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ILLUMINATION INVARIANT FACE DETECTION USING HYBRID SKIN SEGMENTATION METHOD

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ABSTRACT: *This paper describes a new face detection algorithm that retains its performance regardless of variations in illumination. It is a hybrid model that performs skin segmentation through a fast but coarse procedure and an adaptive thresholding process. Logical pixel combination of the results is performed to give a single skin-segmented image, which is then tested for the presence of a face through template matching. The model performed well for face detection especially for detecting dark faces under dark illumination. 83.8% and 76.4% detection rates were achieved when the algorithm was tested with images taken under good and poor illumination respectively.*

KEYWORDS: Face detection, Illumination, Skin modelling, Skin segmentation, Template matching.

INTRODUCTION

A face detection system is used to determine whether or not there are faces in any arbitrary image and if present return the location of each face in the image. The performance of face detection and recognition systems under controlled conditions has reached a satisfactory level [1], but reduces drastically with variations in illumination and pose, which characterises real life scenarios [2]. Illumination influences detection and therefore, generalization of algorithms to all illumination condition would not be ideal [3]. Illumination invariant systems are categorised into Active and Passive approaches; Active approaches uses active sensing techniques to capture face images which are invariant to environment illumination, while Passive approaches compensates and or corrects changes in the image due to environment illumination [4].

Comprehensive surveys have been done on face detection [5-8]. Craw et al [9] proposed a face localization method based on a shape template for a fontal-view face. Viola and Jones [10] presented a robust real-time object detection method using Adaboost and cascade classifiers. Statistical analysis techniques and machine learning have been used for face detection i.e. to find relevant characteristics of face and nonface image. Belhumeur et al [11] used Fisher's Linear Discriminant (FLD) to project samples from high dimensional image space to a lower dimensional features space and have been reported to give better performance for face detection and recognition by Zhao et al [12]. In other approaches, basic rules are first established to encode human knowledge of what constitutes a typical face, for example the knowledge of facial features and the relative distances and positions of the facial features. Combinations of several facial features have also been used to achieve face detection. These methods use the global features such as skin colour, size and shape to find face candidates and then verify these candidates using local, detailed features such as eye brows, nose, and hair. Sandeep and Rajagopalan [13] presented an algorithm for detecting human faces in colour images using the histogram for skin in conjunction with edge information to quickly locate faces in a given image. A comprehensive survey of pixel-based skin colour detection technique is presented in [14]. The problem of face detection under varying illumination is to correctly locate and segment skin from non-skin regions. Of interest is the extraction of skin tones of dark faces captured under poor illumination conditions. Dark surfaces reflects a little of the rays of light incident on it thus making the detection of dark faces under poor illumination a difficult task.

This paper presents a new hybrid face detection algorithm that performs skin segmentation by using fast skin detection algorithm and fine (adaptive) parametric single Gaussian skin distribution modelling method. The results of the two were compared and the image resulting from bitwise addition of the two skin-segmented images was then tested for the presence of a face. We tested the algorithm on a Black Face Database [27], which contains coloured images of black faces captured under real life situations. The model achieved higher detection rates when compared with other methods.

Skin Modelling

Colour images are usually modelled as three-band monochrome image data, where each band of data corresponds to a different colour [15]. The information stored in the digital image data is the brightness information in each spectral band [I_R(r,c), I_G(r,c), I_B(r,c)] at the point (r,c) and these are referred to as the colour pixel vector RGB. In many applications, the RGB colour information is transformed into other colour subspace, which decouples the brightness information from the other colour information. The new colour subspace, consisting of one-dimensional luminance space, and a two-dimensional colour space is referred to as the chromaticity of the image. For example, the HSL (Hue/Saturation/Lightness) colour transform describes colours in terms of hue (the colour information), saturation (how much white is in the colour) and lightness (the brightness of the colour). CIE standards include, the normalised RGB the CIE XYZ, the CIE L*u*v* and the CIE L*a*b* colour spaces. The International Telecommunication Union-Radio (ITU-R) has specified the standard digital video ITU-R 601, which is based on one luminance signal and two colour difference signals (Cr and Cb).

