A dynamic threshold approach for skin tone detection in colour images

Pratheepan Yogarajah*, Joan Condell, Kevin Curran and Paul McKevitt

School of Computing and Intelligent Systems (SCIS),
University of Ulster,
Northern Ireland, BT48 7JL, UK
E-mail: p.yogarajah@ulster.ac.uk
E-mail: j.condell@ulster.ac.uk
E-mail: kj.curran@ulster.ac.uk
E-mail: p.mckevitt@ulster.ac.uk
*Corresponding author

Abbas Cheddad

Umeå Centre for Molecular Medicine (UCMM),
Umeå Universitet,
901 87, Umeå, Sweden
E-mail: Cheddad@gmail.com

Abstract: This paper presents a novel dynamic threshold approach to discriminate skin pixels and non-skin pixels in colour images. Fixed decision boundaries (or fixed threshold) classification approaches are successfully applied to detect human skin tone in colour images. These fixed thresholds mostly failed in two situations as they only search for a certain skin colour range:

- any non-skin object may be classified as skin if non-skin objects's colour values belong to fixed threshold range
- any true skin may be mistakenly classified as non-skin if the skin colour values do not belong to fixed threshold range.

Therefore in this paper, instead of predefined fixed thresholds, novel online learned dynamic thresholds are used to overcome the above drawbacks. The experimental results show that our method is robust in overcoming these drawbacks.

Keywords: skin tone detection; dynamic threshold.

Reference to this paper should be made as follows: Yogarajah, P., Condell, J., Curran, K., McKevitt, P. and Cheddad, A. (2012) 'A dynamic threshold approach for skin tone detection in colour images', *Int. J. Biometrics*, Vol. 4, No. 1, pp.38–55.

Biographical notes: Pratheepan Yogarajah received the BSc (Hons) in Computer Science from the University of Jaffna, Sri Lanka, in 2001. He received his MPhil in Computer Vision in 2006 from the

Oxford Brookes University, UK. Currently, he is a Research Associate at the School of Computing and Intelligent Systems, University of Ulster, UK. His research interests include computer vision, image processing, steganography & digital watermarking and machine learning.

Joan Condell received the BSc in Mathematics, Statistics and Computing from the University of Ulster, Jordanstown, Northern Ireland, in 1997. She received the MSc in Industrial Mathematics with Distinction from the University of Strathclyde and Glasgow Caledonian University, Glasgow, Scotland in 1998 and a PhD from the University of Ulster, Coleraine, Northern Ireland in 2002 with the research theme "Motion Tracking in Digital Images". She is a Lecturer in the University of Ulster, Magee. Her research interests include steganography, image processing, biometrics and vision for robotics and multimedia.

Kevin Curran received a PhD in Computer Science from the University of Ulster and is currently a Senior Lecturer and Group Leader for the Ambient Intelligence Research Group. His achievements include winning and managing UK and European Framework projects and Technology Transfer Schemes. He is a regular contributor to BBC radio and TV news in the UK and is currently the recipient of an Engineering and Technology Board Visiting Lectureship for Exceptional Engineers and is an IEEE Technical Expert for Internet/Security matters. He is a fellow of the British Computer Society (FBCS), a senior member of the Association for Computing Machinery (SMACM), a senior member of the Institute of Electrical and Electronics Engineers (SMIEEE) and a fellow of the higher education academy (FHEA).

Paul McKevitt is Chair in Digital MultiMedia at the Magee Campus of the University of Ulster. Previously, he was Visiting Professor of Intelligent MultiMedia Computing in the Institute of Electronic Systems, Aalborg University, Denmark, a Lecturer and British EPSRC (Engineering and Physical Sciences Research Council) Advanced Fellow in the Department of Computer Science, University of Sheffield, England and Research Scientist and Research Fellow in the Department of Computer Science, New Mexico State University, New Mexico, USA. He has published numerous research papers in international conferences, research books and journals and has been awarded four UK/international patents. He obtained his PhD (Exeter, 1991), MSc (New Mexico, 1988) and BSc (Hons.) (Dublin, 1985) degrees in Computer Science and MEd degree in Education (Sheffield, 1999).

Abbas Cheddad received his MSc in Computer Science from the Universiti Teknologi Malaysia in 2005 and a PhD Degree from the University of Ulster (UK) in 2009 with the thesis entitled "Strengthening Steganography in Digital Images". His research interests fall under the general theme of image processing including its practical applications, e.g., medical imaging, 3D reconstruction, pattern recognition, biometrics, steganography and watermarking. Currently, he is a Post-doc research associate in medical imaging at Umea Centre for Molecular Medicine, Umea Universitet, Sweden.

