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Improved Dynamic Threshold Method for Skin Colour Detection Using Multi-Colour Space

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Abstract: This paper presents a skin colour detection based on an improved dynamic threshold method to reduce false skin detection. Current fixed threshold skin detection fails in certain situations such as misclassification between non skin-like with similar skin-like colour. Any true skin may falsely be detected as non-skin. Research work introduces high-level skin detection strategy based on online sampling where offline training is not required. This strategy shows a promising performance in term of classifying images under skin-like and ethnicity image variations. However, some of the methods produced high false positives that reduced the accuracy of skin detection performance. Therefore, in this study, instead of single colour space and fixed threshold method, an improved skin detection based on multi-colour spaces is proposed. Furthermore, a dynamic threshold method also has been improved by introducing elastic elliptical mask model for online skin sampling. The experimental result shows an improvement in employing multi-colour rather than single colour space by reducing the false positive and increasing the precision rate.

Keywords: Skin Colour Detection, Dynamic Threshold, Online Skin Sampling, Multi-Colour Space

Introduction

The human body is divided into many parts, and skin is one of it. Skin is the largest organ in the human body. Skin colour detection has been studied extensively over the years and is frequently used in many applications such as in security, gaming and also Human Computer Interaction (HCI). Applications such as face detection (Kovac *et al*., 2003), illicit content filtering (Fleck *et al*., 1996; Lee *et al*., 2006), facial recognition (Hsu *et al*., 2002), steganography (Cheddad *et al*., 2009) and Content-Based Image Retrieval (CBIR) (Mofaddel and Sadek, 2010; Wen *et al*., 2009) used skin detection as the primary step in their applications. The main purpose of skin colour detection is to determine the skin pixels in the image and generate skin region by discriminating skin and non-skin pixels. The detected skin region is then examined based on the specific application (Abdullah-Al-Wadud *et al*., 2009). In the past, numerous skin detection techniques have been introduced and successfully applied for skin tone detection using colour information. Hence, the skin colour information gained serious cue for extracting skin pixels in image processing applications. Numerous colour spaces are being used nowadays such as *RGB*, *YCbCr*, *HSV*, *HIS*, normalised *RGB* and *CMYK* (Gonzales and Woods, 2002). *RGB* and *YCbCr* are the most common colour space used in a skin model (Hsu *et al.*, 2002; Khan *et al*., 2012; Phung *et al*., 2002; Vezhnevets *et al*., 2003; Wong *et al*., 2003). However, the skin colour detection often affected by the image variation such as different illumination, skin-like objects, ethnicity, camera characteristics and complex background (Kakumanu *et al*., 2007).

There are many skin colour detection techniques that have been proposed and it can be grouped into four: Explicit threshold method, parametric, non-parametric and dynamic skin modelling (Bianco *et al*., 2013; Osman *et al*., 2012; Kakumanu *et al.*, 2007). Normally, these techniques fall under two ways, either pixel-based or region-based. From literature, the pixel-based approach is the most widely used since it is less computational, robust information against rotation and partial occlusion. The explicit threshold method is fast yet the simplest skin colour modelling to implement single or multiple thresholds in determining a pixel or non-pixel. The threshold values are often obtained from empirical training whereby the researchers trained large image dataset to find optimal boundaries. Since, the thresholds greatly depend on the training dataset, it is difficult to achieve better accuracy through this method. Skin-like object such as leather, wooden or sand could be mistakenly classified as skin.

Instead of one colour space, combining multiple colour space for skin colour model also shows promising result. Several researchers combined multiple colour space to build a skin colour model (Abdul Rahim *et al*., 2006; Samart *et al*., 2011; Wang and Yuan, 2001; Xiang and Suandi, 2013; Zhu *et al*., 2012). For instance, Xiang and Suandi (2013) introduced a fusion of multi-color space for skin segmentation using *YCbCr*-*YUV* and *RGB*-*YUV* colour space. It was found that *RGB*-*YUV* skin colour model is better in handling image with a complex background. Meanwhile, Samart *et al*. (2011) introduced new rule for face detection based on *RGB*-*HSV*-*YCbCr* skin colour model. This showed significant improvement of skin detection on the multi-colour space model. Unfortunately, their skin colour models were fixed and they required offline training. This training needed large image dataset in order to visualise the skin colour distribution.

This paper is presented in five major sections. Firstly, discussion on the related works is done, then details of the face-based adaptation is elaborated. The next part of the paper introduces the implementation details of the proposed method. Following this, discussion is undertaken based on the result obtained from the experiment. Finally, the paper is concluded with some recommendation for future work.

