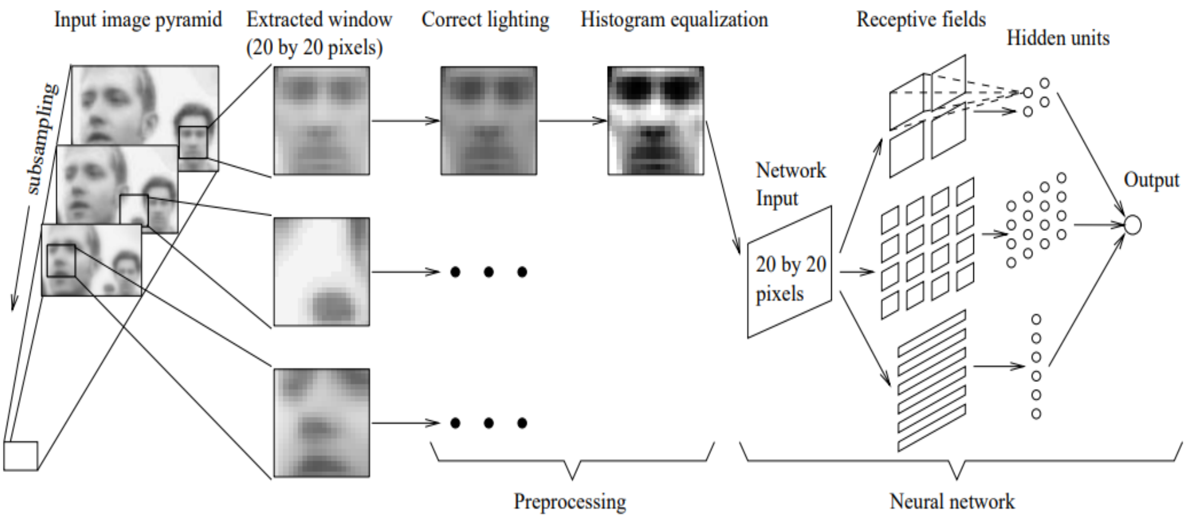


Figure 2.3: Neural network-based face detection [61].

Linear Subspace

Eigen vector is used here for representing human face. In the research work of Turk and Pentland they represented face by eigen vector and named the linear face array “Eigenfaces”. The basic vector is constructed by Principle Component Analysis (PCA). Initially PCA constructs the “Eigenfaces” having the same dimension of original face image. After that PCA reduces the dimensionality in single K-dimension. A sample image having dimension m×n to mn×1 conversion is presented in Fig. 2.4. The similarity of faces is calculated by Euclidean distances.

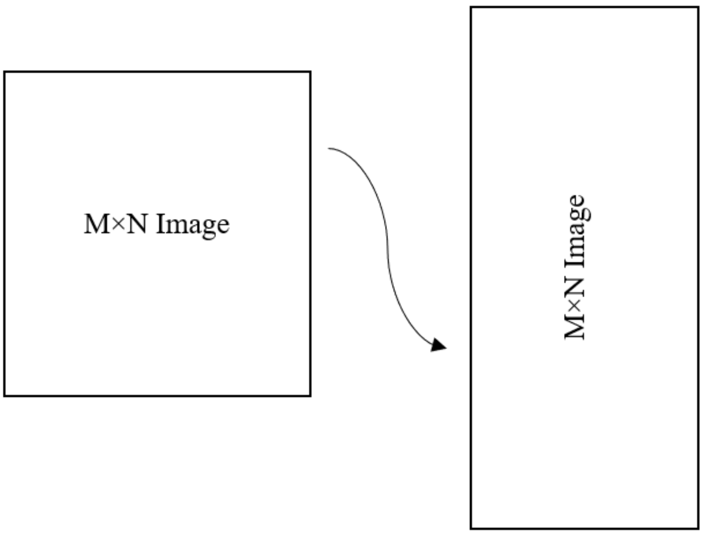


Figure 2.4: Conversion of m×n image in mn×1 image.

Statistical Approach

There are several statistical methods for face detection such as Principal Component Analysis (PCA), Support Vector Method (SVM) etc. All of those methods work with Eigenfaces. SVM is a binary classification method used for finding optimal surface minimizing structural distortion. Details face detection by SVM is found in [15].

2.2 Improved Face Detection Methods incorporating Human Skin Color Detection

There are several standard and hybrid human skin color detection methods. Combining more than one standard human skin color detection methods, some researchers proposed some hybrid skin color detection methods. This section first discusses about four widely used standard skin color detection methods. Then three hybrid skin color detection methods are discussed.

2.2.1 Face Detection with Standard Human Skin Color Detection

There exist several human skin color detection methods. Among those, four methods are found prominent and used in many studies: three use RGB color space and rest one uses YCbCr color space. RGB color model is very easy to understand where R, G and B represent the value of red, green and blue components respectively of a pixel. The range of R, G and B component is 0 to 255. On the other hand, YCbCr color space is the transformation of RGB color space. The brief descriptions of the four widely used standard skin color detection methods are given below.

RGB with Specific Values

It is the most popular skin color detection formula and is investigated and used in several recent studies [46, 47]. In the method, a pixel that represents human color will hold the property of:

$$(R > 95) and\ (G > 40) and (B > 20) and\ (\max(R, G, B) - \min(R, G, B)) > 15\ and\ (|R - G| > 15) and\ (R > G) and (R > B) \tag{2.3}$$

In this study, this method is investigated with various types of images having different illumination intensity. It is found that this method works quite well for the images having bright illumination condition but suffers when the images are darker.

Normalized RGB Ratio

The normalized RGB method to detect human skin color is proposed by Gomez and Morales (2002) [48]. According to the method, a pixel color will be considered as human skin color if it has the property of

$$\frac{r}{g} > 1.185 \; and \; \frac{(r*b)}{(r+g+b)^2} > 0.107 \; and \; \frac{(r*g)}{(r+g+b)^2} > 0.112 \qquad (2.4)$$

where *r*, *g* and *b* are normalized form as:

$$r = \frac{R}{R+G+B}$$
$$g = \frac{G}{R+G+B}$$
$$b = \frac{B}{R+G+B}$$

This approach differs from previous method altering specific RGB values with their normalized ratios in color matching conditions. The RGB values of a dark skin will be less than a brighter skin; thus, equations with specific RGB values for detecting bright skin color will not be able to detect dark skin color. Similarly, equations with similar manner for detecting dark skin color will not be able to detect bright skin color. Authors mentioned that this method worked well for all types of illumination condition. But according to our investigation, this method performs average for all light conditions and different skin colors and it suffered to detect dark face and face under low light.

Simple RGB Ratio

Recently, Asif et al. (2016) investigated the simplest way to detect human skin color [1]; a pixel will be human skin color if:

$$R > G > B \qquad (2.5)$$

Authors worked with all range of skin and all illumination conditions. This simple RGB ratio method works much better than other methods in low light and for dark skinned people. However, it is found that the method works slightly badly in comparison with specific values method in case of bright illumination.

YCbCr

Kukharev Georgy et al. (2004) used YCbCr color model to detect human skin color [49]. The Y represents luminance information; and the chrominance information are found in the chrominance blue (Cb) and in the chrominance red (Cr). RGB components are converted into YCbCr components according to the following formulas.

$$Y = 0.257 \times R + 0.504 \times G + 0.098 \times B + 16$$
$$Cb = -0.148 \times R - 0.291 \times G + 0.439 \times B + 128$$
$$Cr = 0.439 \times R - 0.368 \times G - 0.071 \times B + 128$$

Finally, a pixel color will be considered as human skin color if it holds the property of:

$$(Y > 80) and\ (85 < Cb < 135) and (135 < Cr < 180) \tag{2.6}$$

The equation was built from only 25 people of different skin color except black skinned [49]. Therefore, it is expected that this equation might not work well for dark illumination condition and for dark skinned people. In our investigation, the model is found slightly better than normalized RGB model but slightly worse in compare to specific RGB model where light condition is good and people is not black. The model also fails to detect dark skinned face and face under low light.

2.2.2 Face Detection with Hybrid Human Skin Color Detection

Several hybrid skin color detection methods are proposed combining two or more standard skin color detection methods in purpose of face detection. Among them popular three are analyzed in this study.

Hybrid Method 1: RGB + YCbCr

Georgy and Nowosielski (2004) used this hybrid skin color detection method in their research which is combination of a set of RGB rules and a set of YCbCr rules [49]. In the rule, a pixel that holds human skin color property will satisfy the following rules:

$$(R > G)$$
$$and$$
$$if (G > B) then\ (12 \times G - 7 \times B \leq 5 \times R)\ else\ (12 \times B - 7 \times G \leq 5 \times R)$$
$$or$$
$$(135 < Cr < 180) and\ (85 < Cb < 135) and\ (Y > 80) \tag{2.7}$$

This method is implemented in this study and performance evaluated on three benchmark datasets.

Hybrid Method 2: Red + HSL

Berbar (2014) proposed a hybrid skin color detection method which used four components to detect human skin color [50]. The four components are hue (H), saturation (S), lightness (L) and red value (R). Color of an area or a pixel is described by hue; intensity of the color is described by saturation; and brightness is described by lightness. A pixel having position *p(i,j)* holds human skin color property if:

$$H[i,j] < 24 \; and \; R[i,j] > 125 \; and \; S[i,j] > 20 \; and \; L[i,j] > 80$$
$$or$$
$$H[i,j] > 185 \; and \; R[i,j] > 155 \; and \; S[i,j] > 20 \; and \; L(i,j) > 114 \quad (2.8)$$

This method is not implemented in this study but compared with proposed method. For comparison we used performance measurement values of that research paper [50].

Hybrid Method 3: RGB + YCbCr + HSV

Yadav and Nain (2016) investigated a more complicated hybrid skin color detection method [51]. Authors tested the method on different datasets and found to make very impressive result. Skin color filtering formula of this method as follows:

$$V = [R, G, B]$$
$$(R > 95) \cap (G > 40) \cap (B > 20) \cap (\max(V) - \min(V) > 15) \cap (abs(R - G) \geq 15) \cap (R > G) \cap (R > B)$$
$$and$$
$$(Y \geq 80) \cap (10 \leq Cr \leq 45) \cap (85 \leq Cb \leq 135)$$
$$and$$
$$(0 < H < 35) \cup (325 < H < 360) \cap (0.2 < S < 0.6) \cap (V \geq 20) \quad (2.9)$$

To evaluate our proposed method, it was tested with those datasets. Details result is presented in the experimental result and analysis section.

2.3 Observation from the Existing Methods

Standard skin color detection methods have distinct properties and a particular method works well for a certain condition as we discussed in the previous section. Therefore, incorporation of a standard method with HFFD is not very effective to increase face detection accuracy for images with different illumination conditions. On the other hand, existing hybrid skin color detection methods hold different consequences in face detection due to establishment with relational operators (e.g., “and”, “or”) among the standard human skin color detection methods [46-49]. We have carefully noticed that use of “and” relational operator among them increases true negative, i.e., detector cannot detect a true face. On the other hand, use of “or” increases false positives, i.e., detector identifies a pattern as a face which is not a human face. Besides, it is noticed that different illumination conditions can be existed different images of a particular problem or dataset and even in same image at different portions. Thus, such ideas of using different methods based on illumination are not too much fruitful when illumination condition are not predefined. Therefore, a robust face detection which might work well in different illumination conditions is an open challenge; and in this study, the challenge is carefully addressed and tackled with a new hybrid skin color detection method.

Chapter 3

Robust Face Detection using a Novel Skin Color Matching

A robust face detection method might work well on images with different illumination conditions. To develop such robust face detection method, existing skin color detection methods are investigated with popular face detection method HFFD. It is found that RGB with specific values and standard HFFD together outperformed others methods for light condition is good or human face is white and suffers when light condition is low or human face is dark. On the other hand, HFFD and simple RGB ratio together perform much better comparing to other methods when light condition is low and human face is dark. To overcome those issues, a new hybrid skin color method based face detection is proposed taking the complementary strength from both. The proposed method works differently to the different area of images according to their illumination intensity. There are two major steps in the proposed robust face detection method. Firstly, preliminary face detection is done by standard feature matching. Here we considered HAAR features for face detection purpose. Secondly, preliminary detected faces are filtered by proposed hybrid human skin color matching method. Human skin color matching will reduce many false detections which are preliminarily detected as human faces in the first phase. The following sections describe the steps briefly.