1 Introduction

Skin tone detection aims at determining whether colour pixel has the colour of human skin or not. In the past, many techniques have been developed and successfully applied for skin tone detection using colour information. For skin tone detection many colour spaces have been proposed throughout the literature. The image pixels representation in a suitable colour space is the primary step in skin Tone detection in colour images. A survey of different colour spaces (e.g., RGB, YCbCr, HSV, CIE Lab, CIE Luv and normalised RGB) for skin-colour representation and skin tone detection methods is given by Kakumanu et al. (2007). Recently a new colour SIFT descriptors for image classification is proposed by Verma et al. (2011) with applications to biometrics.

However, skin tone detection using colour information is not an easy task as the skin appearance in images is affected by various factors such as illumination, background, camera characteristics, and ethnicity. On top of the suitable colour space selection, a satisfactory classifier is needed to perform a best skin tone detection in colour images. A satisfactory skin classifier must be able to discriminate between skin and non skin pixels for a wide range of people with different skin tones (white, pink, yellow, brown and dark) and scene illuminations.

Existing classification or segmentation techniques use fixed decision boundaries (also called fixed threshold) (Sezgin and Sankur, 2004; Phung et al., 2005), edge detection (Zhang and Paul, 2004; Paul et al., 2005), region growing and merging (Ning et al., 2010), and active contour models (Zhang et al., 2010a, 2010b). Because of the simplicity, decision boundaries (i.e., thresholding) is the one of the popular techniques in image segmentation or classification (Sezgin and Sankur, 2004). Therefore in this paper we consider decision boundaries classification technique to detect skin tone in colour images. Skin tone detection approaches that rely on pixel-level classification often used a fixed decision boundaries technique. In the decision boundaries classification technique, the decisions boundaries are often fixed by the designer to obtain best skin tone detection results. However, many of the decision boundaries techniques are limited in performance due to real-world conditions such as illumination and ethnicity.

Recently, (Cheddad et al., 2009a, 2009b) developed a new skin tone detection method in colour images using YCbCr colour space and a fixed threshold classification technique. They compared their experimental results with other existing methods (Hsu et al., 2002; Berens and Finlayson, 2000; Kovac et al., 2003) and showed very promising results. They argue that their method is insensitive with ethnicity and robust to illumination as well. In their approach fixed threshold values are learned off-line using a certain amount of manually identified skin pixels and each image pixel is checked whether or not its colour value satisfies the fixed threshold values. They mentioned that, like all existing algorithms, their method is not yet intelligent enough to discriminate whether a scene contains a skin colour or something that looks similar to it, Cheddad et al. (2009b).

Skin colour varies greatly between different human races and very often a fixed threshold for skin boundary is learned from a certain amount of different skin colours. Therefore skin tone detection that uses fixed threshold values may fail in unconstrained imaging conditions. Through experimentation we find that, as in (Cheddad et al., 2009b), their fixed threshold classification technique is not robust

to separate skin region from non skin region which have colours more similar to skin, see Figure 1.

Figure 1 (a) and (b) represent a sample image from Google images and skin tone detection results using Cheddad et al. (2009a) respectively. White pixels represent skin and black non-skin in (b) (see online version for colours)

(a) (b)

Therefore we propose a new skin tone detection technique for colour images that makes (Cheddad et al., 2009a) intelligent and robust to separate skin from non skin which have colours more similar to skin. The proposed technique uses the same colour space used in Cheddad et al. (2009a, 2009b) as it is proved as robust with illumination. But we find the fixed threshold used in Cheddad et al. (2009a, 2009b) is limited in separating skin and non skin in colour images.

Instead of fixed threshold values we calculate dynamic threshold values via online learning by taking the colour information of human face region. Zheng et al. (2004) argue that using the skin colour property of the detected face region, the rest of skin pixels in the image can be detected. Our skin tone detection method also takes advantage of the fact that face and body of a person always share same colours. Using the detected face region colour values we calculate a dynamic threshold and our experimental results show that dynamic threshold is more robust in skin tone detection performance than previous experimental results shown in Cheddad et al. (2009a, 2009b), see Figure 2.

This paper is organised as follows. In Section 2, a classification point of view skin tone detection is analysed. Our proposed method and results and discussion are explained in Sections 3 and 4 respectively. The conclusion is given in Section 5.

