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A Hybrid Face Detection Approach in Color Images with Complex Background

Esmaeil Kheirkhah* **and Zahra Sadri Tabatabaie**

Department of Computer Engineering, Mashhad Branch, Islamic Azad University, Mashhad, Iran; Kheirkhah@mshdiau.ac.ir

Abstract

Human face detection in colour images has been researched extensively over the past decades. Face detection has several applications in areas, such as security access control, visual surveillance, video conferencing, intelligent human-computer interfaces and content-based information retrieval. An ideal face detection system should detect faces from a given image/video regardless of their poses, illumination, scale, age, race, image quality, and image complexity with optimum speed and very low false-positive rate. In this paper a hybrid approach, based on the skin color information and Adaboost-based face detection, is proposed. The key points of the proposed framework are background elimination and down-sizing using the adaptive skin colour classification and segmentation, as well as sub-window size estimation. Therefore, the skin colour segments, as face candidates, were searched instead of the whole image. Meanwhile, the Viola-Jones Adaboost-based face detector was adopted in this research as the final face detector. In order to test the accuracy of the proposed algorithm, the proposed system was implemented and some experiments were also conducted on the standard image datasets such as Caltech (California Institute of Technology) standard image dataset. The proposed hybrid face detection system was compared with the Viola-Jones face detection system. The experiments showed that the proposed approach could efficiently improve the face detection system in both aspects, namely, accuracy (98.88%) and detection time (259.59 ms).

Keywords: Color-Based, Face Detection, Illumination, Skin Color Classification

1. Introduction

Face detection and tracking have been the topics of extensive research for the past decades. The goal of a face detection system is to detect all faces in a given image and determine the exact position and size of the faces. The development of a robust face detection system is essential in a variety of applications, such as computer vision, robotics, security systems, intelligent human-computer interfaces, video conferencing, and video surveillance. In fact, it is usually the first task performed in a face recognition system. Therefore, face detection has a vital role in ensuring and obtaining good results in the applications mentioned above. However, face detection from a single image is still a challenging task because of the high degree of spatial variability in scale, location and pose (rotated and frontal), facial expression, occlusion, and lighting conditions.

The main problem in developing a robust and reliable face detection system arises from tremendous variability that exists in the overall appearance of a face. Moreover, lighting conditions, noisy images, and complicated background can further increase the complexity of face detection process.

In this paper, a robust Hybrid Face Detection System in color images and complicated background is proposed. It is important to note that accuracy and speed are two significant criteria that are applied in the assessment of the performance of any face detection system. Thus, the proposed system has been found to improve the face detection systems in terms of both accuracy and speed.

*Author for correspondence

2. Related Works

Over the past two decades, there has been a great deal of research interest spanning several important aspects of face detection. Robust segmentation schemes (e.g. those using motion and color information), statistics and neural networks have been widely used for face detection in cluttered scenes at different distances from the camera. Furthermore, numerous advances in the design of feature extractors have been achieved, such as active contours and deformable templates which can accurately locate and track facial features.

Numerous face detection algorithms have been proposed by researchers, each of which has its own advantages and disadvantages. These algorithms may fall into four main categories, namely knowledge-based methods, feature invariant approaches, template matching methods, and appearance-based methods. However, the algorithms are usually extremely time-consuming due to the large amount of numerical computation.

2.1 Knowledge-based Methods

These methods construct rules in relation to human facial features, which are used to detect faces. These rules are based on the researchers' knowledge of the facial features of a human face. Moreover, it is easy to come up with simple rules to describe the features of a face and their relationships. For instance, a face often includes two eyes that are symmetrical to each other, a nose, and a mouth. Moreover, features that are relative to distance and position can be used to construct rules for detecting faces in an image, that is, an image which satisfies these rules can be considered as a human face. Nonetheless, this approach is suitable for frontal faces. The difficulties in relation to these methods is translating human knowledge into known rules and detecting human faces in different poses. Nam et al.[1], Jiang[2], Aasia Khanum et al.[3], and Wang et al.[4] are some instances of this category.

2.2 Feature Invariant Methods

These methods depend on extraction of facial features like skin colour, shape of face or other facial features like eyes, nose and mouth that are not affected by the variation in lighting conditions, pose, and other factors. In particular, human skin colour is an effective feature used to detect faces, although different people have different skin colours. Several studies have shown that the basic difference is based on their intensity rather than their chrominance. However, the accuracy of the skin colour detection is important for face detection[5]. Meanwhile, some edge detection and corner detection techniques are used to detect the features of a face. Among other, the multiple feature methods use several combined facial features to detect faces. First, features like skin colour, size and shape are used to find the face and other detailed features such as eyebrows, nose, and hair are then utilized to verify these candidates.