3.1 Preliminary Face Detection by Feature Matching

There are many tools for different types of object detection. OpenCv is one of them. OpenCv is very popular and it can detect any types of objects including human faces. Currently OpenCV is using a cascaded classifier named “Haar Cascaded Classifier” for face detection. The word “Haar” came from Haar wavelet in mathematics. In mathematics, the Haar wavelet is a sequence of rescaled "square-shaped" functions. The Haar sequence is proposed by the scientist Alfred Haar. In object detection Haar feature is similar to Haar wavelet. Haar feature is like rectangular pattern in any object image. To make the cascaded classifier recognize an object, it is needed to train the classifier with a lot of images (positive images) containing particular object like face or others we are interested to be detected, scaled to same size like 20x20 resolution. It is also needed to train the classifier with some arbitrary images (negative images) that does not contain that particular object like face or others of same resolution. After the training is done, the classifier captures frequently happening pattern or features. Then the classifier can detect the similar object it is trained with form an image or video stream. There are many pre-trained classifiers for detecting face, nose, eye, upper body, smile, etc. Next two sections will describe the feature selection process and the detection process of a human face.

3.1.1 HAAR Feature Selection

HAAR features are digital image features used for object detection from any digital image. In image processing it is needed to work with image intensities of each and every pixel of an image. But working with each pixel (i.e., the RGB pixel values) is very computational expensive. Key advantages of Haar feature finding is its very good calculation speed because it uses a computational method called “Integral Image”. Haar features which are used for face detection is presented in Fig. 3.1. Human facial features can be represented with these rectangular haar features very well. Figure 3.2 shows similarity with three haar features and eye area, nose area and mouth area of a human face.

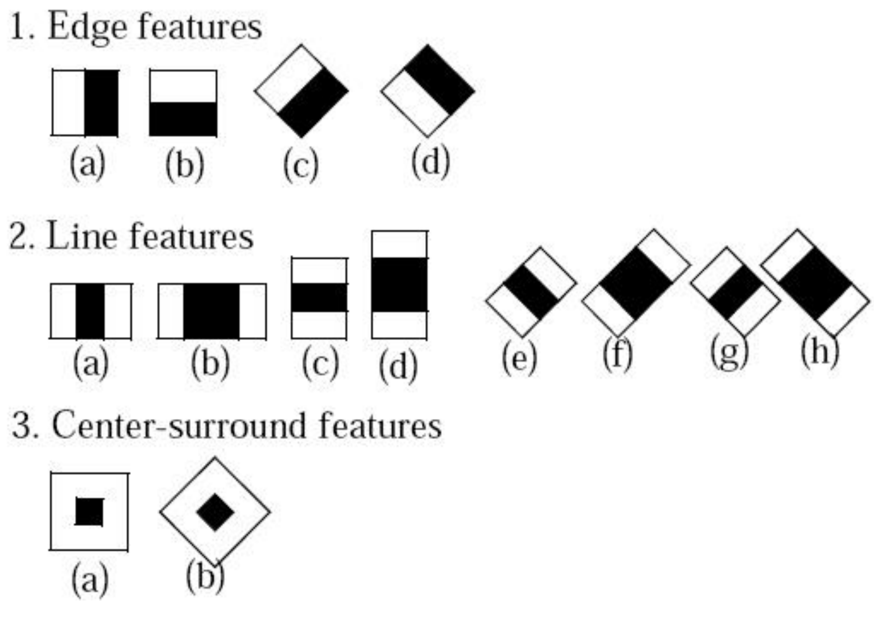


Figure 3.1: Haar features used for face detection.

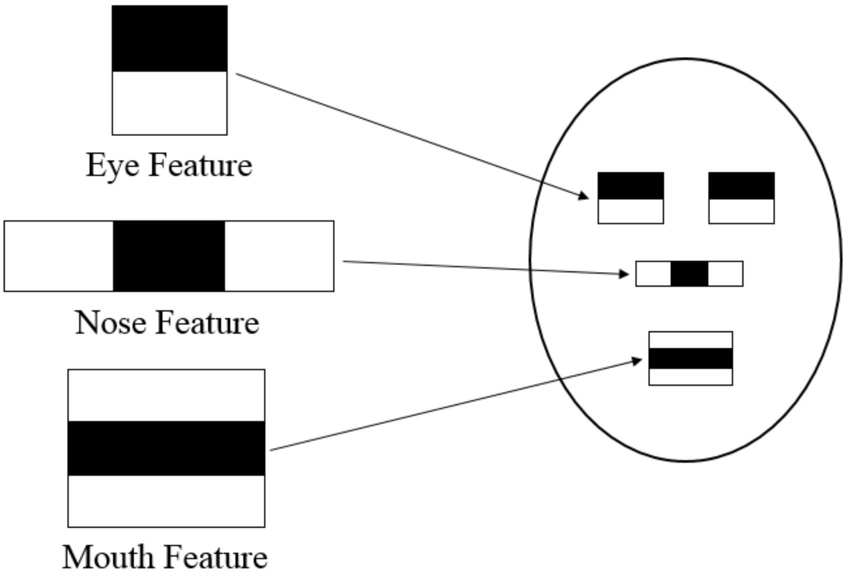


Figure 3.2: Example of three most important rectangular features used for detecting human face.

The classifier finds the features across the detector window. Face position can be anywhere in the picture and face size also varies with the image size. Therefore, the detector window of the classifier can be scaled at any size and can be moved to the any position. Scaling the image has too much computational complexity therefore the detector window is scaled up. The window is moved left to right and upper to down across the whole picture. The classifier finds the haar features throughout this detector window. All of the haar features can be in the image at any scaled. Therefore, classifier have to find the features at many multiply according to image size. If we consider 24x24 resolution detector window, the edge feature 1(a) have to be searched at 2x2 scaled. Then the same feature has to be searched at 4x4, 8x8 and so on. The classifier has to search other haar features in the same way. Therefore, the combination of the features, positioning, scaling become very large; thus, incurs a very high computational cost. This cost is reduced by a technique called "Integral image" which will be discussed later.

To detect a rectangular Haar feature (F) from an image, the sum of the pixel intensity under the shaded rectangles (P_s) were subtracted from the sum of pixels under the white rectangles (P_w).

$$F = P_w - P_s \tag{3.1}$$

If result is positive or above some threshold value, it was considered as a facial feature. Otherwise it is not considered as a facial feature.

Computational cost of finding all of the necessary facial features is very high for a large image. "Integral Image" makes the process of finding the feature value much efficient. It is an intermediate representation of an image in which a location (x, y) contains the sum of the pixel values above and to the left of (x, y), inclusive:

$$I(X,Y) = \sum_{x' \leq X \; y' \leq Y} I(x', y') \tag{3.2}$$

$$Sum\ of\ pixel\ values = I(C) + I(A) - I(B) - I(D) \tag{3.3}$$

Where points A, B, C, D belong to the integral image I, as shown in the Fig. 3.3.

To find the rectangular feature value in the dotted area in Fig. 3.4 with the help of integral image, calculations are as follows.

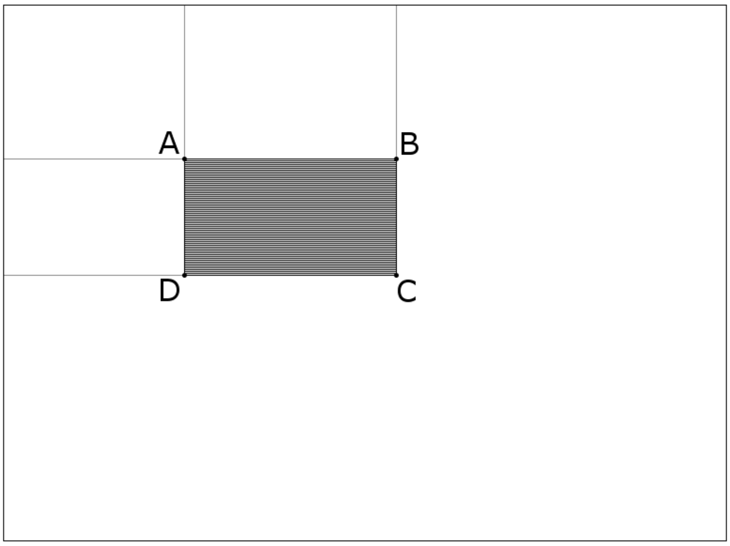


Figure 3.3: Finding pixel values in the shaded area.

Area X = Sum of pixel intensities in the rectangular area from the left-top corner to pixel X.

Area A = 29

Area B = 29+17+18 = 64

Area C = 29+27 = 56

Area D = 29+17+18+27+23+19 = 133

Area E = 29+27+12 = 68

Area F = 29+17+18+27+23+19 +12+45+84 = 274

Sum of pixel values in white area in doted area = (Area C + Area F - Area D - Area E)

= 56 + 274 - 133 - 68 = 129

Sum of pixel values in shaded area in doted area = (Area A + Area D - Area B – Area C)

= 29 + 133 - 64 - 56 = 42

Rectangular feature value in doted area, F = 129 - 42 = 87

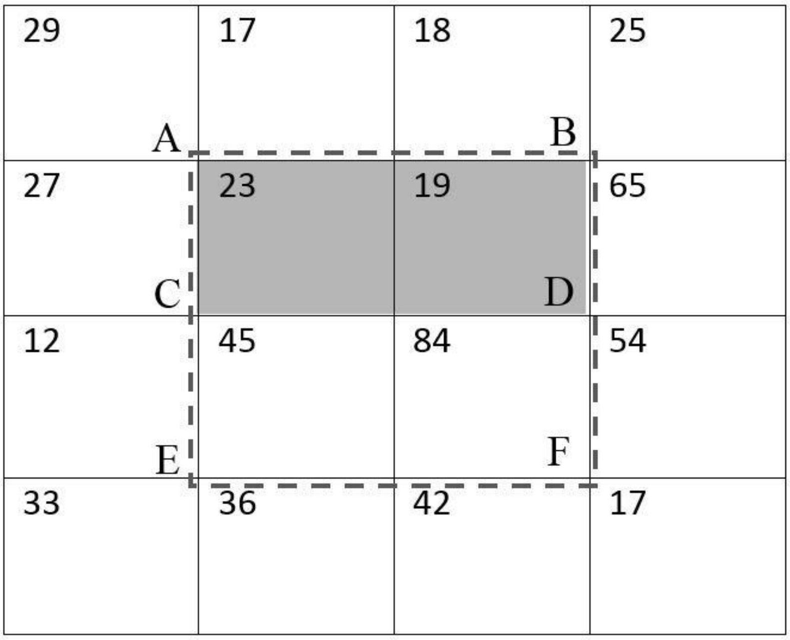


Figure 3.4: Rectangular feature selection from human face.

3.1.2 Face Detection through Cascade Classifier

For 24x24 resolution image there can be found 160,000 features. Adaboost has narrowed down the number of features to a few hundred (frequently happening features). The classifier has 38 layers which are in cascaded style. This cascaded classifier detects facial feature of frontal upright faces. In the cascaded structure 38 classifiers are placed in the hierarchical srtucture. The frontier classifiers are trained with most important features. First and second important feature are shown in Fig. 3.5. First layer classifies only one most important facial feature. Second layer finds out next 10 important features. Third, fourth and fifth layers of the cascaded

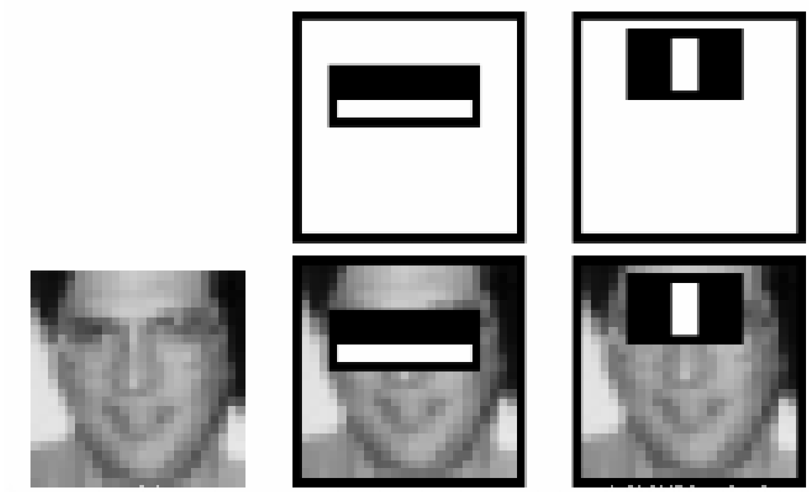


Figure 3.5: The first and the second features selected by Adaboost.

classifier can detect 25, 25 and 50 facial features respectively. Finally, to detect a face from an image, classifiers were applied one by one. If a classifier fails at the first stage, it is discarded and no more classifier is applied on that region of the image. If a classifier finds the features it trained with, then the next classifier is applied on it. If all the facial features are found by the cascaded classifiers then output is positive (i.e., there is a face in the image) otherwise output is negative. The advantage of the cascaded classifier is that it can discard an irrelevant window without matching with all of the features. Figure 3.6 shows the structure of cascade classifier.