2 Skin tone detection a classification point of view

From a classification point of view, skin tone detection can be viewed as a two class problem: skin-pixel vs. non skin-pixel classification. Different researchers have used different techniques to approach this problem. One of the easiest and often used methods is to define fixed decision boundaries for different colour space components. In any given colour space, skin colour occupies a part of such a space, which might be a compact or large region in the space. Such a region is usually called the skin colour cluster, see Figure 3.

Figure 2 (a)–(c) represent a sample image from Google images and skin tone detection results using Cheddad et al. (2009a) and our method respectively. White pixels represent skin and black non-skin in (b) and (c) (see online version for colours)

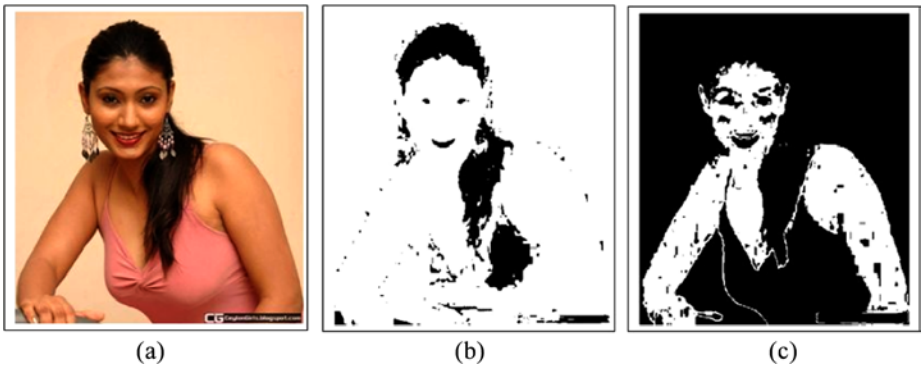
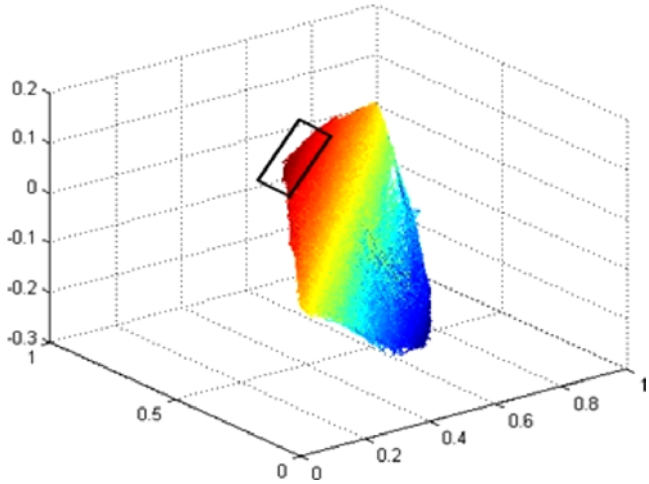


Figure 3 The dark red dot cloud represents the region where skin colour tends to cluster, i.e., the area bounded by a rectangle (see online version for colours)



Source: Cheddad et al. (2009b)

The maximum and minimum values from the skin colour cluster are defined as thresholds in fixed threshold based skin classifiers. Single or multiple ranges of threshold values for each colour space component are defined and the image pixel values that fall within these predefined range(s) for all the chosen colour components are defined as skin pixels.

Dai and Nakano (1996) used a fixed range on I component in YIQ space for detecting skin pixels from images containing mostly people with yellow skin. All the pixel values in the range, $R_I = [0, 50]$ are described as skin pixels in this approach. Sobottka and Pitas (1998) used fixed range values on the HS colour space. The pixel values in the range $R_H = [0, 50]$ and $R_S = [0.23, 0.68]$ are defined as skin pixels. These values have been determined to be well suited for discriminating skin pixels from non-skin pixels on images of yellow and white skin people.

Chai and Ngan (1999) proposed a face segmentation algorithm in which they used a fixed range skin-colour map in the CbCr plane. The pixel values in the range $R_{Cb} = [77, 127]$, and $R_{Cr} = [133, 173]$ are defined as skin pixels. Wang and Yuan (2001) have used threshold values in rg space and HSV space. The threshold values in the range $Rr = [0.36, 0.465]$, $Rg = [0.28, 0.363]$, $RH = [0, 50]$, $RS = [0.20, 0.68]$ and $RV = [0.35, 1.0]$ are used for discriminating skin and non-skin pixels.