It is important to note that skin colour detection can be a very challenging task due to various factors which include illumination, camera characteristics, ethnicity and some individual characteristics like age, sex, makeup, hairstyle and glasses. Furthermore, background colours, shadows and motions also can influence skin-colour appearance. Colour spaces and skin colour detection methods are discussed in more details in the subsequent sections. Researches such as Gizatdinova et al.[6], Yan et al.[7], Akagunduz et al.[8], and Liu et al.[9] are fallen in this category.

2.3 Template Matching Methods

Several facial templates or patterns have been created and used as a means to detecting faces. It is crucial to note that the similarities between the facial patterns and input image are computed for detection purposes. Some examples of the features used in the template matching techniques include edge maps and active contours. Meanwhile, the intensity ratio template and deformable templates are examples of classifiers. The presence of the face is inferred based on the geometric relationships of the features.

In another approach, known as the template-based method, shape and appearance models are used. These models are deformable templates that are used to represent faces. The templates are deformed by translation, rotation and scaling. Furthermore, the statistical shape analysis is also used to classify the input pattern. Some examples of this category are Perez et al.[10], Wang et al.[11], Wei Chen et al.[12], Xiaoping Li et al[13].

2.4 Appearance-based Methods

Appearance-based methods adopt machine learning techniques to extract discriminative features from a prelabelled training set. The Eigen-face method is the most fundamental method in this category. These methods are constructed using training images which capture facial variation. Meanwhile, the trained classifiers are used for face detection. In these methods, a predefined standard facial pattern is used to match with the segments in the image to determine whether or not they are faces. The training algorithms are used to classify regions into two classes (face and non-face classes). These techniques have high detection rates but are slower than the feature-based techniques. Neural networks, support vector machine, Eigen-faces, principal component analysis are some examples of appearance-based methods. These approaches have the advantage of being simple to implement, but they cannot effectively deal with variations in scale, pose and shape. Vadakkepat et al.[14], Ruan and Yin et al.[15], Lang and Gu et al.[16], and Pavani[17] are examples of this category.

3. The Proposed Approach

3.1 An Overview of the Proposed Approach

In this section, an overview of the **H**ybrid **F**ace **D**etection **S**ystem (HFDS) is given. In this method, a color-based approach was adopted to find face candidates. Furthermore, an improved appearance-based approach, that is, Adaboost-based face detection system, was also applied to finalize the face detection process. Meanwhile, the block diagram of the proposed approach is given in Figure 1. The HFDS includes two main stages, namely Face Candidates Extraction stage (using skin color), and Face Detection stage. The first stage is intended to extract the regions which have more potential to be faces in the image. In this stage, some significant processes, such as image illumination correction, skin tone extraction, skin region segmentation, and connected component separation, are accomplished. Furthermore, in order to reduce false alarms, background elimination is done in this stage. In the second stage, face candidate segments produced in the previous stage would be processed. First, a set of face candidates would be refined by applying some rules. Subsequently, the final detection process would be accomplished to accurately detect human faces among the refined set of face candidates.

The prominent contributions in this research are as follows:

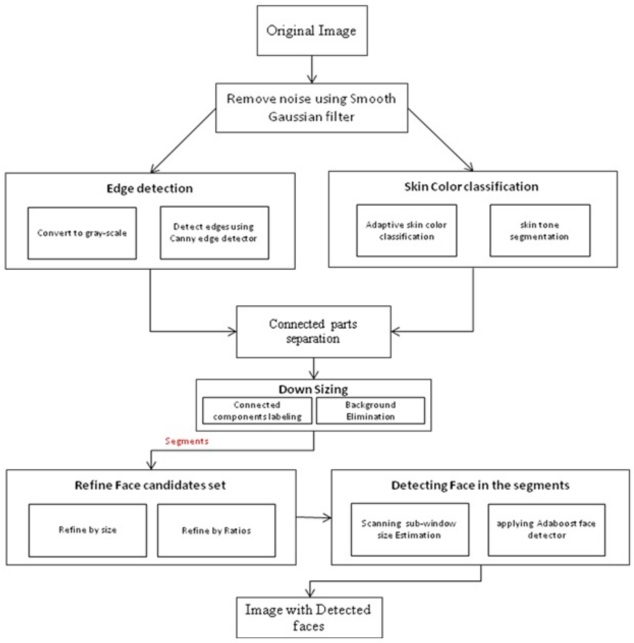

Figure 1. The proposed framework for Hybrid Face Detection System.