Related Works

For the past few years, researchers have shifted to dynamic or adaptive approach which is based on the face or hand adaptation as detailed in Table 1 (Bianco *et al.*, 2013; Hsieh *et al.*, 2012; Hwang *et al.*, 2013; Ibrahim *et al.*, 2012; Tan *et al.*, 2012; Taylor and Morris, 2014; Yogarajah *et al.*, 2012). This approach requires no offline training of skin samples and it is less complex. The motivation of this approach was that the skin samples were obtained directly from the image using face or eye detector which known as online skin sampling technique. The adaptability of the modelling skin colour of the faces gives many benefits in term of performance and no offline training needed. The skin colour models were generated based on the individual faces. Yogarajah *et al.* (2012) and Ibrahim *et al.*, (2012) proposed dynamic skin detector using threshold method. It was reported that, there were many ‘black spot’ in the segmented area which is the false positive pixels (Yogarajah *et al.,* 2012). This dynamic skin detector classified many non-skin pixels as skin, even though, the method improved in term of classifying skin in different skin tones rather than explicit static cluster. Therefore, an improved skin colour detection based on the dynamic threshold with a combination of multi-colour spaces has been proposed in this study. Initially, four types of face mask have been analysed as to which one generates less non-skin pixels. An elastic elliptical mask model based on eye angles was also introduced.

Face-Based Adaptation

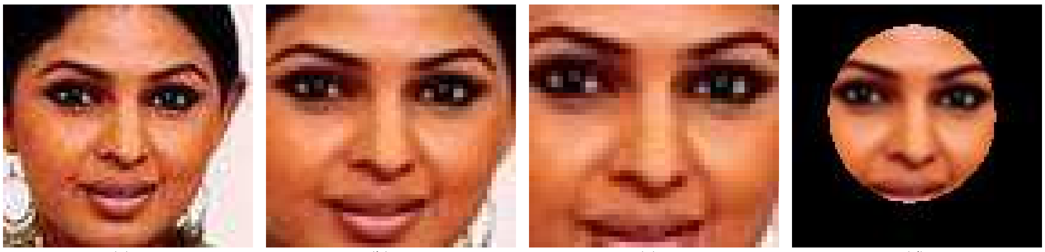
From Table 1, numerous skin detections that were based on face adaptation had been proposed. These face-based adaptations were employed under different approaches and colour spaces. Some of the researchers used threshold approach due to less complex and easier to implement. In addition, the different face mask model has been adopted to obtain the skin sample from the detected face. Other researchers implemented rectangular, circular and elliptical shape for the face mask generation. Only Kawulok (2008) used trapezium face mask to extract the face skin sample. Notice that, the human face can be detected without the colour information, providing an advantage in the face-based adaptation approach. Most of the researcher adopts Viola and Jones (2004) and Fasel *et al*. (2005) face detector as their main pre-processing phase.

Face Skin Mask

Initially, four types of face mask models have been studied which presented in Fig. 1. As for our analysis, Viola-Jones face detector was chosen to locate the human faces in the colour image.

Figure 1 illustrates skin samples that were obtained using different face mask models. Figure 1(a) is the face region in which the original dimension of the rectangular size. On the other hand, Fig. 1(b)-(c) are the reduced dimension where both of them were reduced based on these parameters, [0.25, 0.2] and [0.36, 0.36]. Reducing dimension would reasonably reduce any non-skin regions. The empirical analysis was done to analyse the percentage of non-skin pixels detected in all the skin samples. The purpose is to select a suitable face mask model for the Region of Interest (ROI) during the skin colour extraction process.

Based on the empirical analysis done, reducing the dimension of the face region greatly reduce the non-skin pixels. As illustrated in Fig. 1, the skin area highly located as the human face shape is oval with less background detected. Therefore, slightly rotated face views were also taken into consideration as there is a high possibility of skin pixels occurrence in slightly rotated face angles. To solve this, an elastic elliptical mask model introduced that based on the eye angle. By employing face mask model, the possible numbers of detected skin pixels from the face region can be increased. Non-skin pixels such as background, hair and lips can be reduced significantly.



(a) (b) (c) (d)

Fig. 1. Skin sample using face mask models, (a) Original rectangular, (b) reduced dimension of width 0.25, height 0.2, (c) reduced dimension of width 0.36 and height 0.36 and (d) our elastic elliptical mask

Table 1. Several face-based skin colour detection

Author's	Approach	Face/Eye detector	Face Mask	Dataset
Zheng *et al.* (2005)	Threshold values based on *YCbCr* colour space	Viola-Jones face detector	Elliptical	Internet
Lee *et al.* (2006)	Adult image filtering using Adaboost classifier	Viola-Jones face detector	rectangular	Internet
Kawulok (2008)	Proposed face-based joint with statistical *RGB* for detecting skin in digital image for Polish sign language recognition	Hough transform and SVM	Trapezium	ECU
Yogarajah *et al.* (2012)	Proposed novel learned dynamic threshold using Cheddad *et al.* (2009) colour space	Fasel face detector	Elliptical	Pratheepan
Hsieh *et al.*, (2012)	Proposed an adaptive skin colour classifier to segment dynamic skin regions (face and hand) in real time application using normalized *RGB* colour space	Viola-Jones face detector	Rectangular	Not mention
Tan *et al.* (2012)	Combines smoothed 2-D histogram and Gaussian model using *IByRg* colour space	Fasel face detector	Elliptical	Pratheepan, ETHZ
Ibrahim *et al.* (2012)	Developed adaptive margins of skin detector that the skin pixels are collected from the major and minor axes of bounding rectangle. Using *YCbCr* colour space	Viola-Jones face detector	Rectangular	Pratheepan
Bianco *et al.* (2013)	Proposed two high level skin detection strategies: Adaptive Single Gaussian (AGM) and Colour Gamut Mapping (CGM)	Not mention	Rectangular	TDSD
Hwang *et al.* (2013)	Proposed new skin detection algorithm that considers the luminance value in modelling the colour distribution adaptive chrominance model (*YCb*, *YCr*)	Fasel eye detector	Rectangular	Jones and Pratheepan
Taylor and Morris (2014)	Employed unimodal Gaussian function in the normalized *RG* colour space.	Viola-Jones face detector	Circle	Not mention