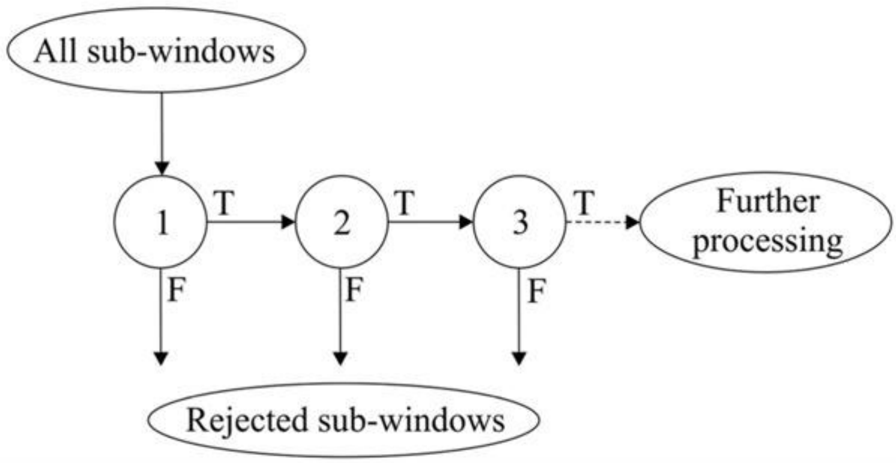


Figure 3.6: Facial feature finding through cascade classifiers.

3.2 Elimination of Wrong Faces by a Novel Hybrid Skin Color Matching Method

The outcome of HFFD is considered as the preliminary faces which might contain false positives. Human skin color matching formulas are applied on those regions which are detected as preliminary face by standard HFFD to discard false positives. As matching every pixel with human skin color criteria is much time consuming, this method selects pixels at 5-pixel interval throughout the detected face area by Rectangular HAAR-like feature process. Then the color matching is done for selected pixels. If more than 50% of the selected pixels satisfy the color matching criteria, then it is considered as a true face otherwise not. 100% of pixels do not satisfy human skin color because of the existence of some other parts like beard, eyes, mustache etc. It is very hard to tell how much portion (%) in human face contain human skin color property because it varies person to person. Some people keep beard. Obviously, the portion of human skin color in their face is less than the people who doesn’t keep beard. If we set the value too high, it might cause some true face cannot be detected. On the contrary if we set the value too low then it might cause some false regions be detected as human faces. Beside HFFD worked with rectangular shaped sub-window where human face is round shaped. Therefore, definitely there will be some non-face region (around 20% related to the shape of a face) around the human face. Considering all those aspects, maximum 50% of pixels is allowed to not satisfy human skin color property. Average light intensities throughout those preliminary faces are considered for selecting appropriate color filter for filtering them. Light intensity (L(pi)) of a pixel (p) having index number (i) is found by the equation (3.4) [29]. And the average light intensity R(Lav) of a region (R) having (n) number of pixels is found by the equation (3.5). MAX pi (R, G, B) returns the maximum value among R, G and B of a pixel (p) having index number (i). MIN pi (R, G, B) returns the minimum value among R, G and B of a pixel (p) having index number (i).

$$\boldsymbol{L(p^i)} = \frac{\text{MAX pi (R,G,B)+ MIN pi (R,G,B)}}{2} \tag{3.4}$$

$$\boldsymbol{R(L^{av})} = \frac{\sum_{i=0}^{n} L(pi)}{n} \tag{3.5}$$

If average light intensity is high Rule 1 (RGB with Specific Values) will be used as color filter. Otherwise Rule 2 (Simple RGB Ratio with a minor modification) will be used for filtering preliminary detected faces. This minor modification of Simple RGB Ratio makes the detection process more accurate. This modification is brought after analyzing it with many faces containing complex images. Rule 1 and Rule 2 are found by the equation (3.6) and equation (3.7) respectively.

Rule 1 (HFFD-RGB**):**

$$(R > 95) and\ (G > 40) and (B > 20) and\ (\max(R, G, B) - \min(R, G, B)) > 15\ and\ (|R - G| > 15) and\ (R > G) and (R > B) \tag{3.6}$$

Rule 2 (Modified HFFD-S-RGB-R**):**

$$(R > G > B) or\ (R > G > \max(B - 10{,}0)) \tag{3.7}$$

A threshold value for light/illumination intensity is chosen, under that ‘Simple RGB Ratio’ with a minor modification will be used (as it performs much better comparing to others) and above that ‘RGB with Specific Values’ will be used (as it is good at bright illumination condition). The threshold value of light intensity is tuned very carefully for the best outcome. Fine tuning for this threshold value is also provided in the experimental result and analysis section. From this experiment the best result is found when the light intensity threshold value is set 35. Flowchart and algorithm of proposed robust face detection method is presented later.

3.3 Flowchart

Consideration:

$F_{p(I)} = I_{th}$ number of preliminary detected face region

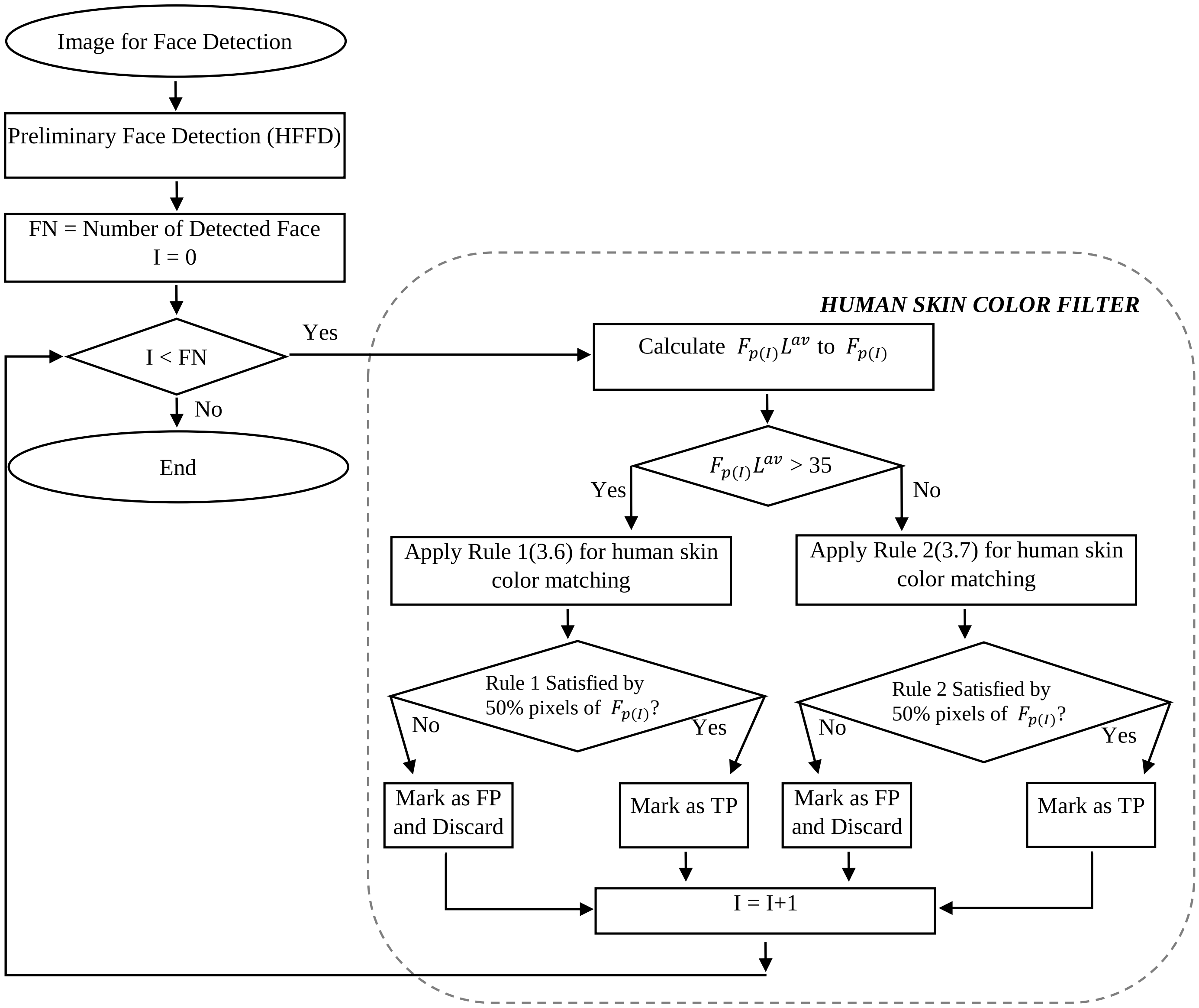
$F_{p(I)}L^{av}$ = Average light intensity of I_{th} preliminary detected face

FN = Number of preliminary detected face

I = Increment variable

TP = True Positive

FP = False Positive



An image may contain multiple faces. Therefore, it is needed to work with each preliminary detected face to find out whether it is a true face or not. In the very first step, input image is passed through the Haar cascaded classifier. The cascaded classifier finds faces preliminarily in that images. Number of faces in an image is denoted as FN in the flowchart. Then human skin color filter is applied to each of the (among the total FN number of faces) preliminarily detected faces. In the color filtering process at first the average light intensity $F_{p(I)}L^{av}$ of I_{th} (among the total FN number of faces) preliminarily detected face $F_{p(I)}$ is calculated. If $F_{p(I)}L^{av}$ is greater than 35, rule 1 (3.6) is applied for the filtering process to the face $F_{p(I)}$. Otherwise rule 2 (3.7) is applied for color filtering process. If preliminarily detected face $F_{p(I)}$ satisfy the color filter criteria then it is count as true face, otherwise it is marked as false positive. This way for each preliminarily detected face the same thing is done to make sure that it is a true human face.

3.4 Algorithm

Step 1: ***Preliminary Face Detection*****:** facial feature finding from an image.

Step 2: ***Light Intensity Calculation:*** calculate average light intensities $\int_{i=1}^{i=n} F_{p(i)}L^{av}$ among the preliminary detected face $F_{p(i)}$ having index number i.

Step 3: ***Human Skin Color Matching:***

If $F_{p(i)}L^{av}$ >35 apply $Rule$ 1 to $F_{p(i)}$
$Else$ apply $Rule$ 2 to $F_{p(i)}$

Step 4: ***True Positives and False Positives Detection:***

If 50% of the selected pixels of $F_{p(i))}$ satisfy human color matching rules mark $F_{p(i)}$ as true positive $F_{p(i)}$
$Else$ mark that preliminary detected face as false positive $F_{p(i)}$.

Step 6: ***False Positive Removal:*** Discard all false positives $F_{p(i)}$

In the Section 3.4 the algorithm of proposed method is given. In the step 1 preliminary detected faces are found out by finding Haar features in input image. In the step 2 average light intensities among the preliminary detected faces are calculated. In the step 3 human skin color filtering process are done to those preliminary detected faces accordingly their average light intensities. If average light intensity is found higher than 35, rule 1 of color filtering is applied to that preliminary detected face, otherwise rule 2 is applied on that preliminary detected face. In the step 4 true positives and false positives are detected. If 50% of the pixels in a face area satisfy human skin color filter, that face is marked as true face and for below 50% it is marked as false positive. Finally, in the step 6 all false positives are discarded.

Chapter 4

Performance Evaluation

This section investigates the effectiveness of four standard and three hybrid human skin color-based methods of face detection on a large number of images along with new proposed method. For better understanding standard HFFD without skin color incorporation is also considered. The section first explains the experimental setup and benchmark datasets which are used in this study. Illumination intensity threshold value selecting and the experimental results are presented later.