- The Adaptive Skin Color Classification (ASCC) method.
- A technique for separating connected components.
- A technique for estimating sub-window size.

3.2 Image Noise Removal

The HFDS adopts skin region segmentation to select face candidates for the subsequent face detection processes. In order to achieve a meaningful segmentation, the incorrect boundaries that were created by noise must be reduced. Several methods have been proposed to remove noises from an image. Among other, the Smooth Gaussian filter[18] was adopted in this research to reduce the negative effects of the noise. It is important to note that the Gaussian filter, that is usually used as a smoother is a linear low-pass filter which can decrease the high frequency, responds and passes the low frequency responses of the input signals.

3.3 Skin Color Classification

The performance of the color-based approaches for face detection was found to have been affected by illumination conditions. Illumination conditions refers to issues like low-illumination, high-illumination, biased lighting, and shadow. In order to cope with this, the Adaptive

Skin Color Classification (ASCC) method[19] which has efficiently increased the performance of the skin color classification is adopted.

The proposed Hybrid Face Detection System uses the skin color as a detection cue. Using this feature, i.e. color, the processing cost can be considerably decreased and the performance of the face detection system can be increased as well. The experience suggests that the human skin has specific characteristics, which are easily recognized by humans. There are several skin color classification techniques which can categorize colors in a given image into skin and non-skin colors. This classification helps the Face Detection System to eliminate the components that are not face exactly. Most of the proposed skin color models work well but in a normal situation, that is, in some cases, skin color may look quite different, depending on illumination, camera settings, shadows, people's make up, people's tans, ethnic groups, and biased lighting. This variation is a challenging aspect of skin color classification.

According to[19], skin color detection starts with checking the pixels to classify them into skin and non-skin pixels using the pixel-based skin color classification technique proposed by Murad Al Haj et al.[20]. According to Murad Al Haj[20], a pixel with R, G, B should be classified as skin, if:

$$R > 75 \text{ and } 20 < R\text{-}G < 90 \text{ and } R/G < 2.5$$

As for the pixels that are classified as non-skin, the ASCC algorithm calculates the average intensity value around the pixel to classify them into either "bright" or "dim" pixels. The "dim" pixels will be further processed and adjusted to be classified as skin or non-skin pixels. Furthermore, the bright pixels with very high intensity will be adjusted and checked to be further classified as skin or non-skin pixels. On the contrary, the "bright" pixels, that are not too bright, are classified as non-skin. Figure 2 illustrates the activity diagram of the proposed Adaptive Skin Color Classification method.

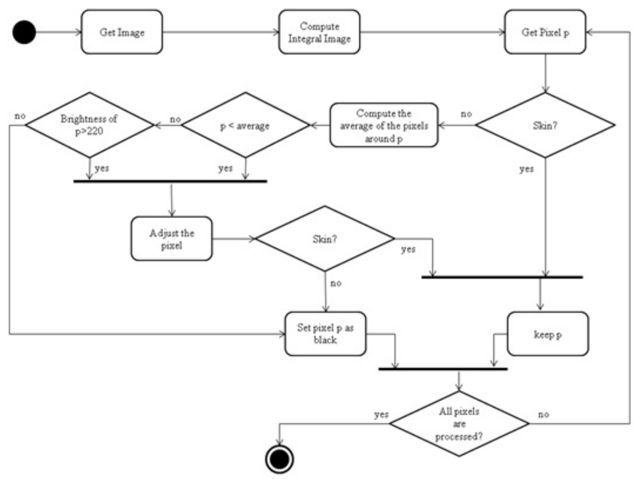

Figure 2. Activity diagram of the ASCC method[19].

3.4 Edge Map Extraction

The edges in an image can be considered as its significant features and thus play a crucial role in the proposed HFDS approach. The edge detection techniques transform images to edge images using the changes of grey tones in the images. Several edge detection techniques have been proposed, such as Sobel, Canny, Prewitt, and Robert's method. The main difference between these methods is the assigned weights of the kernels used to compute the gradients. The Canny edge detector[21] is adopted in this research work. The Canny edge detector is arguably the "best" edge detector. It achieves three useful objectives, namely good localization, good detection, and good representation for locating an object contour. The result of the Canny Edge Detector is an edge map of the image (white) in a black background. The edge map of the image is used in the subsequent steps of the proposed face detection algorithm.