This process is important in order to generate an optimum threshold values to be used in the dynamic skin classification. Table 2 demonstrates the face mask under different skin colour space respectively, *RGB*, *YCbCr* and *HSV*. It is clear that the reduced dimension and elliptical mask model performs well in classifying the skin regions. However, rectangular shape without reduced dimension mostly fails to generate better skin regions due to a lot of non-skin region extraction. Notice that, *HSV* colour space sometimes fails to generate better skin region rather than *RGB* and *YCbCr*. Therefore, elliptical mask model have been employed by improving it based on the eye angle to overcome this problem.

The Proposed Method

Figure 2 presents the overall structure of our proposed dynamic skin detector using a combination of multi-colour spaces. Three different colour spaces used are *RGB*, *YCbCr* and *HSV*. These colour spaces conversions can be found in (Vezhnevets *et al.*, 2003). *YCbCr* and *HSV* colour space are defined in Equation 1 and 2:

$$YCbCr = \begin{cases} Y = 0.299R + 0.58G + 0.11B \\ Cb = B - Y \\ Cr = R - Y \end{cases} \tag{1}$$

$$\begin{aligned} H &= arccos \frac{\frac{1}{2}\left((R-G)+(R-B)\right)}{\sqrt{\left((R-G)^2+(R-B)(G-B)\right)}} \\ S &= 1 - 3\frac{min(R,G,B)}{R+G+B} \\ V &= \frac{1}{3}(R+G+B) \end{aligned} \tag{2}$$

The initial experiment showed that combining colour spaces in our skin detector outperforms single colour space by reducing the false positive and increasing the precision rate.

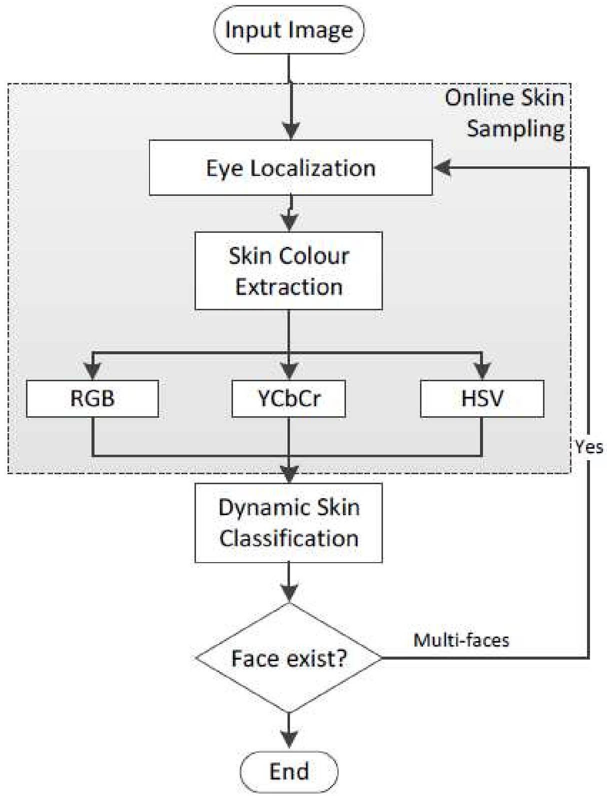


Fig. 2. The flowchart of the proposed dynamic skin detector

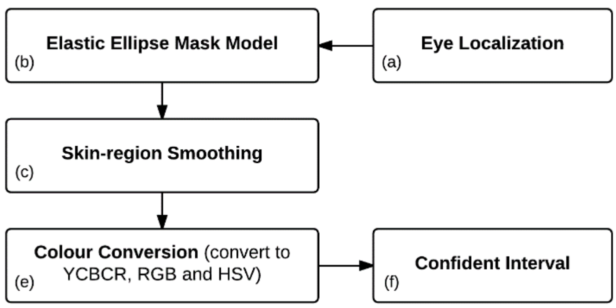


Fig. 3. Online skin sampling processes

Online Skin Sampling

During this phase, several processes involved which were eye localization, skin colour extraction and generation of single dynamic threshold. The detail processes of online skin sampling are illustrated in Fig. 3. Our proposed skin detector began with the eye localization phase where the face was detected first, then using SVM to locate the two points of eye angle. It was noted that locating the eyes in the face region requires a considerable amount of time; hence slowing the speed of our skin colour detector.