4.1 Experimental Settings

All the experiments were implemented by Java programming on NetBeans 7.4 IDE. Experiments have been conducted on a single machine (Dell OptiPlex 3050, Intel (R) Core i5 CPU 3.40 GHz, 4 GB RAM) with 64 bit Windows 8 Professional OS. The widely used OpenCv library is used for implementing HFFD. OpenCV uses the cascade classifier named lbpcascade_frontalface for frontal face detection.

4.2 Datasets

Four popular image databases, Caltech database [53], Put Face database [54], Bao database [55], Muct database [56] are considered in this study. There were total 450 images containing 466 human faces in Caltech Dataset. The height of each image was 896 pixels and width of each image was 592 pixels. On the other hand, Put Face Database has 10 frontal face dataset each contains around 10000 images. Each image contains one face. 10 datasets have around similar illumination condition and properties. So that we have considered one of them. The dataset we have considered is named “Images_031_040”. There were total 1028 images containing 1028 human faces. The height of each image was 2048 pixels and width of each image was 1536 pixels. In the Bao database we have found two set of images. In one set there was 221 multiple face containing images having 1206 human faces. Among the 1206 faces 1152 are frontal faces. Rest of the faces were partial faces having different orientation angle. In that set images have different size. In Bao database another set contains 149 images. In each image there was only one human face. There were 122 frontal faces among 149 images. Sizes of the images are also different here. In the Muct database there were 5 sets of images. Each set contains 751 images of same type having different rotation angle of face. We have used only the set named “muct-a-jpg-v1” which has only frontal face as we used frontal face detection classifier of OpenCV “lbpcascade_frontalface”. The height of each image was 640 pixels and width of each image was 480 pixels. Many of the images were in artificial bluish lighting effect. Therefore, many of them lost original human color property. We have also made a Self-prepared Dataset containing especially black skinned people. The images were randomly collected from internet. There were 20 images of different resolutions containing 310 human faces. Those were very critical images from which detecting face correctly by any method is a challenging task because there was different illumination to the different part of an image and there was combination of different skinned color people in a single image.

4.3 Fine Tuning of Illumination Intensity Parameter

We will present those incorporations of skin color detection methods with HFFD by following short forms for better representation from here to the rest of the manuscript.

HFFD-RGB: HFFD + RGB with Specific Values

HFFD-N-RGB: HFFD + Normalized RGB Ratio

HFFD-S-RGB-R: HFFD + Simple RGB Ratio

HFFD-YCBCR: HFFD + YCbCr

Setting up this threshold value of average illumination intensity is very important for the best performance. This threshold value is chosen from 0 to 100 for finding the best value. This investigation is conducted on three datasets (Caltech database, Put Face database and Self-prepared database) as they covered a good variety. Step by step this threshold value is incremented by 5 the result is plotted in Fig. 4.1. From this experiment it is clearly observed that proposed face detection method performs the best for all the dataset when the threshold value is set 35. To the x-axis illumination rate threshold value is presented and to the y-axis accuracy is presented. Blue line is for Caltech dataset, Red line is for Put Face dataset and green line is for Self-prepared dataset. We can see that, for the Caltech dataset we got the highest accuracy (91.93%) when the illumination threshold value is set to 35. For Put Face dataset we got the accuracy maximum (95.55%) when the illumination threshold value is set 0 to 55. The reason behind this situation is that this dataset contains the images which have very high illumination intensity (normally more than 55) and clean backgrounds. That is why it is likely that HFFD-RGB will perform better. Till threshold value is set to 55 that means almost all images will be filtered by HFFD-RGB. As a result, we have found maximum accuracy for the threshold value 0 to 55. For the Self-prepared dataset we also found the maximum accuracy for the threshold value 35. In the self-prepared dataset the images were darker. That is why it is likely that HFFD-RGB will not work well on this. Setting the threshold value low means filtering most of the images by HFFD-RGB. For that reason, we can see the accuracy grows gradually as the threshold value increase till 35.

Another experiment was conducted for this purpose. Some variety of images have been chosen for this experiment. Brighter images were darkening gradually and found out at which value of illumination intensity HFFD-RGB fails to detect face but HFFD-*S-RGB-R* can detect face. And for darker images the images were made lighten gradually and found out at which value of illumination intensity *HFFD-RGB* start detecting faces from the images. In this experiment we also found that bellow the illumination rate around 35%the *HFFD-RGB* do not work well. For a sample image the output of this process is presented in the Fig. 4.2. Red rectangles are the outcome of standard HFFD. Green rectangles are the outcome of *HFFD-S-RGB-R* and the yellow rectangles are the outcome of HFFD-RGB. The average illumination rate in the detected region by standard HFFD is shown to the left-top corner on each image. The initial average illumination intensity was 62.7142. This average illumination intensity is decreased gradually. It is observed that both of the methods can detect face till the average illumination rate is above 31.658. Bellow that average illumination rate HFFD-RGB cannot detect faces from images but *HFFD-S-RGB-R* still can detect face till average illumination rate is 2.5394. This experiment

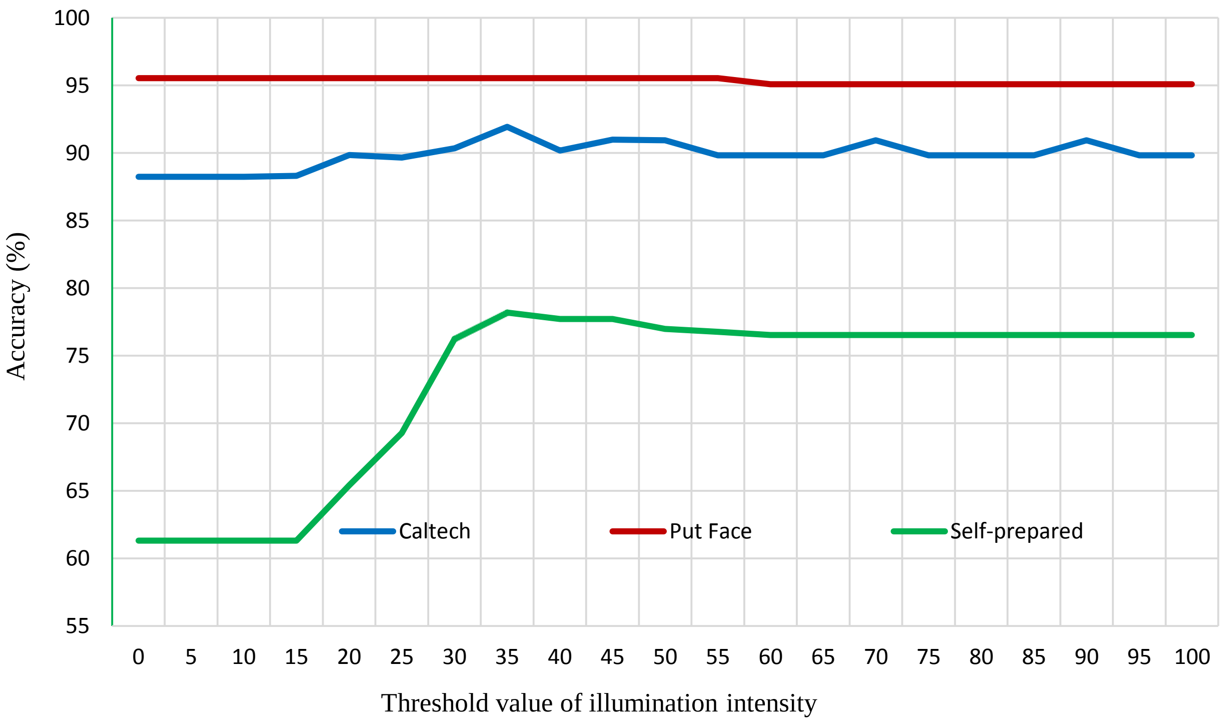


Figure 4.1: Accuracy analysis and fine tuning of the threshold value of illumination intensity parameter.

shows that proposed technique is able to detect faces form very low light images. Usually images have illumination intensity far above than 2.5394. So that it is a very optimum choice to set the illumination rate threshold value 35.

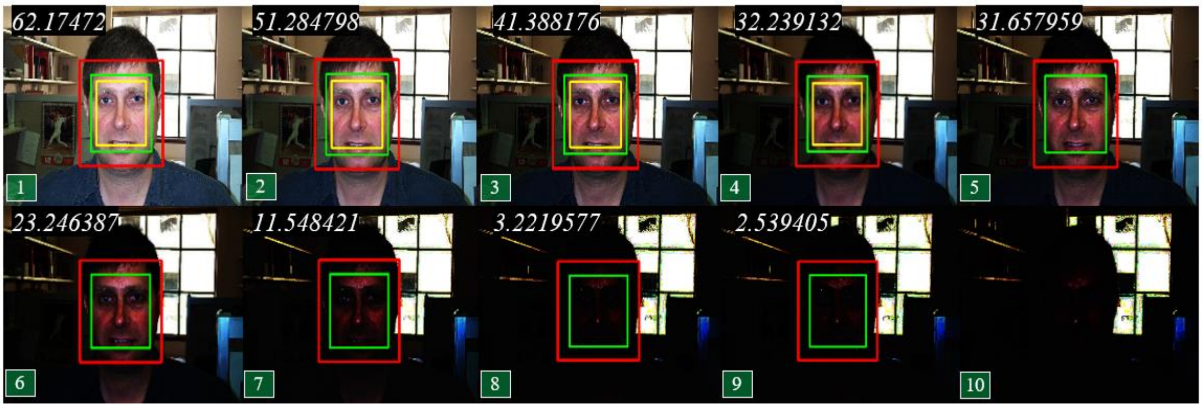


Figure 4.2: Observation of the behavior of HFFD-RGB and HFFD-S-RGB-R on a sample image by gradually darkening it (none of them can detect face when light intensity is less than 2.539405).

4.4 Demonstration of Face Detection with a Sample Image

For better understanding the whole face detection process was explained in Fig. 4.3. In the first step original image is passed through cascaded classifier. Preliminarily face detected image is generated by Cascaded classifier by facial feature matching (standard HFFD). Red rectangles are the results of standard HFFD. In Fig. 4.3 it is seen that in the sample image there are 5 real faces. Standard HFFD detects 7 faces in the sample image which are marked as F1, F2, F3, F4, F5, F6, F7. In the second step average light intensities among the standard face detected area are calculated. Average light intensities in F3, F6 and F7 below 35. Therefore, Rule 2 was applied to filter them. But only F3 satisfied Rule 2 and therefore marked as green rectangle. F6 and F7 did not satisfied Rule 2. Light intensities in F1, F2, F4 and F5 are above 35. Therefore, Rule 1 was applied for skin color matching to them. F1, F2, F4 and F5 satisfied Rule 1 and thus marked as yellow rectangles. Then the proposed system successfully removes these 2 false positives.