3.5 Connected Components Separation

One of the most frequent challenges in the color-based face detection approaches is the problem of connected components. The connected components make the face candidate regions more complicated because in these cases, several important parameters which are significant for the proposed face detection approach, such as region shape and size, are changed. This problem arises from the contiguity of the face with other faces or other parts of a human body like hands and arms (see Figure 3). Skin-like colors, which do not belong to the human skin in an image, form another challenge which causes the connected component problem. In this case, some objects with skin-like colors from the background are connected to the human skin regions (especially faces) and they strongly affect the face candidates' segmentation results.

In order to solve the problem of connected components, a technique based on the edge map of the images is proposed in this research. In most cases, there are some differences among the intensity of various objects

Figure 3. An example of connected component.

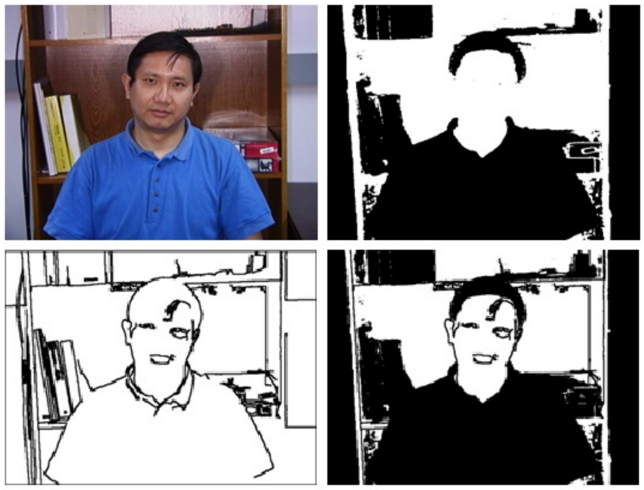

Figure 4. Steps involved in separating connected components.

in a scene. The differences between the intensities of the objects indicate that there are some edges which determine the boundaries among the objects. Using this fact, the connected components can be separated easily. In order to cope with this, the negative image of the edge map, which was extracted in the previous step, is computed first. Moreover, the negative edge map image is refined by applying a morphological operator, that is, erosion. Then, the result is combined with the output of the adaptive skin color classification step using "and" operator. In the combined image, the connected components are separated from each other effectively. This process helps to achieve more adequate face candidate regions, and consequently, increases the accuracy and performance of the face detection system. Figure 4 demonstrates the separation process of the connected components.

3.6 Background Elimination

The proposed Hybrid Face Detection System accelerates the face detection process using skin color feature, that is, the process of face detection is accomplished only in the regions which are classified as skin color instead of the whole image. This particular approach does not only speed up the process of face detection by downsizing, but also eliminates the background of the image.

Downsizing refers to the process of decreasing the scanning area of an image. The face detection systems usually scan the whole image to find faces in the image. Meanwhile, decreasing the search area can effectively reduce detection time. Past experiences show that small area of images often includes human faces. Therefore, skin color can be considered as a very useful feature for this particular purpose.

Background of an image is one of the most significant sources of false positives (detected objects as faces which are exactly not face). Removing the background of an image effectively decreases the false positive rate. Therefore, the accuracy of the face detection system can be increased by eliminating the image background. The human face is the most important object for a face detection system; therefore, any other objects in the image can be considered as background objects. Thus, as an important cue for human face, skin color can help to eliminate background objects for a given image.

Both the above mentioned processes, namely downsizing and background elimination, are accomplished by detecting and keeping skin color pixels and replacing the non-skin pixel with black ones.

3.7 Connected Components Labeling

So far, a binary image which consists of skin color regions as face candidates was created. However, the regions which are distributed in the image cannot be used unless a unique identification value is assigned for each connected skin region or blob. This process is called Connected Components Labelling. The Connected Components Labelling scans the image and classifies its pixels into blobs based on pixel connectivity, i.e. all the pixels in a connected blob share similar label values and are in some way connected to each other.

The connected component labeling works based on scanning an image, pixel-by-pixel, to identify the connected pixel regions, i.e. the regions of adjacent pixels which share the same intensity values. In order to check for the connectivity of the pixels in the connected components labeling method, different measures of connectivity are possible. For the proposed face detection system, however, the binary image and 8-connectivity were assumed. A representation of the labeled image is given in Figure 5.

After labeling the binary image, each blob or segment will have a unique identifier. Using these unique identifiers (labels), each segment can be separately accessed and processed. In fact, these blobs or segments are the actual face candidates for the proposed face detection system.

Considering the fact that each segment must be processed separately as a sub-image, the smallest rectangle which includes the segment has to be computed and obtained. These rectangles are used to copy the parts of the image which may contain a face (see Figure 6).