Skin Colour Extraction

In the face-based skin colour detection, skin samples were obtained directly from the image. As mentioned before, an elastic elliptical mask model was introduced based on the eye angle. According to our initial finding, elliptical mask model generate better skin segmentation with less false positive as shown in Table 2 previously. The elliptical shape is rotated based on the eye angles as shown in the Fig. 4. Parameter '*d*' is the distance between the two eyes, while '*a*' and '*b*' is the major and minor axis of the ellipse size. Value '*c*' is the degree of rotation.

The aim of this process is to extract skin pixels that exist in the face region as much as possible. However, the face region may contains non-skin pixels such as lips, eyebrow and hair that need to be removed. Possibility of non-skin pixel recognition can be done by employing skin-region smoothing using Sobel detector to filter out any pixels of non-skin. The pseudo-code for the proposed skin colour detection can be found in Algorithm 1:

Algorithm 1: Skin Colour Detection using Dynamic Threshold

```
Input Parameter
    Input: Input Image
Procedure
    Read images from folder, JPG format
    WHILE Input image not end of file
        Detecting faces using Viola-face detector
        IF number of detected faces ≥ 1 THEN
          FOR all detected faces, do
          Locating eye position to create elastic elliptical mask
          Generate dynamic threshold: Extracting skin pixels from the elastic elliptical mask
          Skin-region smoothing by employing Sobel Edge detector
          Convert a matrix of extracted skin pixel to YCbCr and HSV
          Dynamic skin classification
             Read skin pixel based on the dynamic threshold values
             IF (T1≤R≤T2 AND T3≤G≤T4 AND T5≤ B ≤ T6 THEN
                 Label the pixel as skin pixel
             ENDIF
                 Label the pixel as non-skin pixel
        ENDFOR
    ENDIF
ENDWHILE
```

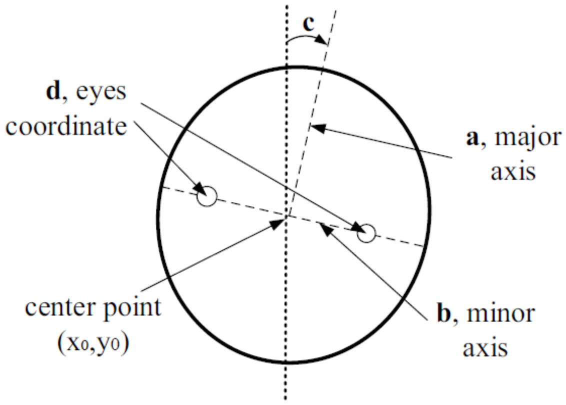


Fig. 4. Elastic elliptical mask model according to eye angle. '*c*' is the rotation angle, d is the distance between two eye points, (a) and (b) respectively 1.2d major axis and 1.1d minor axis

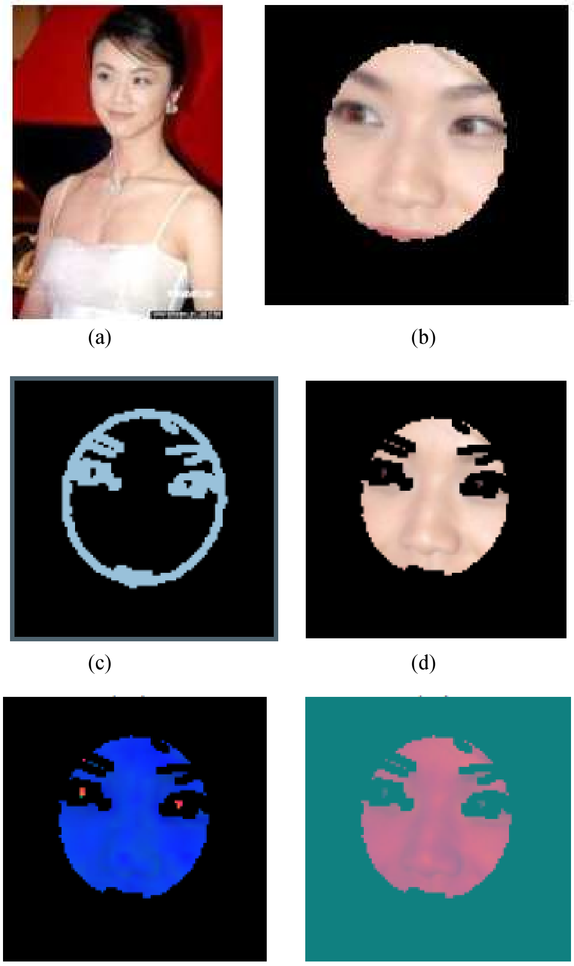


Fig. 5. Online skin colour extraction obtained from the face. (a) Input image, (b) elastic elliptical mask region based on eye rotation, (c) smooth skin region using Sobel edge detector and dilation process, (d)-(f) *RGB*, *YcbCr* and *HSV* smoothed skin region