A common method used to build a skin colour model is to define a region of skin tone pixels using Cr, Cb values i.e. $R_{(Cr,\ Cb)}$, from samples of skin colour pixels. With carefully-chosen thresholds, (Cr_1, Cr_2) and (Cb_1, Cb_2), a pixel is classified to have skin tone if values (Cr, Cb) falls within the thresholds [16] i.e.

$$Cr_1 \leq Cr \leq Cr_2\,, \qquad (1)$$

$$Cb_1 \leq Cb \leq Cb_2. \qquad (2)$$

Skin colour models have been extracted from different colour spaces such as the normalized RGB [17], HSV colour space [18], YCbCr [14], YIQ [19], YES [20], CIE XYZ [21] and CIE LUV [22]. In [23] a fast face detection algorithm using the YCbCr colour space was proposed. The algorithm performs illumination compensation and noise filtering and then the skin segmentation using the Cr component of the colour image since it can represent the human skin well and reduce the computation time. The human skin is then classified by;

$$S_{ij} = \begin{cases} 1, & 10 < Cr < 45 \\ 0, & otherwise \end{cases} . \quad (3)$$

Skin-colour blocks are thereafter tested for the eyes and mouth to ascertain the presence of a face. A detection rate of 92.3% was reported. Hsu et al [22] used single Gaussian modelling method for skin segmentation and other methods for localization of facial features such as eyes, mouth and face boundary, detection rated ranging from 80.58 – 96.6% were reported.

Proposed hybrid skin segmentation model

Our model as shown in Figure 1 performs skin segmentation by using a combination of fast (coarse) skin detection algorithm and parametric single Gaussian skin distribution modelling method. The 'optimal skin region' is selected by an adaptive thresholding method as descibed in [24]. The skin-likelihood area is modelled by an elliptical Gaussian joint probability density function and was obtained from skin samples of 26 individuals.

$$P(S|skin) = \frac{1}{2\pi\sqrt{|C_s|}} e^{-\frac{1}{2}(c-m_s)^T C_s^{-1}(c-m_s)}, \quad (4)$$

where c is the colour vector of the chromatic pair (Cb, Cr), i.e.

$$c = (Cb, Cr)^T, \quad (5)$$

and m_s is the mean vector of c used to generate the Gaussian model.

$$m_s = \frac{1}{n}\sum_{j=1}^{n} c_j , \quad (6)$$

C_S is the covariance matrix given as

$$C_s = \frac{1}{n-1}\sum_{j=1}^{n}(c_j - m_s)(c_j - m_s)^T . \quad (7)$$

The areas of skin-likelihood are modelled by the Mahalanobis distance;

$$P_s = e^{-\frac{1}{2}[(c-m_s)^T C_s^{-1}(c-m_s)]}. \quad (8)$$

The output is a greyscale image with the grey value at each pixel showing the likelihood of the pixel belonging to skin. The skin region is segmented from the rest of the image through a thresholding process. The process determines the best threshold value for each image under test. When the threshold value is decreased, the segmented region increases and will increase sharply when the threshold value is too small such that non-skin regions are also accommodated. To select the optimal threshold value, the increase in the segmented region size is monitored and the value at which the minimum increase occurs is taken. This is followed by a bitwise combination of the two skin-segmented images (fast segmentation procedure and the adaptive segmentation). The skin segmented image is transformed to a binary image (containing 0s and 1s), the 1s represent the skin regions, while the 0s represent the holes inside the skin regions.

$skin = P_s + S_{ij}$, (for bitwise OR); (9)

$skin = P_s \times S_{ij}$, (for bitwise AND). (10)