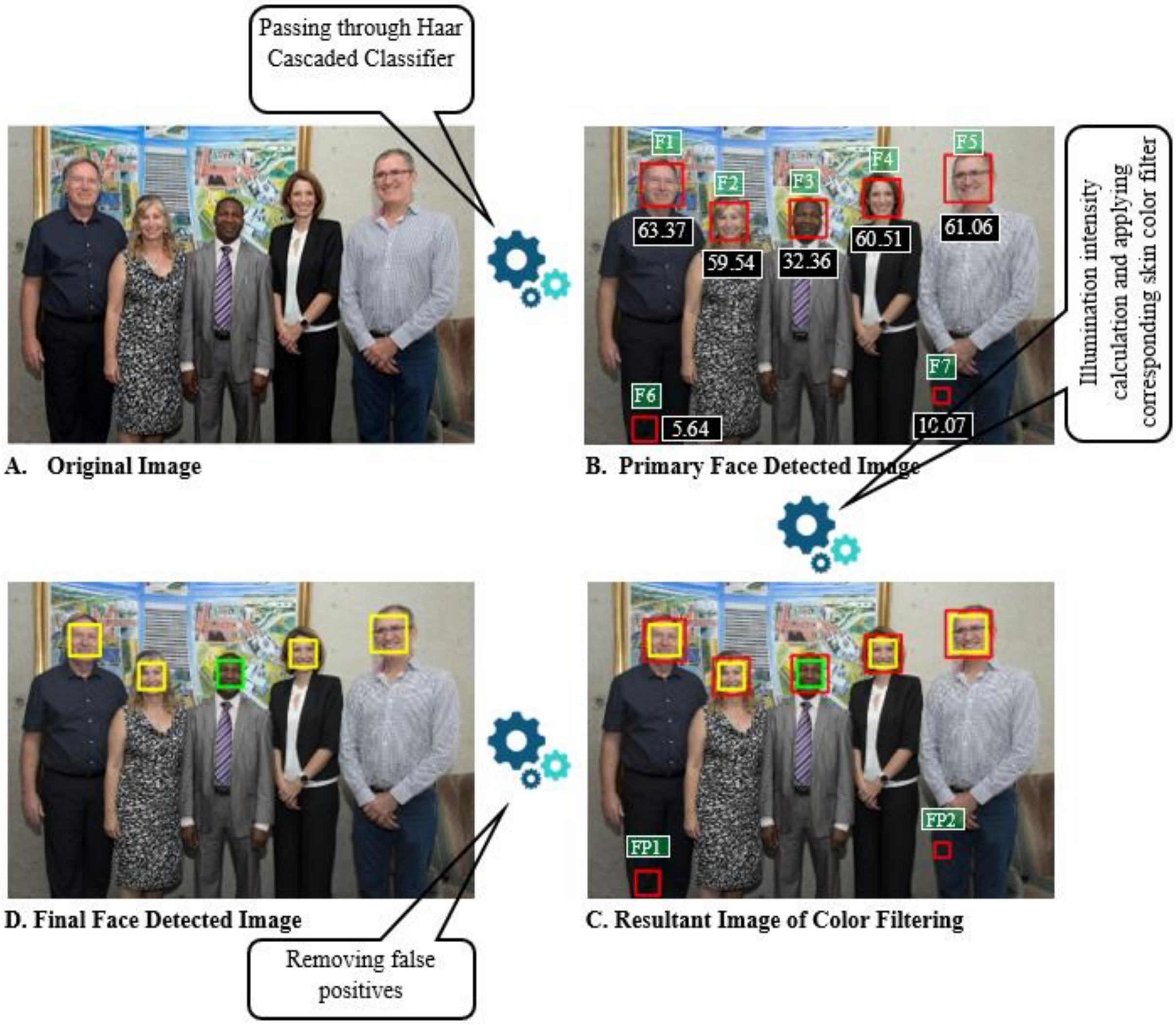


Figure 4.3: Demonstration of proposed face detection method step by step. Red rectangles are the results of preliminary face detection by HFFD; yellow and green rectangles are the results of color filtering by rule 1 and rule 2 respectively.

4.5 Experimental Results and Analysis

Performance measurement of those methods are presented by True Positive (TP), that means detector output is positive (detects a face) and which is a true face, True Negative (TN), that means detector result is negative (does not detect any face) but there is a true face exists, False Positive (FP), that means detector output is positive (detects a face) which is false (actually there exist no face). Accuracy measurement is found by the following formula.

$$Accuracy = \frac{\text{TP}}{\text{TP+FP+TN}}$$

4.5.1 Comparison with Methods having Standard Human Skin Color Detection

It is noticed that most of the methods suffer especially for dark people and low light condition. Our contribution is designing a skin-color-based face detection method which can detect dark skinned face very accurately as well as not degrading detection process for bright skinned people. Surprisingly it is found that proposed method improves face detection process from images having all variety skinned of face and almost all range of illumination intensity.

Three databases are used here having different type of images for proper evaluation. Put database contains images having high resolution. Caltech data base contains images having standard images. And Self-prepared database contains images having people of dark skinned and under lowlight conditions. This section depicts the strength and limitations of several standard human skin color detection methods especially. Details result is presents in Table I. Performance measurement of proposed method is also presented for understanding the improvement of proposed method. Performance measurement is presented separately for each database. Sample resultant images of each database is presented later. There are 4 sample resultant images for Caltech database and Put database and 1 sample image for Self-prepared database as it contains many faces. Red color is used to present standard HFFD. Yellow, Orange, Blue and green color represent HFFD-RGB, HFFD-N-RGB, HFFD-YCBCR, HFFD-S-RGB-R respectively. And purple color is used to represents proposed method.

Comparison on Caltech Database

Although TP value of standard HFFD was good but its FP was very high which decreases its accuracy. HFFD detected 457 faces truly from 466 and made 70 false positives. Proposed method is found the best because it was able to detect 435 faces correctly with only 18 false positives and 31 true negative and the accuracy is 89.88% which is the highest among others methods. Standard HFFD get the accuracy 85.26% which is 4.62% less than proposed method. Here HFFD-RGB was a close competitor of proposed method for this dataset. It has 6 less false positives but 11 more true negatives. It gets accuracy 88.7% on Caltech dataset. The result of other methods is also shown in table I. But they are not competitor of proposed method at all for their much lower accuracy. Figure 4.4 shows the performance measurement with a histogram presentation on Caltech database. Four sample image of Caltech database is shown in Fig. 4.5.

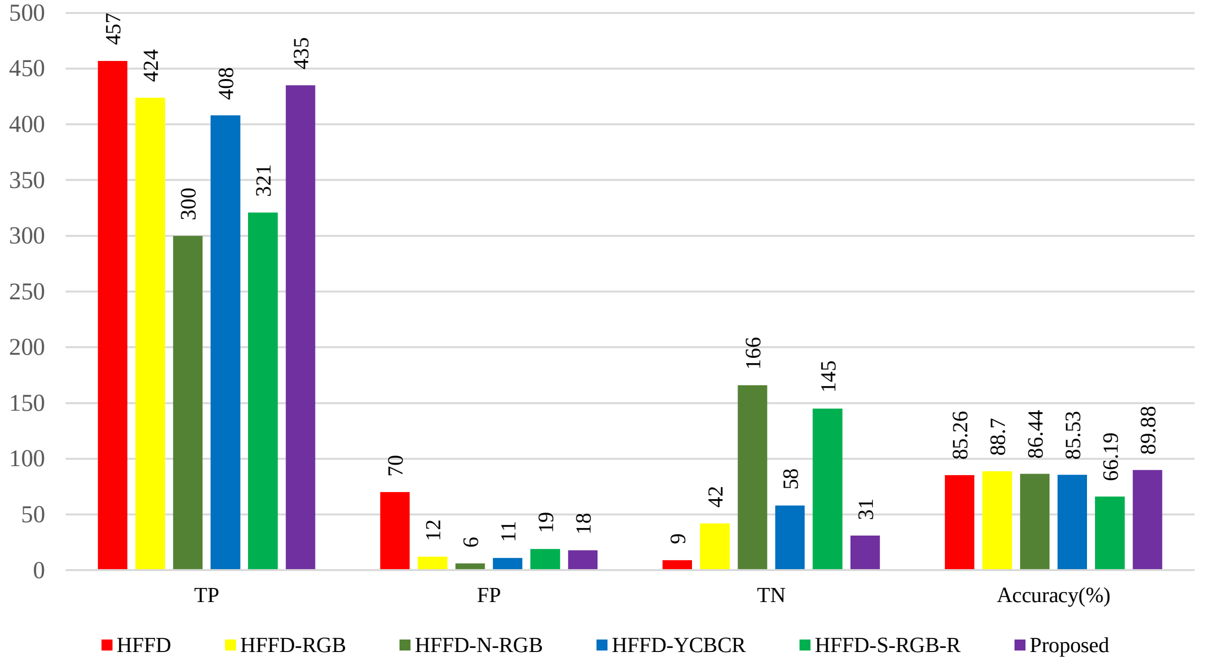


Figure 4.4: Performance measurement of five standard methods with proposed method on Caltech database.

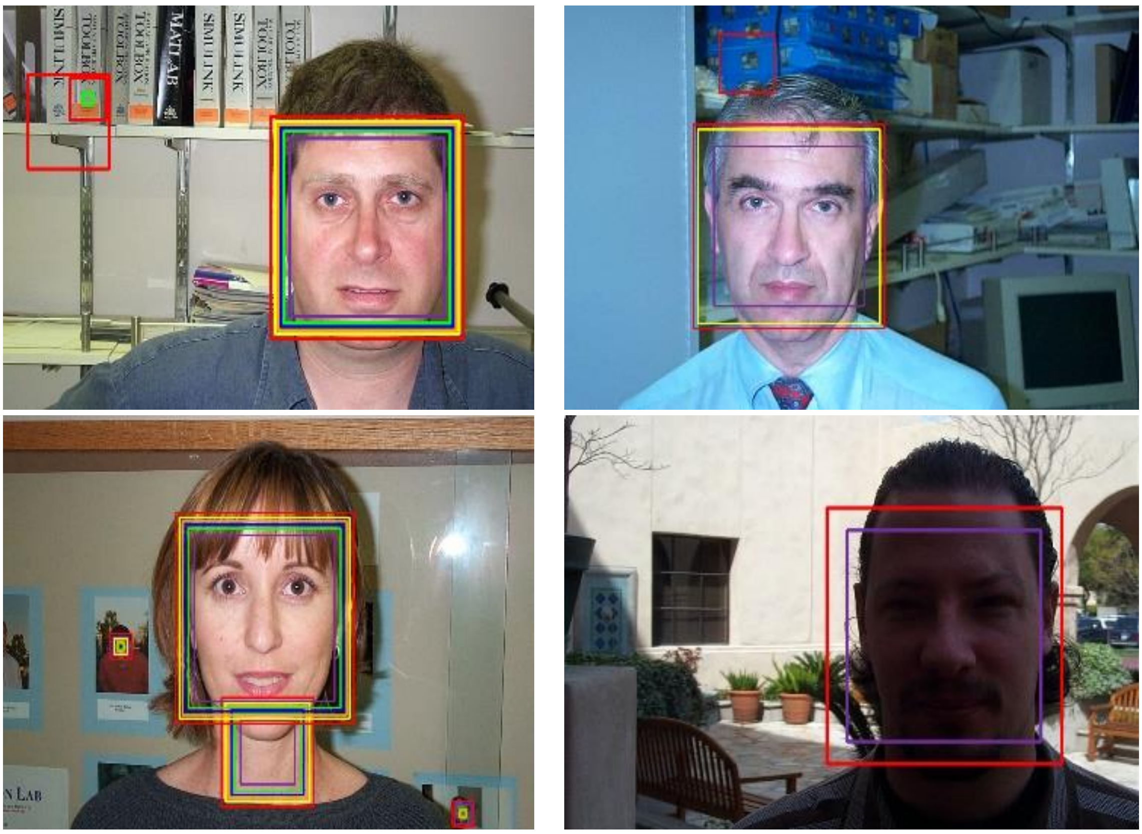


Figure 4.5: Four sample face detected images by five standard methods with proposed method from Caltech database.

Comparison on Put Face Database

The images of this database were very clean and the illumination condition is very good. Therefore, all the methods perform very well except standard HFFD and they are closely to each other. Only standard HFFD makes a lot of false positives for this database. Here HFFD-RGB and proposed method show the height accuracy. All of the methods except HFFD-N-RGB makes 1008 true positives among 1028 faces. HFFD-N-RGB makes 1004 true positives. Here it is noticeable that standard HFFD makes 240 false positives where other methods make false positives less than only 33. Thus, standard HFFD shows the lowest accuracy (79.50%). Proposed method shows the accuracy 95.55%. Figure 4.6 shows the performance measurement with a histogram presentation on Put database. Four sample images of Put dataset is shown in Fig. 4.7.