The Sobel edge detector was used since it gave better outcome in detecting the edges in the image than other existing edge detector. The Sobel edge detector applied to the region as in Fig. 5(b), which is the elastic elliptical mask region with dilation process to expand the detected edges. The white pixel presented in the Fig. 5(c) was the possible existence of non-skin pixels that needs to be removed. Finally, a smooth skin region with minimal non-skin pixels was generated. It was then converted into *YCbCr* and *HSV* colour space as presented in the Fig. 5(e) and 5(f). However, the smooth skin region may still contain non-skin pixels during the previous process since there is no guarantee that all the non-skin pixels had been properly removed. Therefore, histogram analysis of confidence interval with two-side 95% acceptance of normal distribution $N(\mu, \sigma 2)$ for each of the colour components to determine the accepted region and classified them as skin pixels were carried out. Maximum distribution of skin pixels (with 95% confidence interval) in the histogram was considered to be as the threshold values. Therefore, *n*-rules of the threshold value were implemented based on multi-colour space. In order to get the locus skin cluster, the skin colour distributions were represented in the form of histogram. By using the mean and standard deviation, the 95% confident interval is calculated using the following statistical formula:

$$T_n = \pm 2\sigma \tag{3}$$

where, T is the threshold value for '*G*' colour channel.

Figure 6 and 7 illustrates the 1*D* colour distributions of '*R*' and '*G*' channel obtained from the smooth skin sample of the detected face. Based on the experiments done, it shows that the '*R*' maximum distribution always greater than *G* and *B* value. Therefore, the skin colour for *RGB* colour space modelled whereby *R* is greater than $G(R>G)$ and *R* is greater than $B(R>B)$.

Dynamic Skin Classification

The purpose of this phase was to combine multi-threshold values from the multi-colour space of *RGB*, *YCbCr* and *HCV*. Three colour space were analysed into our proposed skin colour detector. Initially, proposed single dynamic threshold employed in the skin detection based on individual colour space *RGB*, *YCbCr* and *HSV*. Then, several combinations of *YCbCr-RGB*, *CbCr-RGB*, *YCbCr-SV* and *CbCr-SV* were respectively presented. Equation 4 shows one example of the combinations of two colour space into a single skin colour model for *CbCr-SV*:

$$\begin{aligned}
&IF\ Cb_{min} \le Cb \le Cb_{max}, Cr_{min} \le Cr \le Cr_{max} \\
&AND \\
&S_{min} \le S \le S_{max}, V_{min} \le V \le V_{max} \\
&THEN\ skin(CbCr, SV) = 1 \\
&ELSE\ skin(CbCr, SV) = 0
\end{aligned} \tag{4}$$