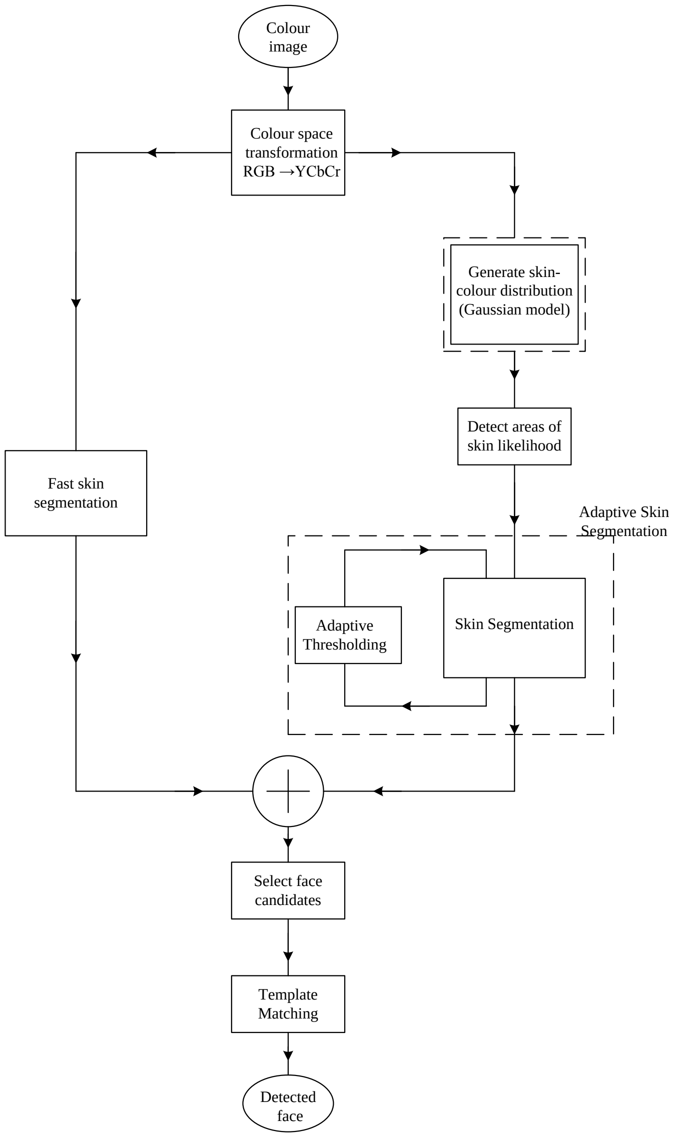

Figure 1. Proposed Hybrid Model

To select a face candidate, the skin regions are scanned to determine areas that are connected using 8-connected neighbourhood of each pixel as the sampling window. Every connected region is given a label and later tested for the presence of a face. The skin regions are tested for the presence of face(s) using a rule based technique [25]. A face should contain at least one hole (a frontal face would contain two eyes, a nose and mouth), then other skin regions without any hole can be discarded. The skin region containing one hole would then be considered as a face candidate. The existence of the hypothesized face(s) is verified by template matching [26].

RESULTS AND DISCUSSION

The model was tested on our face detection database, Black-face database (BFDB) [27] containing 100 images with more than 140 faces of men, women and children, with varying poses, orientation, complexion and illumination. Some of the images were downloaded from the internet while some were adopted from other existing databases. The database is

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categorised into two, one contains images taken under good illumination while the other contains images taken under poor illumination. Two of the earlier methods [10, 23] were also tested on the same database and the result obtained was compared as shown in Table 1.

Table 1: Detection rates for images taken under good and poor Illumination

Detection Method	Good Illumination			Poor Illumination		
	Detection Rate	False Positive	False Negatives	Detection Rate	False Positive	False Negatives
Hybrid Model	83.8%	36	11	76.4%	29	13
Adaboost [8]	35.29%	10	21	31.94%	8	23
Fast Dectect [21]	66.18%	121	47	56.9%	247	29

For images taken under poor illumination, the highest detection rate of 76.4% by the hybrid model, followed by 56.9% by the Fast Detect model [23] and 31.9% by the Adaboost and Classifier method [10] as shown in Table 1. However, the least number of False Positives (part(s) of the image wrongly detected as faces) was recorded in the Adaboost method followed by the Hybrid model while the Fast Detect model [23] recorded the highest number of False Positives.

However, the hybrid model recorded the least number of False Negatives of faces that are present in the images but not detected and the highest False Negative was recorded in the Fast Detect method. Some samples of these are shown in Figure 2. The results obtained when tested with images taken under good illumination were similar but with higher detection rates. The hybrid method recorded the highest detection rate of 83.8% followed by 66.18% from the Fast Detect and 35.29% from the Adaboost method as shown in Table 2. The least number of False Positives was recorded in Adaboost method [10] and the highest number of False Negative was recorded in the hybrid model. Some of these are shown in Figure 3

Bitwise logic combination of the outputs of the fast skin segmentation and the Adaptive segmentation procedure makes a significant improvement to other methods. The best performance was recorded for bitwise AND. Table 2 and Figures 4a & 4b show the results for the bitwise OR combination when tested with BFDB images..

Figure 2: Images in the database (taken under good lighting conditions) showing detected faces.