Figure 5. An example of a labeled image.

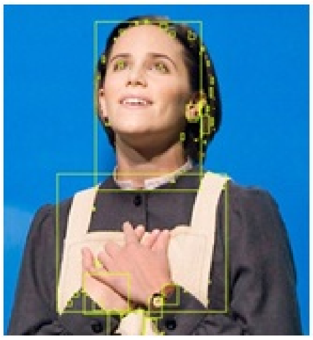

Figure 6. Face candidate rectangles.

3.8 Refining the Set of Candidates

The set of face candidates produced from the previous stages may include some non-faces that can be discarded before applying the final face detector using some rules. These non-face objects can be parts of the human bodies, such as hands, arms, and legs, as well as skin-like objects from the background. In particular, this stage helps the proposed face detection system to get better results in terms of the face detection process time and accuracy by refining the face candidate set. Figure 7 demonstrates such non-face objects.

As can be seen in Figure 7, all the segments are non-face, which differ in their shapes and sizes, except for one face. Most of these non-face objects can be discarded easily by applying some simple rules. Refinement rules can be classified into two categories, namely refinement based on size and refinement based on ratios.

3.8.1 Refinement based on Size

The smallest face that can be detected by the final face detector in the proposed face detection system has the size of 24x24 pixels. Meanwhile, the objects which are smaller than this size are considered as non-face objects. In order to check the size of the objects, the width and height of the rectangle, that include the objects, are taken into consideration. Therefore, most of these non-face objects are eliminated using the following rules:

- Object with WR < 24 and HR < 24 is non-face.
- Object with WR < 24 and HR > = 24 is non-face.
- Object with WR > = 24 and HR < 24 is non-face.

In which, WR and HR are width and height of the rectangle including the object, respectively.

Among the above mentioned rules, second and third rule are applicable for those objects that their shape is

Figure 7. The set of face candidates (white blobs) including face and non-face objects.

either vertical or horizontal. Nevertheless, some objects of these types are diagonal, whereas the rectangle width or height is not applicable. For these types of objects, the width and height of the smallest box containing the object are considered. Therefore, the following rules are applied after obtaining the smallest box containing the object (see Figure 8):

- Object with WB < 24 and HB < 24 is non-face.
- Object with WB < 24 and HB > = 24 is non face.
- Object with WB > = 24 and HB < 24 is non face.

Where, WB and HB are width and height of the smallest box including the object, respectively.

3.8.2 Refinement based on the Objects' Ratios

The ratio between the width and the height of a face obey the golden ratio of the human faces, which is approximately 1.6[22]. Therefore, the golden ratio of the human face can be considered as a criterion to discard the non-face segments from the face candidates set. However, this ratio cannot be exactly used for the face candidate segments due to some variations related to the pose and rotation of the face, as well as other issues related to skin colour segmentation. Therefore, a wider range for the face ratio is chosen based on the observations done in the present study, as shown in equation below:

$$GR - 0.5 < \frac{H}{W} < GR + 0.5$$

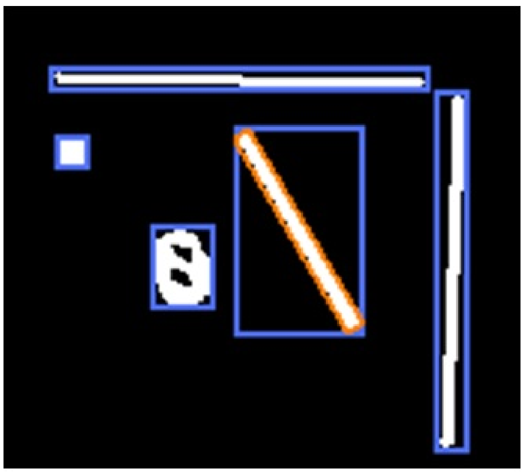

Figure 8. Examples of the non-face segments that are discarded by the rules.

Where, GR=1.6 is the Golden Ratio for the human face. Using this criterion, the objects which have width that is larger than their height are discarded. Similarly, those objects which have very large heights as compared to their widths are also discarded. Figure 9 illustrates the golden ratio of a human face and some face and non-face segments, as well as other related issues.

In addition to the above stated cases, the non-face objects in some cases are not discarded by the above rules (see Figure 10 below). In these cases, the percentage of the white pixels in the rectangle including the object is taken into consideration. Therefore, the rule associated with the particular cases is as follows:

If the number of the white pixels is less than 25% of the size of the rectangle, the object will then be discarded.