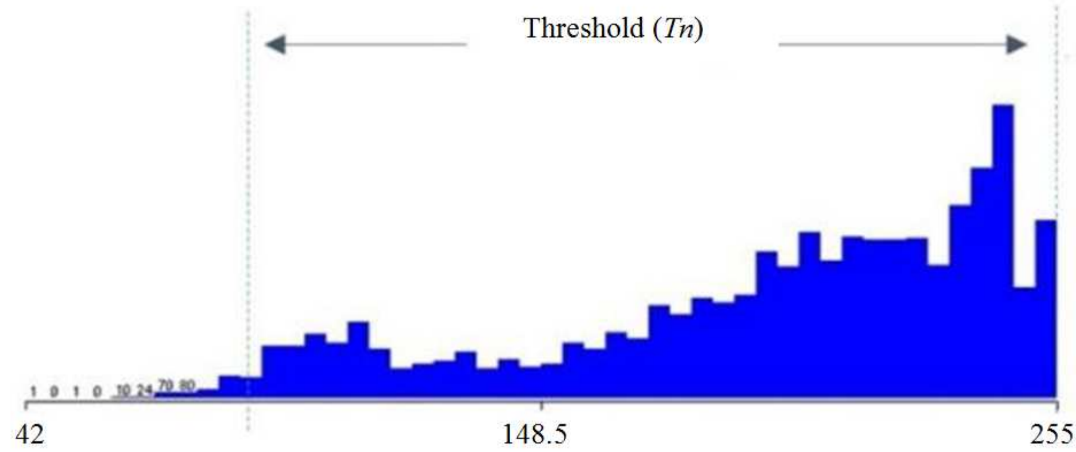


Fig. 6. Threshold value of '*R*' channel in *RGB* colour space

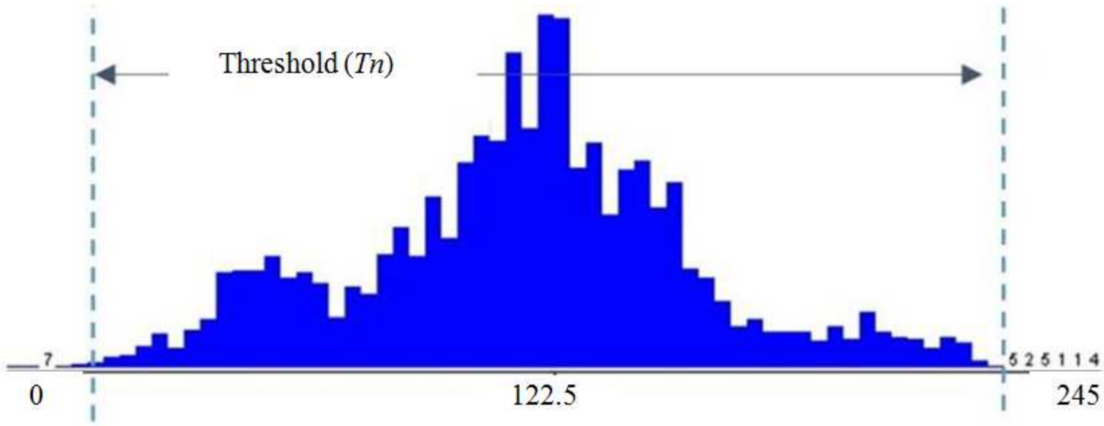


Fig. 7. Threshold value of '*G*' channel in *RGB* colour space

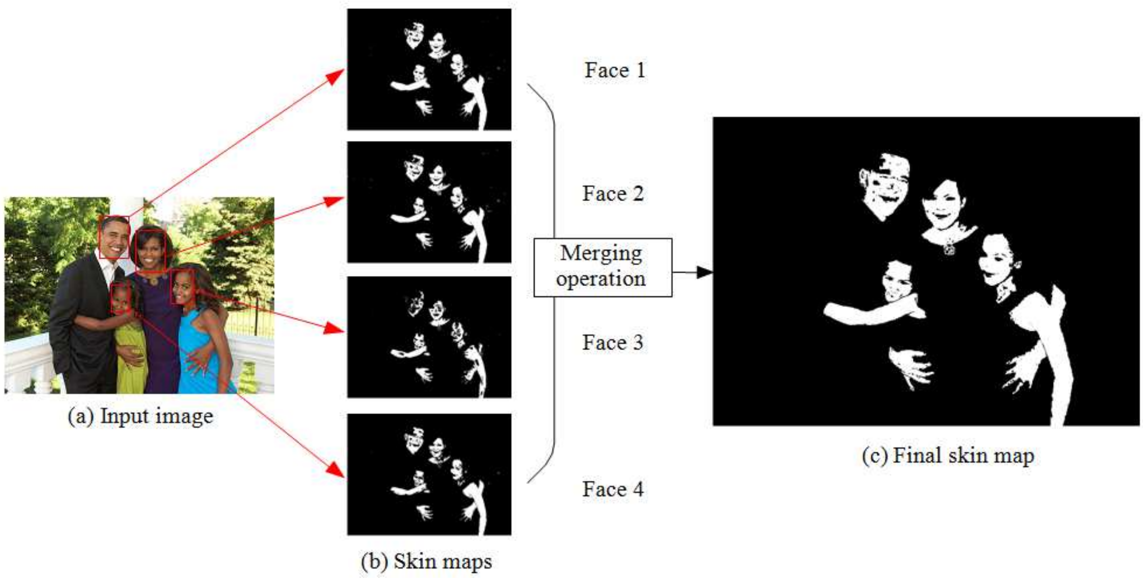
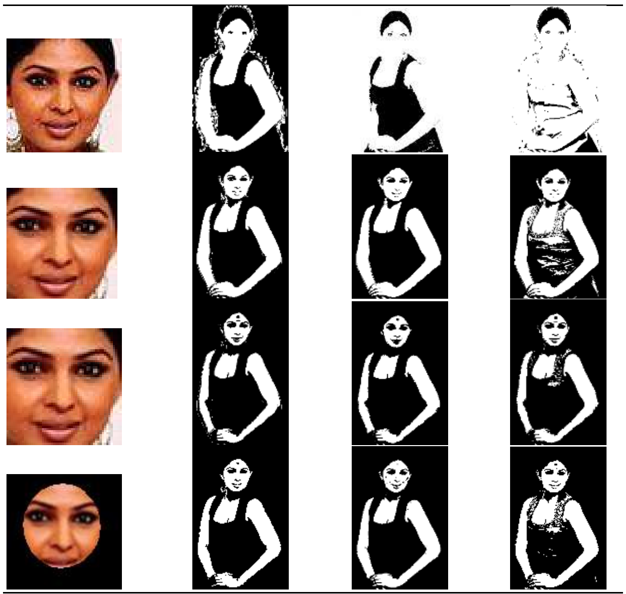


Fig. 8. Merged result for more than one faces. (a) Input image, (b) individual threshold result, (c) final result

Table 2. The effect of using a different face mask under different colour space

	Colour space		
Face mask model	*RGB*	*YCbCr*	*HSV*



The minimum value was the lower bound while the maximum value act as the upper bound threshold value. Multiple threshold values calculated during the online skin sampling process. This dynamic threshold values then were used to classify the skin and non-skin pixels for still images by creating binary image. Value '1' represented the skin pixels while '0' the non-skin pixel.