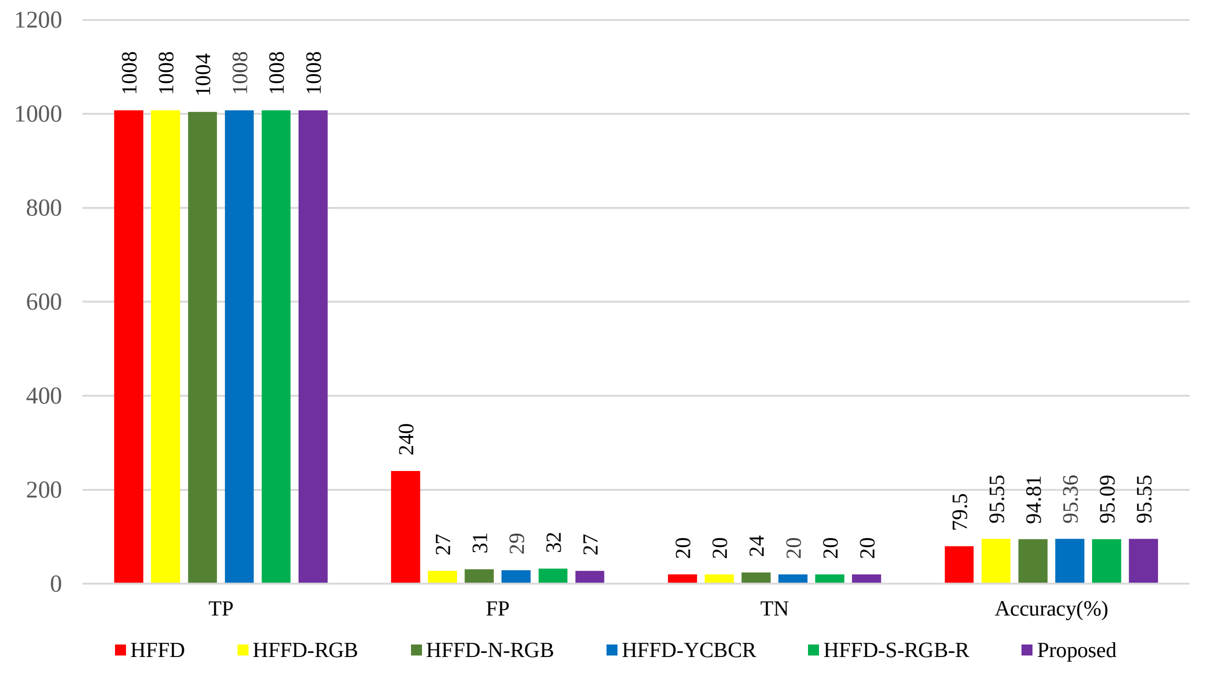


Figure 4.6: Performance measurement of five standard methods with proposed method on Put database.

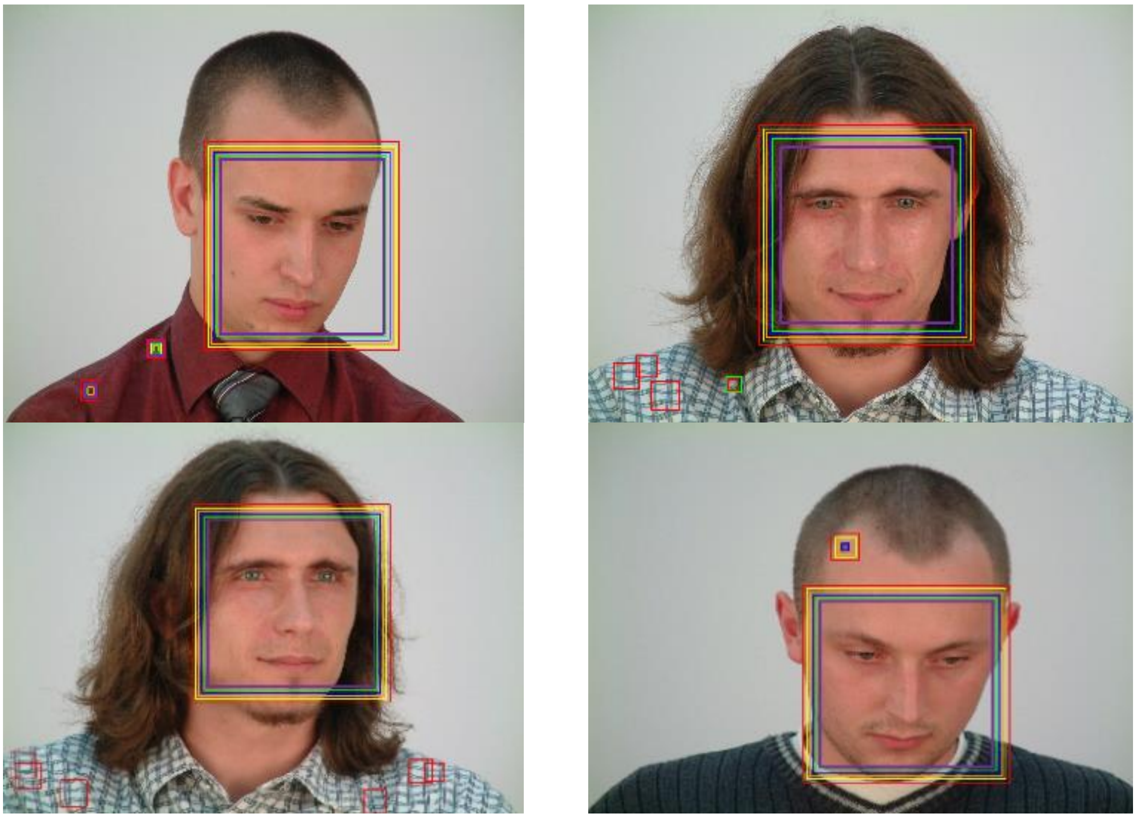


Figure 4.7: Four sample face detected images by five standard methods with proposed method from Put database.

Comparison on Self-prepared Database

It is clearly observed that propose method is much better on this dataset than the others. We have found that all of the color methods suffer for the dark-skinned people and for the low light condition. This phenomenon is clearly observed in the histogram as this dataset contains low light images and images of dark-skinned people. Proposed method has same true positive as the standard HFFD but it minimized false detection rate significantly. Other methods had much lower true positive rate with much higher true negative rate. Proposed method got the accuracy of 84.21%. It got at least 5.6% higher accuracy comparing with other methods. So that it can be said proposed method is a robust system for face detection for all kind of conditions. Figure 4.8 shows the performance measurement with a histogram presentation on Put database. One sample image of Put dataset is shown in Fig. 4.9.

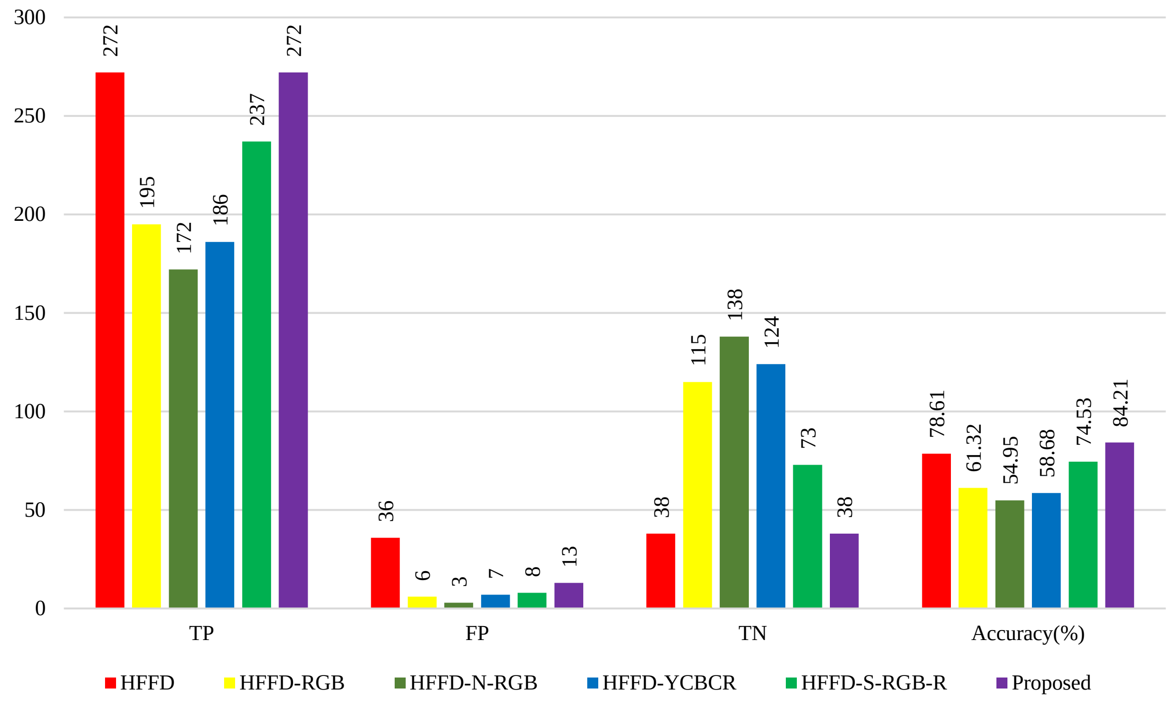


Figure 4.8: Performance measurement of five standard methods with proposed method on Self-prepared database.

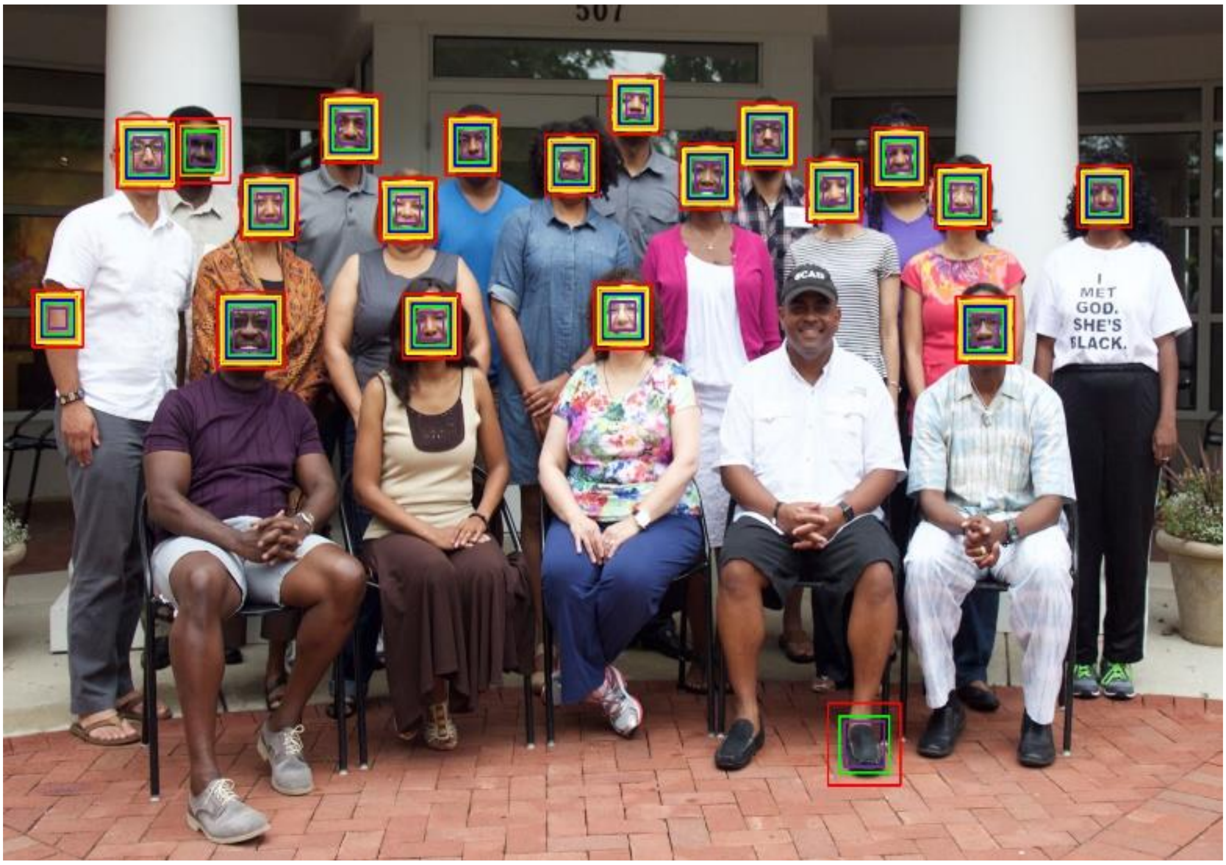


Figure 4.9: A sample face detected image by five standard methods with proposed method from Self-prepared database.

Comparison on Combine Database

However, overall performance of those six methods is also shown in Fig. 4.10. The result of three datasets (Caltech, Put face and Self-prepared) is integrated here. Three dataset contains total 1806 faces. Proposed method truly detects 1715 faces. That means true positive (TP) rate is (1715/1806) % = 95.07%. False positive rate is only (61/1806)% = 3.38% and true negative rate is (89/1806) % = 4.93%. According to those parameters proposed method shows the accuracy 91.96% which is the highest among these six methods. On the other hand, HFFD has slightly better true positive rate (96.28%) and true negative (4.82%) but suffers from very high false positive rate (20.84%) having accuracy 78.96%. Other methods significantly minimize false positives but they make high true negatives and low true positives. HFFD-RGB is the close competitor of proposed method. It got the accuracy 87.99%. Still it got 3.97% less accuracy than proposed method.