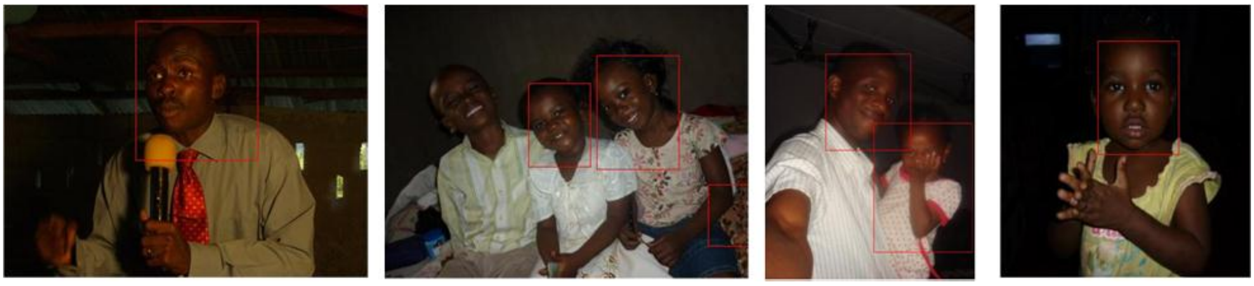
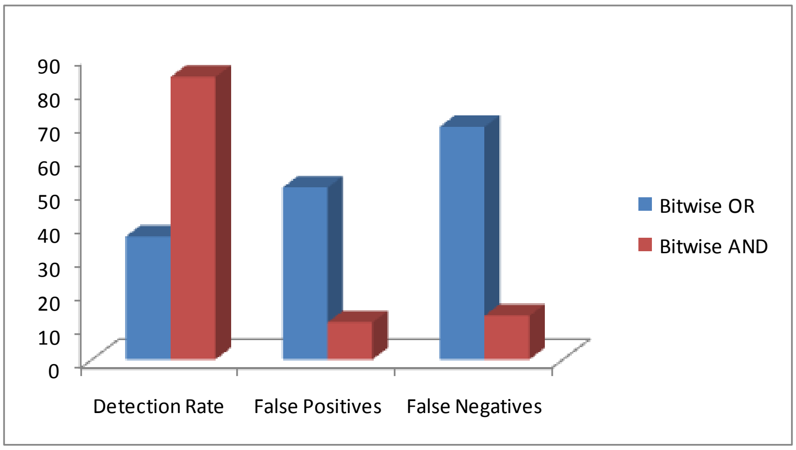


Figure 3: Images in the database (taken under poor lighting conditions) showing detected faces.

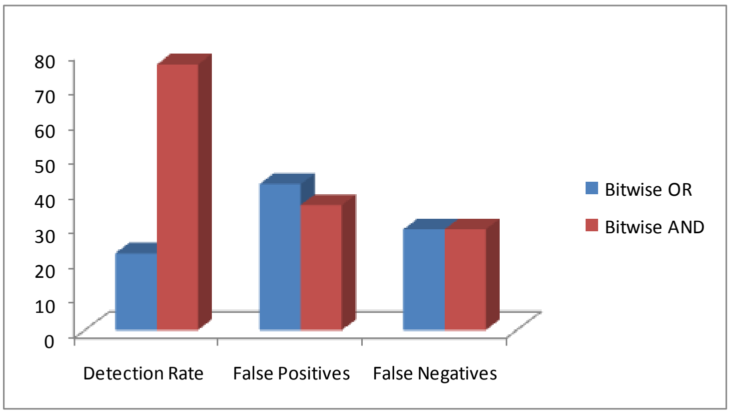
Detection rates of 36.43% and 22.14% were achieved when tested with images taken under good and poor illumination respectively, which is much lower compared with 83.8% and 76.4% of the bitwise AND.

Table 2: Images taken under Good and Poor Illumination conditions using Bitwise OR and AND for the Hybrid Model

	Bitwise OR		Bitwise AND	
	Good	**Poor**	**Good**	**Poor**
Detection Rate	36.43%	22.14%	83.8%	76.4%
False Positive	42	29	36	29
False Negative	51	69	11	13



(a)



(b)

Figure 4 Bar charts showing results for bitwise OR and AND for face detection

CONCLUSION

This paper has presented an illumination invariant face detection system, which uses a combination of a fast procedure and an adaptive thresholding process for skin segmentation, template matching was used to detect the presence of faces in the skin segmented images. The hybrid model performed better in face detection than some earlier algorithms, especially for detecting dark faces under dark illumination. 83.8% and 76.4% detection rates were achieved when tested with images taken under good and poor illumination respectively, compared with 66.18% and 56.9% by fast detection algorithm and 35.29 and 31.9% by the Adaboost and classifier method. The algorithms were tested on the Black Face Database (BFDB), a newly created database to handle the deficiencies in existing databases.

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