Based on the above, it is noticeable that most of the fixed threshold based skin classifiers were successfully applied in controlled imaging conditions, e.g. detect white and yellow skins. Figure 4 also shows that skin colour pixels from different people races cannot be easily bounded with fixed threshold boundaries. Say if we want to consider all skin colour pixels for African skin, then that means we accept some non-skin colour pixels from Asian and Caucasian as well.

Therefore we argue that fixed thresholds are not robust with wide varieties of skin colours. In order to handle wide variety of skin colours a dynamic threshold classification technique is needed and so a new dynamic threshold approach is developed in our proposed method. The next section explains our proposed method.

3 Our proposed method

Skin tone detection normally has two phases: training and detection. Training a skin classifier involves three steps:

1. Collecting a database of skin pixels from different images. Such a database typically contains skin-colour pixels from a variety of people under different imaging conditions.
2. Choosing a suitable colour space.
3. Learning the parameters of a skin classifier.

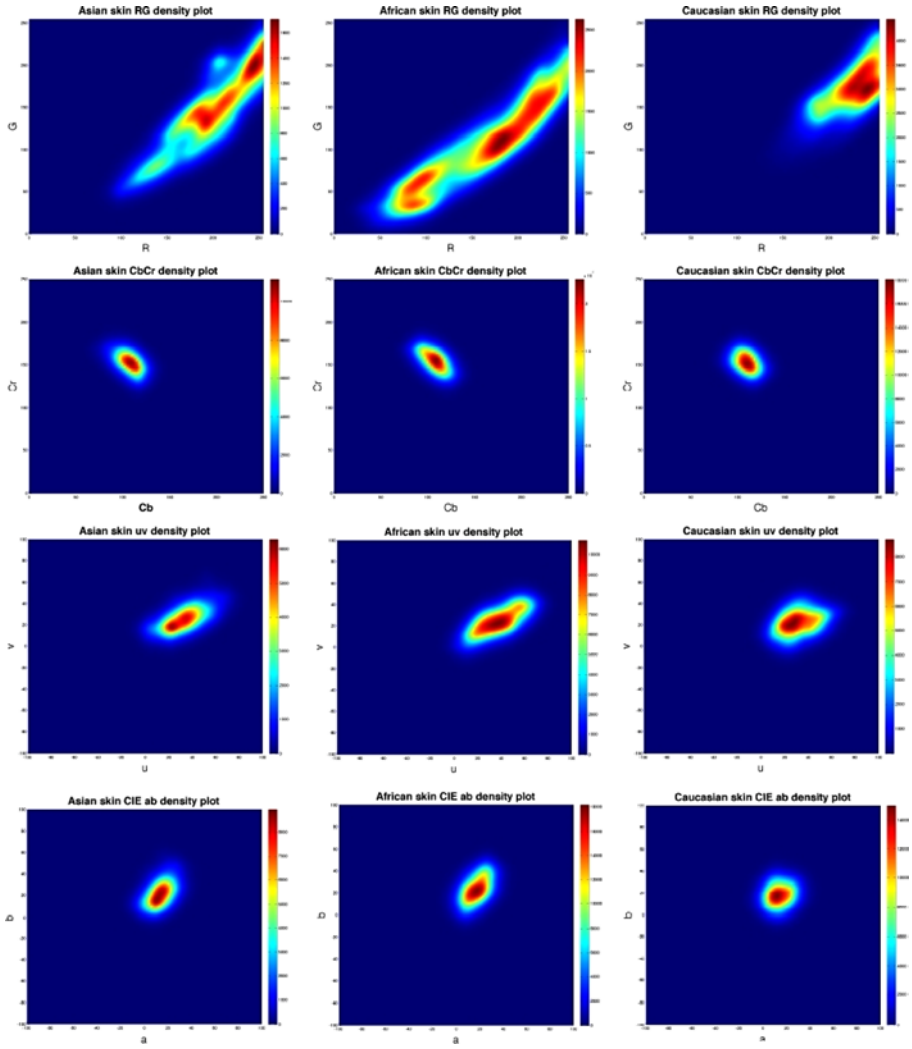
Given a trained skin classifier, identifying skin colour pixels in a given image involves:

1. Converting the image into the same colour space that was used in the training.
2. Classifying each pixel using the skin colour classifier as skin or non-skin.

As we use dynamic threshold, we do not need to learn any predefined fixed threshold from the collected database. Therefore we do not have any training phase in our proposed skin tone detection method. Our proposed method is given as follows:

1. Converting the given image into a suitable colour space, we use same colour space used in Cheddad et al. (2009a).
2. Learning the parameters of a skin classifier using our novel method.
3. Classifying each pixels in the given image using the online learned skin colour classifier as skin or non-skin.