Multi-Faces Condition

The proposed skin colour detection method also can handle images with multiple faces condition. This was done by repeating the processes of skin detection as in Fig. 2 until there were no faces detected. Then, the generated dynamic threshold was applied to the individual. Figure 8 illustrates four individual results of each detected faces and the merging operation implemented to produce the final result. From the result, a better skin segmentation was produced by merging each of the individual results based on and Boolean operator. This was because each person possesses different skin tone that leads to generation of different threshold values.

Experimental Results

The proposed skin colour detection method was constructed using MATLAB 2014a. The aim of this section is to evaluate the performance of the proposed skin colour detection method applied to different image conditions, skin tones and skin-like objects compared to the state-of-art works. In our study, only frontal face images with slightly face rotation were considered for evaluation. The performance of the skin colour detection could be archived by two methods, i.e., qualitative and quantitative analysis. Qualitative analysis focuses on observing the ability of the proposed skin colour detection to classify skin and non-skin pixels from images. Pratheepan dataset (Tan *et al.*, 2012) was used for this qualitative analysis. However, the ground truth for Pratheepan dataset was not available, therefore the ground truth image were provided by manual selection through Adobe Photoshop CS5. The skin dataset with the ground truth can be accessed at (Chee Seng, 2014). The performance evaluation was based on the following description shown in the Table 3.

Performance measurement of the proposed skin detection was based on the F-measures, precision, recall, specificity and accuracy. The F-measure is the harmonic mean of precision and recall and can be calculated by weighting between precision and recall. The formula for the measurement is shown in Equation 5-9:

$$F - measure = 2\left(\frac{Precision \times Recall}{Precision + Recall}\right) \quad (5)$$

Where:

$$Presicion = \left(\frac{TP}{TP + FP}\right) \quad (6)$$

$$Recall = \left(\frac{TP}{TP + FN}\right) \quad (7)$$

$$Specificity = \left(\frac{TN}{TP + FP}\right) \quad (8)$$

$$Accuracy = \left(\frac{TP + TN}{TP + TN + FP + FN}\right) \quad (9)$$

The qualitative analysis showed that the proposed skin colour detection by combining multi-colour space provides better performance in terms of classifying the skin pixels with less false positive regions.

Figure 9 shows the result of Pratheepan dataset (single face) of (Yogarajah *et al*., 2010; Tan *et al*., 2012) method. The Fig. 9(b) column is the benchmark or ground thruth image. White colour indicates as skin pixels while black colour indicates the non-skin pixels. The last column Fig. 9(e) with red boxed is the result of performed by our proposed method.

As for the quantitative analysis, comparison of our proposed method based on several combinations of colour space was carried out, where three combinations of colour space were analysed with a single colour space. The results in Table 4 clearly shows that false positive can be reduced significantly from ~19.61% to ~6.99% by combining multi-colour space into single skin colour colour mode. On the other hand, high accuracy was achieved by skin colour model of *CbCr* with 85.86%.