3.9 Detection of Faces

The Adaboost-based face detector, proposed by Viola and Jones[23], has been recognized as one of the most accurate and fast face detection techniques. In some cases, however, this technique faces some problems such as issues related to false positive rate and face detection time, especially in complex background scenes. In the present study, a combination of two approaches, namely colour-based[20] and Adaboost-based[23] face detection approaches, is adopted to develop the Hybrid Face Detection System by improving and resolving some problems related to each approach.

3.9.1 The Sub-window Size Estimation

One of the issues related to the Viola-Jones face detection technique is determining the size of scanning sub-window. The assumption for this particular technique

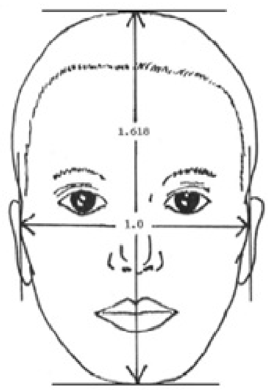

Figure 9. Human face golden ratio.

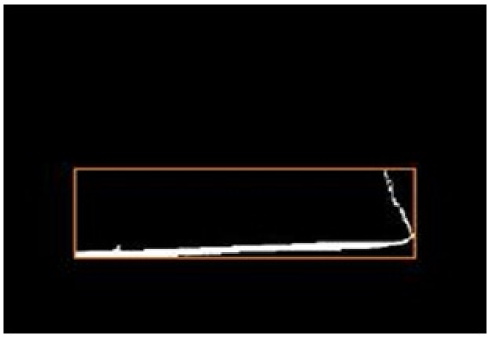

Figure 10. A non-face segment.

is that faces can be appeared in any size in an image. In the Viola-Jones technique[23], the best result is achieved by scanning the image in a 24×24 sub-window size and a scale factor of 1.25. Meanwhile, precisely estimating the sub-window size can help to improve the face detection time because the number of sub-windows that must be scanned will be reduced if an accurate estimation of sub-window size is available.

In the Viola-Jones face detection technique[23], the estimation of the starting sub-window size is not possible because there is no prior information about the faces in the image. In the proposed approach, nevertheless, this estimation can be accomplished using the size of the face candidate segments. To this end, the following rule is applied:

$$S = \begin{cases} 0.8\,W & \text{if } W \geq 30 \\ 24 & \text{if } W < 30 \end{cases}$$

where S is sub-window size and W is the width of the rectangle including the segment.

For example, a face candidate segment sub-window size of 120×100 pixels is equivalent to 80×80 pixels. It means 882 (21×41+20×1 = 881) sub-windows will be scanned and not more than 27000 sub-windows (approximately) in the Viola-Jones technique (almost 2.6% of total sub-windows in original case).

3.9.2 Applying the Viola-Jones Face Detector

So far, the previous stages have been associated with the colour-based approach. After this, the output of the last step, that is, face candidate segments will be processed using the Viola-Jones face detection technique to distinguish the faces from the non-faces. Therefore, the refined set of face candidate segments is processed using the Adaboost technique.

For each segment, the sub-window size must first be estimated using the equation which has been defined in the previous section. The Viola-Jones face detector technique, with the estimated sub-window size and re-scale factor of 1.25, is then applied to identify the face segments and localize the exact location of the face in the segment. The output of this process is the coordinates of a rectangle, including the face in the face segment (i.e., X, Y, width, and height) which must be transformed into the coordinates of the original image. After this transformation, a rectangle is drawn in the image using the new coordinates to show the detected face, as illustrated in Figure 11. The process is continued until all the segments have been examined using the Viola-Jones technique.

4. Experiments and Results

In this study 5 different scenarios of experiments are conducted to analyze the merits of the proposed method. These scenarios are listed as follows:

- Detecting faces using the Hybrid Face Detection System.
- Detecting faces using the Hybrid Face Detection System without the SSE and ASCC (to evaluate the effects of absence of the ASCC and SSE).
- Detecting faces using the Hybrid Face Detection System with the sub-window size estimation technique (SSE) only, to examine the effects and capabilities of the SSE.