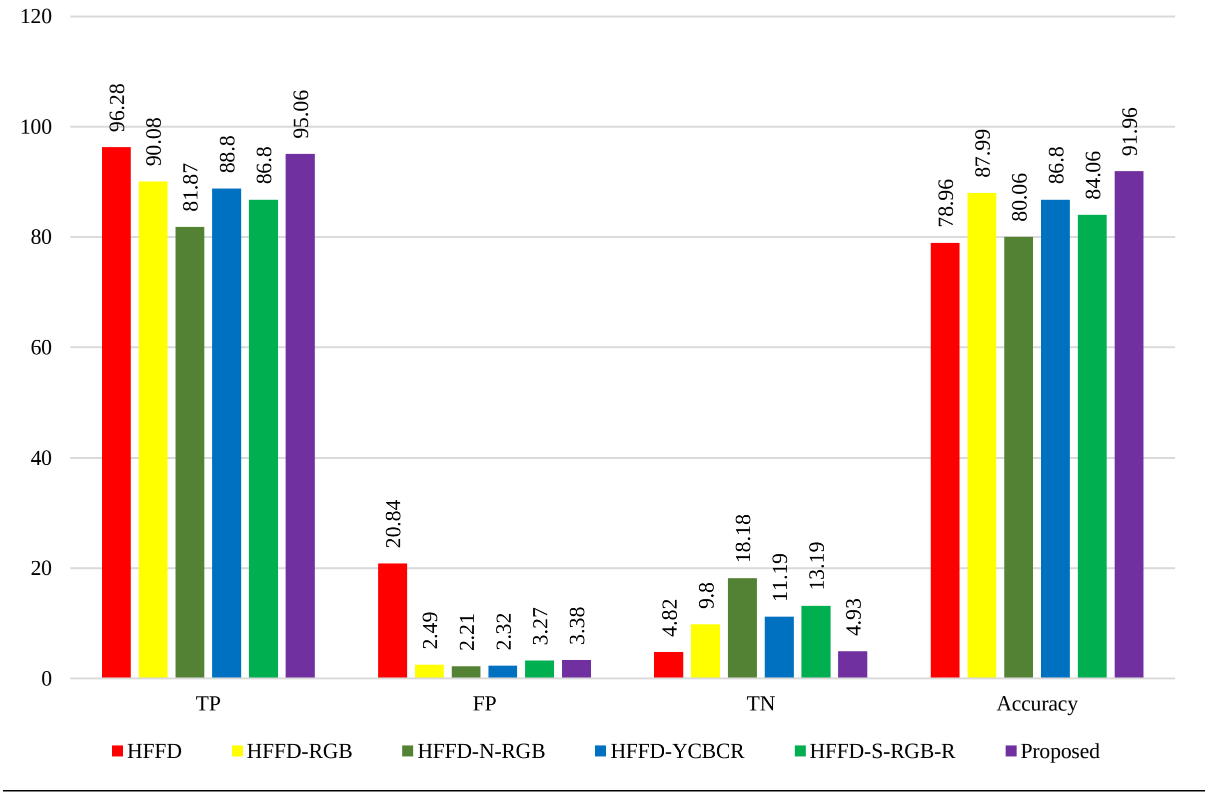


Figure 4.10: Performance measurement (%) of five methods with proposed method on Combine database.

Observation

Three database represents the weakness and strength of different methods very clearly. It is seen that among the standard color detection methods HFFD-RGB performs better for Caltech database which contains standard type of images but suffer for detecting face from Self-prepared database which contains images dark skinned people and images having low illumination condition. On the other hand, HFFD-S-RGB-R work much better than HFFD-RGB on the Self-prepared database but gets lower accuracy than HFFD-RGB for Caltech database. Besides, standard HFFD performs better than the other standard method on Self-prepared database but gets much lower accuracy than other methods for Caltech database and Put database. Therefore, it is clearly understood that no one is winner for all database. Interestingly, we have found proposed method shows the highest accuracy for all those three databases. Therefore, it is clearly understood that proposed method is a balanced face detection method which is suitable all types of image.

Table 4.1: Comparative result of standard human skin color incorporated face detection methods with proposed hybrid method.

Database	Method	TP (%)	FP (%)	TN (%)	Accuracy (%)
Caltech	HFFD	**98.07**	15.02	**1.90**	85.26
	HFFD-RGB	90.99	2.57	9.01	88.70
	HFFD-N_RGB	64.38	**1.29**	35.62	86.44
	HFFD-YCBCR	87.55	2.36	12.45	85.53
	HFFD-S-RGB-R	68.88	4.08	31.12	66.19
	Proposed	93.35	3.86	6.65	**89.90**
Put	HFFD	**98.05**	23.35	**1.95**	79.50
	HFFD-RGB	**98.05**	2.63	**1.95**	95.55
	HFFD-N_RGB	97.67	**3.02**	2.33	94.81
	HFFD-YCBCR	**98.05**	2.33	**1.95**	95.36
	HFFD-S-RGB-R	**98.05**	3.11	**1.95**	95.09
	Proposed	**98.05**	2.63	**1.95**	**95.55**
Self-prepared	HFFD	**87.74**	11.61	**12.26**	78.61
	HFFD-RGB	62.90	1.94	37.10	61.32
	HFFD-N_RGB	55.50	**0.97**	44.50	54.95
	HFFD-YCBCR	60.00	2.26	40	58.68
	HFFD-S-RGB-R	76.45	2.58	23.55	74.53
	Proposed	**87.74**	**4.19**	**12.26**	**84.21**
Combine	HFFD	**96.28**	20.84	**4.82**	78.96
	HFFD-RGB	90.08	2.49	9.80	87.99
	HFFD-N_RGB	81.87	**2.21**	18.18	80.06
	HFFD-YCBCR	88.80	2.32	11.19	86.80
	HFFD-S-RGB-R	86.80	3.27	13.19	84.06
	Proposed	95.06	3.38	4.93	**91.96**

4.5.2 Comparison with Methods having Hybrid Human Skin Color Detection

We have also chosen three databases for comparing proposed method with several existing hybrid methods. Bao database, Muct database and Caltech database were found to be used in several research work those presents several hybrid methods. Therefore, for the fruitful comparison of proposed methods with those existing hybrid methods we also used those three databases. Details result is presents in Table II. Performance measurement of proposed method is also presented for understanding the improvement of proposed method. Performance measurement is presented separately for each database. Sample resultant images of each database is also presented individually. As those hybrid methods were not implemented in this study, only the results of proposed method are shown by purple color.

Comparison on Bao Database

There were total 1206 faces in the multiple face containing set. Among the 1206 faces true positive were 1117 for proposed method. That means proposed method got (1117/1206) = 92.62% true positive rate. Similarly, true negatives were 89 (7.37%) and false positives were 14(1.16%). The proposed method got the overall accuracy 91.56%. For all images of multiple face containing data set method 1 has accuracy 88.62%. Among 1206 faces method 1 makes 1075(89.14%) true positives, 7(.6%) false positives and 131(10.86%) true negatives. But according to research paper [49] method 1 got 92.41% accuracy as it has true positive rate 97.5 %, true negative rate 2.5% and false positive rate 5.5%. They have got the accuracy on only 157 images of Bao face dataset. But there was no clear specification on which 157 images they got this performance measurement as there is more than 157 images in Bao database.

On the other hand, if we consider only frontal face among 1206 faces, we got 94.65% accuracy for the proposed method which is 2.95% higher than method 1 and 2.24% higher than method 3. Proposed method makes 1098 (95.31%) true positives among 1152 frontal faces. True negatives were 54 (4.68%) and false positives were 8 (.69%). Among 1152 frontal faces method 1 makes 1061 true positives, 5 false positives and 91 true negatives.

For the single face containing set of Bao database proposed method got 97.54% accuracy which is .98% higher than method 1 and 5.13% higher than method 3. Among 122 frontal faces proposed method makes 119 true positives, not a single false positive and only 3 true negatives. Among 122 frontal faces method 1 makes 118 true positives, 0 false positive and 4 true negatives. It is clearly seen that proposed method got higher accuracy than method 1 and method 3.

Performance analysis of proposed method with other methods on Bao database is shown in Fig. 4.11. Some sample images of Bao database are shown in Fig. 4.12. Two images of first row are from multiple face containing set and two images of second row are from single face containing set of Bao database. Second image of first row contains partial faces. Therefore, it is likely that proposed system will not detect partial face from images as we used frontal face classifier of OpenCV.

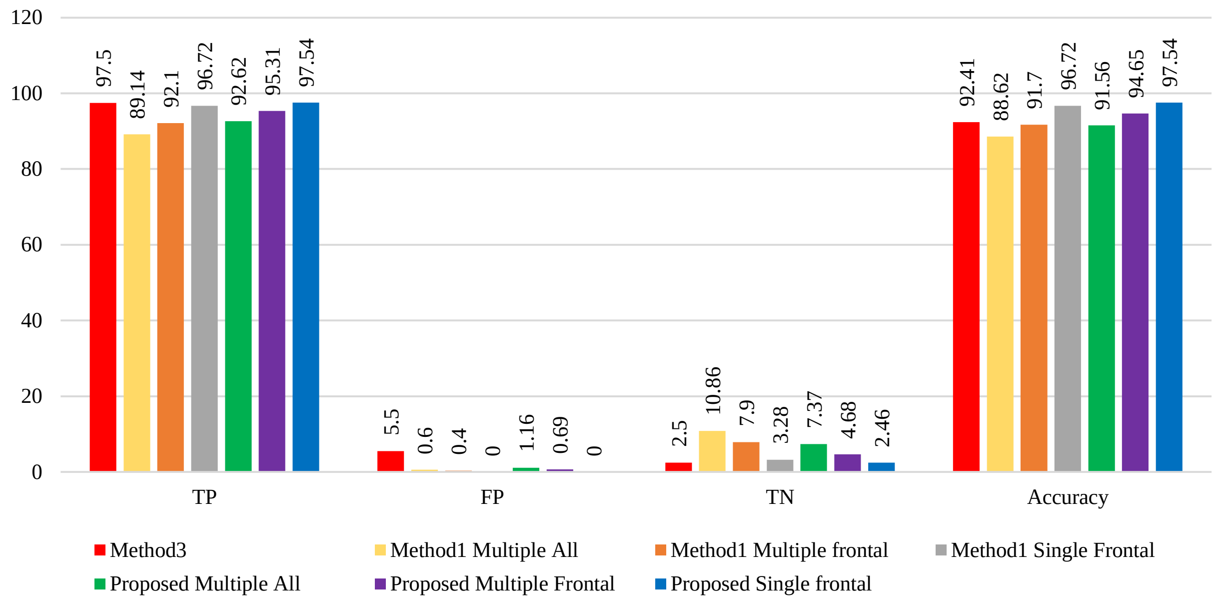


Figure 4.11: Performance measurement (%) of hybrid methods with proposed method on Bao database.

Comparison on Muct Database

As we have already said this database images were distorted by artificial light, we have represented the performance measurement in two class for this dataset. Firstly, performance measurement is done for all of the images without considering the color distortion of the images. Secondly the extremely distorted colored images were not considered for the performance evaluation. In this data set there were 751 images. Among them 27 have distorted extremely and do not holds human skin color properties at all.

Proposed method got the accuracy 93.8% considering all images of Muct database and 97.17% without considering extremely distorted images. Among the 751 faces true positive were 724 for proposed method. That means proposed method got (724/751) = 96.4% true positive rate. Similarly, true negatives were 27(3.6%) and false positive were 21(2.8%). The proposed method got the overall accuracy 93.8%. Discarding extremely distorted images we found 724 images. Among them proposed method made 721 (99.59%) true positives, 3 (.41%) true

Figure 4.12: Four sample face detected images by proposed method from Bao database.

negative, 18 (2.5%) false positives. Method 1 got the accuracy 81.04% considering all images of Muct database and 83.64% without considering extremely distorted images. Method 2 got true positive rate 87.1%, True negative 12.9%, false positive 8.65%. Thus, this method got overall accuracy 80.17%. Here method 3 got 97.27% accuracy as it has true positive rate was 99.6 %, true negative rate was .4% and false positive rate was 2.4%. Accuracy of method 2 for this dataset is much lower than proposed method because this dataset contains many dark faces which were net detected by this method. This hybrid method suffers to detect dark faces because it combines two standard methods with “and “operation among them one is YCbCr method which was previously found badly to detect dark faces or faces under low light.