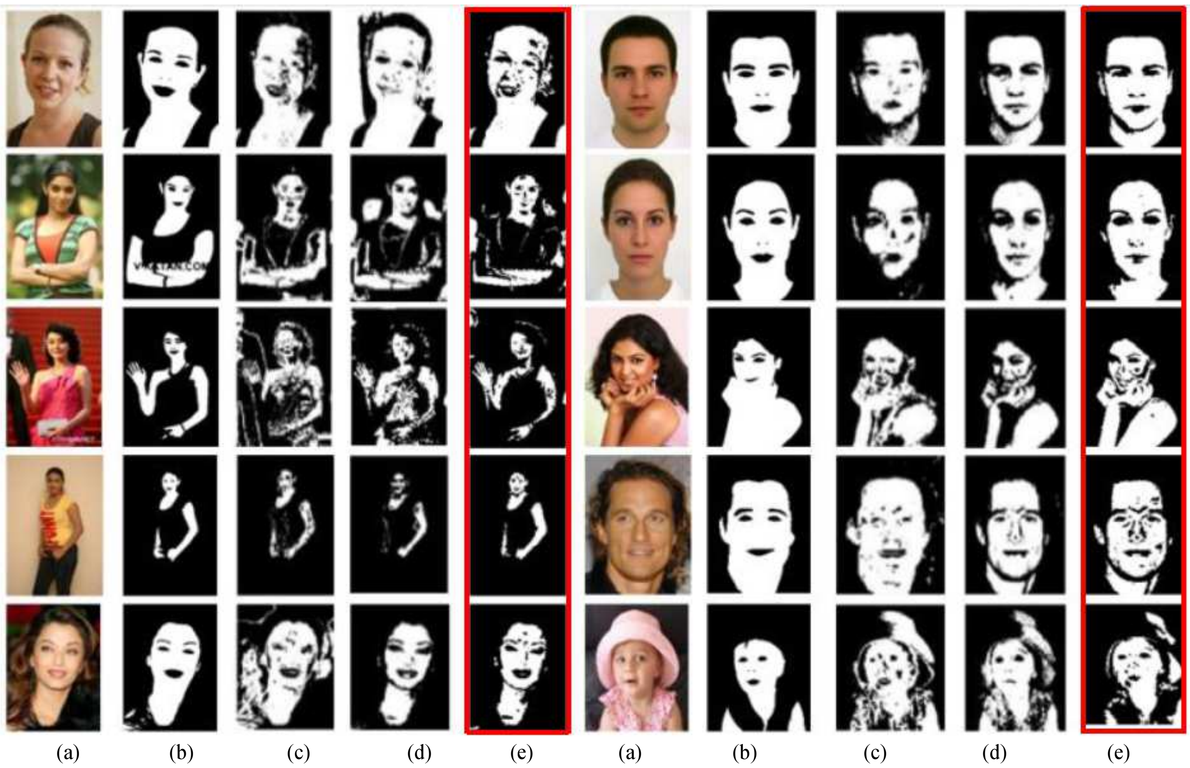


Fig. 9. Qualitative comparison using Pratheepan dataset of single faces. From left to right represents the input image (a), ground truth (b), Yogarajah *et al*. (2010) method (c), Tan *et al*. (2012) method (d) and our proposed method (e)

Table 3. Description of the performance evaluation

True Positive (TP)	The skin pixels are correctly identified
True Negative (TN)	The non-skin pixels are correctly rejected
False Positive (FP)	Incorrectly identified as skin pixels, but actually non-skin pixel
False Negative (FN)	Incorrectly rejected as non-skin pixels, but actually skin pixel

Table 4. Comparison result of the proposed method using different colour space

Skin colour model	FP (%)	Accuracy (%)	Precision (%)
YCbCr-SV	6.9887	84.05	91.49
CbCr-SV	6.9984	83.48	91.48
YCbCr-RGB	8.3235	83.48	90.04
CbCr-RGB	8.8040	83.81	89.67
CbCr	14.8803	85.86	85.45
RGB	17.6375	83.32	85.33
HSV	19.6069	81.57	81.27

The result in Table 4 also shows that *YCbCr-SV*, *CbCr-SV* and *YCbCr-RGB* were better than single skin colour model. It can be concluded that *YCbCr-SV* skin colour model generated the least positive, with reasonable accuracy and high precision.

Discussion

People such as Asian, African and Caucasian have different skin tones that may fall under the different threshold. Adopting dynamic skin colour detection using detected face as the skin sample is the easiest way to classify skin and non-skin under skin-like and ethnicity image variations. This is due to dynamic threshold values that are obtained individually from the detected face to be used in dynamic skin classification. From the literature, current skin colour detection using dynamic threshold method fails to generate better skin regions. In the proposed skin colour detection, elastic elliptical mask model was introduced according to the eye angle. The skin probably located at which employing rotation in the masking model. Any non-skin region such as eyebrow, lips and hair are removed using non-skin filtering. This process was done by implementing Sobel edge detector to detect the non-skin edges. However, not all the non-skin regions are filtered out. Then, 95% histogram acceptance employed from the extracted skin colour distribution as the final dynamic threshold values. Finally, skin classification with dynamic threshold values employed to the skin colour image.

In multiple faces condition, an iteration of processes was carried out. In this case, initial results of each dynamic threshold value of detected faces were merged to generate the final result of the skin region. The iteration required time to process depending on the number of faces detected in the first place. This process is suitable for an image that contains various skin tones from different people.

Based on the qualitative result obtained, it was proven that our proposed improved skin colour detection generates better skin regions rather than the state-of-the-art skin colour detection. Proposed multi-colour space is better than a single colour space. *YCbCr-SV* skin colour model presents the highest precision and lowest false positive. Minimal false positive of skin regions detected where skin-like colour such hair, background were successfully eliminated. However, any skin-like colour region that belongs to the dynamic threshold values remained detected as skin that may reduce the accuracy of the skin detection performance.

Conclusion

Skin colour detection is important in many applications and is continually being researched until now. Hence, developing a dynamic skin detector with flexibility is a great need to model the skin colour for handling image variations. Therefore, in this study, a skin colour detection based on improved dynamic threshold using the multi-colour space have been proposed to detect human skin in coloured image (s). Elastic elliptical face mask model that based on the eye angle was also introduced. Initial analysis found that, elliptical shape more suitable due to human faces are nearly oval, thus lead to reduced possibility of non-skin regions. Experimental results showed false positive was reduced compared to the previous dynamic skin detection methods. In a nutshell, the improved skin colour detection also increased the precision rate compared to the single colour model through the implementation of multi-colour space model. Our proposed skin detection highly depended on the performance of the face detector. Any undetected faces will generate false threshold values, hence resulting in poor detection of skin regions. As for future improvement, we would like to solve this issue by adding adaptability using trained multi-colour model for undetected faces in the images. In addition, a new dataset will be carried out to support this improvement by collecting image under different ethnicity, skin tones and different illumination.

With this, the success in classifying skin pixel with less false positive region, is potential to be applied in skin segmentation for illicit image detection purpose.

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Author's Contributions

All authors of this research have equally participated in the planning, execution and data analysis as well as article preparation.

Ethics

This article is original and contains unpublished material and no ethical issues involved. The corresponding author confirms that all of the other authors have read and approve the manuscript.

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