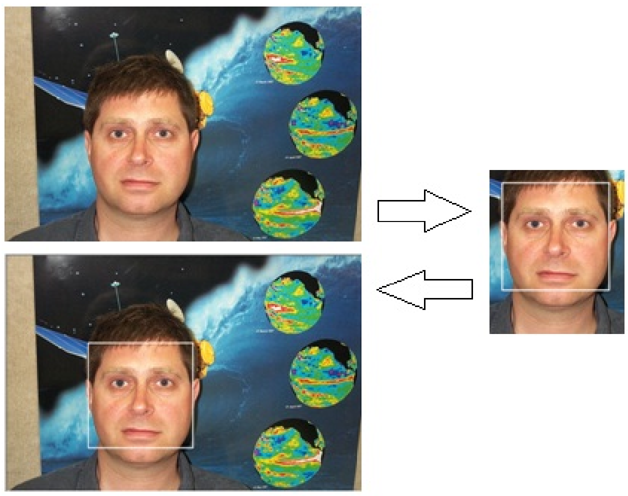

Figure 11. A face candidate with detected face.

- Detecting faces using the Hybrid Face Detection System with the Adaptive Skin Color Classification technique (ASCC) to examine the effects and capabilities of the ASCC.
- Detecting faces using the Viola-Jones conventional face detection system.

In order to evaluate the proposed method, the Caltech (California Institute of Technology) standard image dataset[24] was adopted to accomplish the experiments. The Caltech image dataset was selected for this purpose due to following reasons:

- Caltech image dataset consists of color images.
- Caltech image dataset consists of complex background images.
- Caltech image dataset consists of images with varying illuminations.

This image dataset included 450 images including 447 faces with 896 x 592 pixels resolution in the Jpeg format. Furthermore, it also consisted of 27 or so unique people under with different lighting conditions, expressions, and backgrounds.

The criteria for all the cases were the accuracy of the system and detection time. The accuracy of the system is dependent upon two other criteria, namely the false positive and false negative rates which are defined as follows:

$$\text{Accuracy} = 100\text{-}(\text{FPR} + \text{FNR})$$

Where, FPR (False Positive Rate) and FNR (False Negative Rate) can be computed as follows:

$$FPR = \frac{number\ of\ \ false\ alarms}{total\ number\ of\ detected\ \ faces} \times 100$$

and

$$FNR = \frac{number\ of\ missed\ \ faces}{total\ number\ of\ \ faces} \times 100$$

In order to realize the proposed approach, the Hybrid Face Detection System was implemented using the C# language and some functions are used from the EmguCV library (a wrapper for openCV library in C#) on .Net Framework 3.5, whereas the MS Access 2007 was used as the system database. Furthermore, the Viola-Jones face detector was added to and implemented in this system. The system has been found to enable the user to examine both approaches easily and give useful information about the face detection process, such as the detection time and the total number of faces detected. Moreover, batch processing is another useful feature of the implemented software as it provides users with batch processing of the image datasets and records the results of the process in the database of the system. Figure 12. illustrates a screenshot of the user interface.

In order to have an accurate comparison of the results, all the experiments were conducted on a laptop computer with 4 GB of RAM, Centrino Core 2 Duo 2.00 GHz CPU, and Microsoft Vista (Home Basic) operating system.

Each of the experiments that are conducted using the implemented system reveals different aspect of the capabilities of the HFDS based on various scenarios that are stated earlier. Total number of detected faces, detection time, and images with detected faces are the main output of the system for each experiment. However, to calculate the accuracy of the system for each experiment, the total truly detected faces, and the number of false positives are among variables that must be measured manually.

4.1 The Efficiency of the ASCC and the Sub-window Size Estimation

The Adaptive Skin Colour Classification (ASCC) and Scanning Sub-window Size Estimation (SSE) are two important features of the proposed method. In order to evaluate the efficiency of these two features, some experiments were conducted. The results of these experiments are shown in Tables 1. Note that the sub-window size in case of disusing SSE is 24×24 pixels.

Table 1 indicates the performance of the proposed method in terms of detection rate, accuracy, and detection time, whereby these were found to be better than

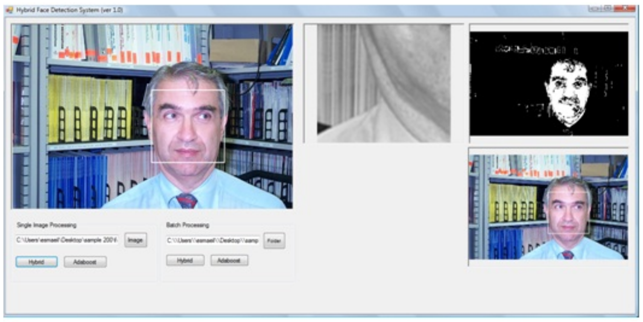

Figure 12. A screenshot of the software user interface.