Performance analysis of proposed method with other methods on Muct database is shown in Fig. 4.13. Some sample images of Bao database are shown in Fig. 4.14. First two are distorted images and third and fourth are normal images. So that it is likely that proposed method will not detect faces from two images of first row as it classifies human skin color very accurately.

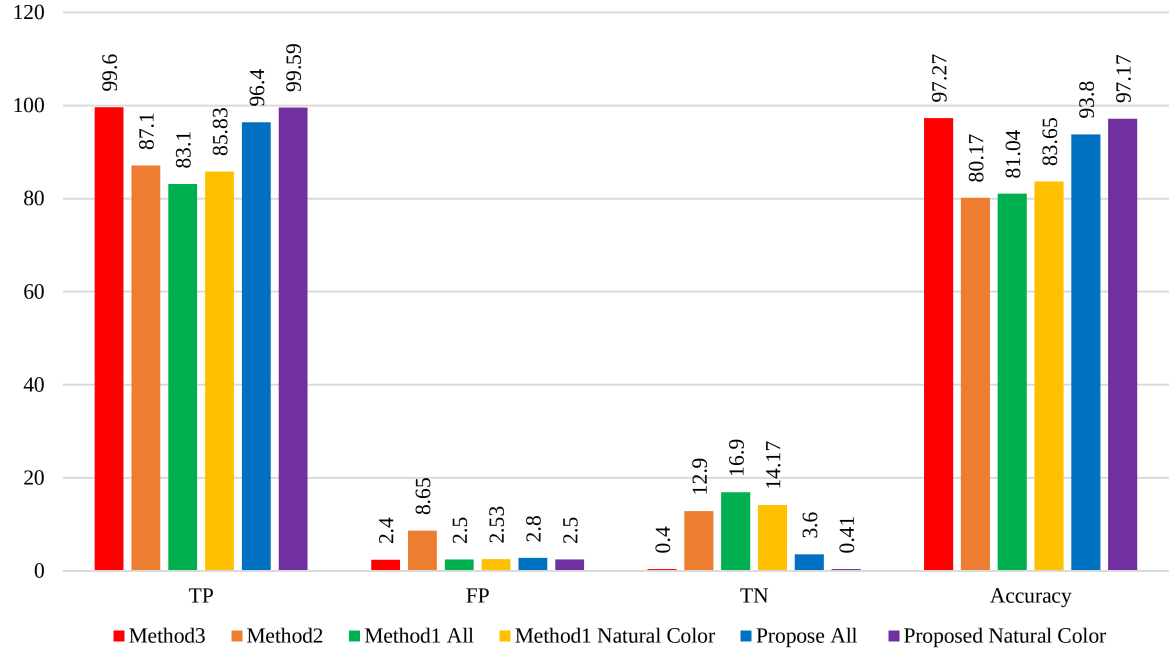


Figure 4.13: Performance measurement (%) of hybrid methods with proposed method on Muct database.

Figure 4.14: Four Sample Face Detected Images by Proposed Method from Muct Database.

Comparison on Caltech Database

Proposed method has 93.35% true positive rate, 6.65% true negative and 3,86% false positive rate. Overall accuracy is 89.9 %. Method 1 got 85.53% accuracy. %. It has true positive rate 87.55%, true negative rate 12.45% and false positive rate 2.36%. Method 2 got the accuracy 88.57%. It has true positive rate 91.1%, true negative rate 8.9% and false positive rate 2.86%. Proposed method has4.37% higher accuracy than method 1 and 1.33% higher accuracy than method 2 for this database. Performance analysis is presented in Fig. 4.15.

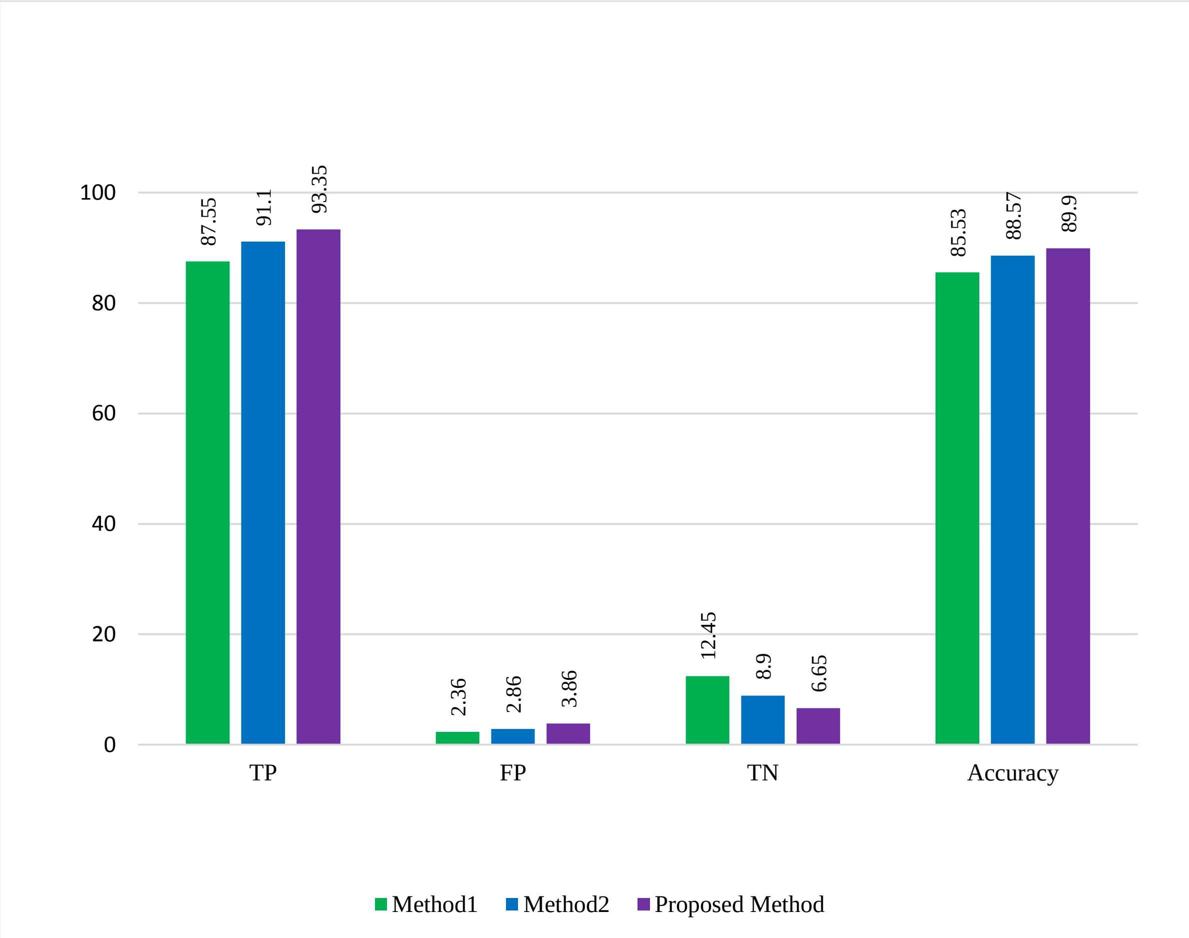


Figure 4.15: Performance measurement (%) of hybrid methods with proposed method on Caltech database.

Observation

From the performance measurement it is clearly seen that proposed method is far better than Hybrid method 1 and Hybrid method 2 for all the dataset from all aspects. If we consider frontal faces and single face containing set of Bao database proposed method shows much higher accuracy than method 3. As we have already said there is no clear specification of which 157 images of Bao database were used to measure the performance of hybrid method 3 [51]. Therefore, it is not possible to draw a clear conclusion that which hybrid method is better. On the other hand, the images of Muct database were distorted from the original color of human skin. Therefore, it is not wise to choose that database to determine the better performer. Still if not considering the extremely distorted images proposed method shows almost similar accuracy comparing with hybrid method 3. In that case proposed method shows .1% less accuracy comparing with method 3. Besides, for hybrid method 3, the performance was not measured for the dark-skinned people and under low light and in this study, it is found that almost all the human skin color detection methods suffer in such condition.

Table 4.2: Comparative result of hybrid human skin color incorporated face detection methods with proposed hybrid method.

Database	Method	Tested Faces Type	TP (%)	FP (%)	TN (%)	Acc (%)
Bao	Method 1(RGB+ YCbCr)	All faces	-	-	-	-
	Method 2 (red + HSL)	All faces	-	-	-	-
	Method 3(RGB + YCbCr +HSV) [51]	All faces (only on nonspecific 157 images)	**97.50**	5.50	**2.50**	**92.41**
	Proposed	All faces	93.07	**1.05**	6.33	92.1
	Method 1(RGB+ YCbCr) [49]	Multiple all faces	89.14	**0.60**	10.86	88.62
	Method 2 (red + HSL)	Multiple all faces	-	-	-	-
	Method 3(RGB + YCbCr +HSV)	Multiple all faces	-	-	-	-
	Proposed	Multiple all faces	**92.62**	1.16	**7.37**	**91.56**
	Method 1(RGB+ YCbCr) [49]	Multiple frontal faces	92.10	**0.40**	7.90	91.70
	Method 2 (red + HSL)	Multiple frontal faces	-	-	-	-
	Method 3(RGB + YCbCr +HSV)	Multiple frontal faces	-	-	-	-
	Proposed	Multiple frontal faces	**95.31**	0.69	**4.68**	**94.65**
	Method 1(RGB+ YCbCr) [49]	Single frontal faces	96.72	**0.00**	3.28	96.72
	Method 2 (red + HSL)	Single frontal faces	-	-	-	-
	Method 3(RGB + YCbCr +HSV)	Single frontal faces	-	-	-	-
	Proposed	Single frontal faces	**97.54**	**0.00**	**2.46**	**97.54**
Muct	Method 1(RGB+ YCbCr) [49]	All faces	83.10	2.50	16.9	81.04
	Method 2 (red + HSL) [50]	All faces	87.10	8.65	12.9	80.17
	Method 3(RGB + YCbCr +HSV) [51]	All faces	**99.60**	**2.40**	**0.40**	**97.27**
	Proposed	All faces	96.40	2.80	3.60	93.80
	Method 1(RGB+ YCbCr) [49]	Natural color faces	85.83	2.53	14.17	83.65
	Method 2 (red + HSL)	Natural color faces	-	-	-	-
	Method 3(RGB + YCbCr +HSV)	Natural color faces	-	-	-	-
	Proposed	Natural color faces	**99.60**	**2.50**	**0.40**	**97.17**
Caltech	Method 1(RGB+ YCbCr) [49]	All faces	87.55	**2.36**	12.45	85.53
	Method 2(red + HSL) [50]	All faces	91.10	2.86	8.90	88.57
	Method 3(RGB + YCbCr +HSV)	-	-	-	-	-
	Proposed	All faces	**93.35**	3.86	**6.65**	**89.90**

Chapter 5

Conclusion

Face detection is a very popular authentication system nowadays. A potential way to improve the accuracy of standard face detection technique is presented in this thesis. A short summary of this thesis work is presented in this chapter. Also, this chapter discusses possible future works based on the outcome of the present work.

5.1 Summary

In this study, different human skin color characteristic measures are incorporated with HFFD to reduce wrong detections. It is found that each color detection method performs well to a specific lighting intensity and for a specific type skin color. Here a new robust face detection method has been proposed which will be effective to a wide range of illumination condition and skin color. We have designed an illumination based generalized method. This method works differently to the different parts of picture according to different illumination rates. This is completely a novel idea. Experiments have been conducted on four benchmark datasets and a self-prepared dataset. From the experimental results it is observed that proposed face detection technique is suitable for detecting face from almost all kind of skin color and illumination intensity.

5.2 Future Scope

Face authentication system is becoming more and more popular day by day. Therefore, there is a huge scope for researchers to work with face detection. Further research scope of this thesis are follows:

We will analyze about the hue factor, saturation factor etc. deeply on images and include that measurements on human skin color detection methods. For more detection rate human skin color correction into face detection method can be introduced. Including edge separation method into face detection method can reduce false positives. In future we will incorporate human skin color detection methods into other traditional face detection methods like artificial neural network based face detection system, template matching based face detection system, SVM based face detection system and many more to find out which one is the best.

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