Table 1. Results for the proposed method with SSE and without ASCC

No.	Criteria	Without ASCC and SSE	SSE only	ASCC only	HFDS
1	Number of all detected	599	480	632	514
2	Number of truly detected faces	416	419	435	442
3	Detection Rate	93.06%	93.7%	97.31%	98.88%
4	Number of false positives	83	61	197	72
5	False positive rate	13.86%	12.7%	31.17%	14%
6	Number of false negatives	31	28	12	5
7	False negative rate	6.94%	6.30%	2.69%	1.12%
8	Accuracy	79.2%	81%	66.14%	84.87%
9	Average detection time (ms)	245.167	172.88	353.38	259.59

the other cases, except for detection time in the cases of disusing ASCC, which is normal because the process of Adaptive Skin Colour Classification is rather time consuming.

The results for SSE only show that in this case the detection time was efficiently improved in comparison to the other cases. Furthermore, detection rate and accuracy was found to be slightly improved in comparison to the cases "ASCC only" and "without SSE & ASCC". In case of ASCC only, the detection rate was found to be improved in comparison to the "SSE only" and "without SSE & ASCC". However, detection time has increased because the ASCC process is relatively time consuming. Finally, the HFDS that include both SSE and ASCC has achieved the highest detection time and accuracy in comparison to the case "without SSE and ASCC". However, detection time was found to be slightly increased which is normal because as already mentioned the ASCC is a time consuming process.

4.2 The Overall Comparison of the Proposed Method

As another evaluation of the proposed method, the experimental results were compared to Viola-Jones base face detector. Note that there are three images with 3 hand drawn faces in the Caltech image dataset, in which based on the researcher's assumptions, they are considered as artificial faces.

The overall results of the Viola-Jones face detection system are shown in Table 2. As shown in Table 2., the number of false positives in the proposed Hybrid method was found to be significantly decreased. Meanwhile, the detection rate in the proposed methods was found to be slightly better than that of the Viola-Jones method (see Figure 13). However, the accuracy of the face detection system in the proposed method was also found to have been strongly improved (see Figure 13). Furthermore, the detection process in the proposed method was found to be faster than the Viola-Jones method. Therefore, the objectives of the research are met in terms of both accuracy and detection time.

Table 2. Overall comparison

No.	Criteria	Viola-Jones	Proposed (HFDS)
1	Total number of faces in images	447	447
2	Number of all detected	836	514
3	Number of truly detected faces	441	442
4	Detection Rate	98.66%	98.88%
5	Number of false positives	395	72
6	False positive rate	47.25%	14%
7	Number of false negatives	6	5
8	False negative rate	1.34%	1.12%
9	Accuracy	51.41%	84.87%
10	Average detection time (ms)	294.47	259.59

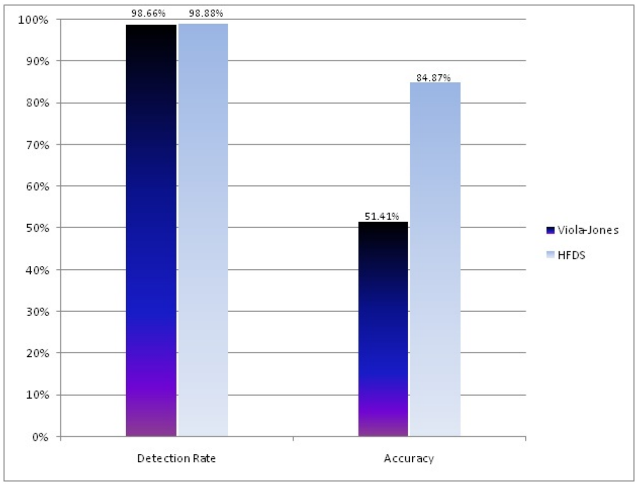

Figure 13. Comparison of two methods in terms of detection rate and accuracy.

5. Conclusion and Future Works

The main objective of this research was detecting faces within color images with complex background and increasing the performance of the face detection systems in terms of detection rate, accuracy, and time by eliminating the background of the image and down-sizing of the search space. The main contributions in the proposed face detection method are use of Adaptive Skin Color Classification method, Connected Component Separation technique, and Sub-window Size Estimation in which the objectives of this research are met using these features of the proposed HFDS method.

The proposed method cannot be considered as the final solution for all the problems related to face detection. In addition, there are some problems which must be solved, such as rotated and occluded faces. Apart from the merits of the HFDS method proposed in this research, some limitations have also been identified. Some of the limitations which must be solved are listed below:

- Rotated faces cannot be detected in this method.
- Illumination-related issues, such as biased lighting and camera setting still exist.
- The implementation of the proposed face detection system can still be improved.

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