Figure 4 Density plots of Asian, African and Caucasian skin in different colour spaces, Elgammal et al. (2010). Each row represents different colour spaces. The columns from left to right represent Asian, African and Caucasian skins respectively (see online version for colours)



3.1 Skin tone detection and colour space

As discussed previously, the colour space discussed below is based on previous work (Cheddad et al., 2009a). The utilised transformation matrix is defined in equation (1).

$$\hat{\alpha} = [0.29893602129377539 \quad 0.58704307445112136 \quad 0.14020904255103250]^T \quad (1)$$

where the superscript T denotes the transpose operator to allow for matrix multiplication. Let ϕ denote the 3D matrix containing the RGB vectors of the host

image and let $x\epsilon[1, 2, \ldots, n]$, where n = length(R) = length(G) = length(B). Note that this method acts here on the RGB colours stored in double precision, i.e., linearly scaled to the interval [0 1]. The initial colour transformation is given in equation (2).

$$I(x) = (\phi(r(x), g(x), b(x)) \otimes \hat{\alpha}) \tag{2}$$

where $\otimes$ represents matrix multiplication. This reduces the RGB colour representation from 3D to 1D space. The vector $I(x)$ eliminates the hue and saturation information whilst retaining the luminance. It is therefore regarded formally as a grayscale colour. Next, the algorithm tries to obtain another version of the luminance but this time without taking the R vector into account. Most skin colour tends to cluster in the red channel. The discarding of red colour is deliberate, as in the final stage it will help to calculate the error signal. Therefore, the new vector will have the largest elements taken from G or B:

$$\hat{I}(x) = \arg \ \max_{x\epsilon 1,\ldots,n}(G(x), B(x)). \tag{3}$$

Equation (3) is actually a modification of the way Hue, Saturation and Value (HSV) computes the V values. The only difference is that the method does not include in this case the red component in the calculation. Then for any value of x, the error signal is derived from the calculation of element-wise subtraction of the matrices generated by equations (2) and (3) which can be defined as $e(x) = I(x) - \hat{I}(x)$.

3.2 Skin tone detection and classifier

In Cheddad et al. (2009a) method, a collection of 147852 pixel samples was gathered from different skin regions exhibiting a range of races with extreme variations in lighting effects. Lower and upper decisions boundaries were calculated as 0.02511 and 0.1177 respectively. Finally $e(x)$ values in the range $[0.02511, 0.1177]$ were classified as skin.

Our experimental results showed that their fixed threshold $[0.02511, 0.1177]$ can not perform efficiently when background and cloths colours are more similar to skin colour. Here our motivation is to get a dynamic threshold value via online learning for a particular image using human face skin colour information. To get the face skin colour information, human eyes are detected using the Machine Perception Toolbox (Fasel et al., 2005). When the eyes are detected, see Figure 6(a), the elliptical face region is generated, see Figure 6(b), using an elliptical mask model, see Figure 5.

Here (x_0, y_0) is the centre of the ellipse as well as the eyes symmetric point. Minor and major axes of ellipse are represented by $1.6D$ and $1.8D$ respectively, where D is distance between two eyes.

We can see that the detected face region contains the smooth (i.e., skin) and non-smooth (i.e., eyes and mouth.) textures. As we only want to keep the smooth regions, the non-smooth regions are detected and removed. It is well studied that edge pixels can be generated in non-smooth regions (Gonzalez and Woods, 2008). We applied the Sobel edge detector as it has computational simplicity (Phung et al., 2005), see Figure 6(c). The detected edge pixels are further dilated using dilation operation to get the optimal non-smooth regions, (Gonzalez and Woods, 2008), see

Figure 5 Elliptical mask model generated using eyes coordinates

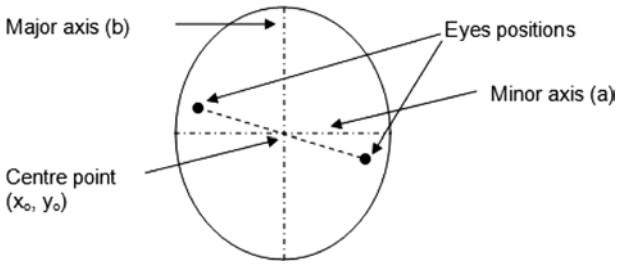
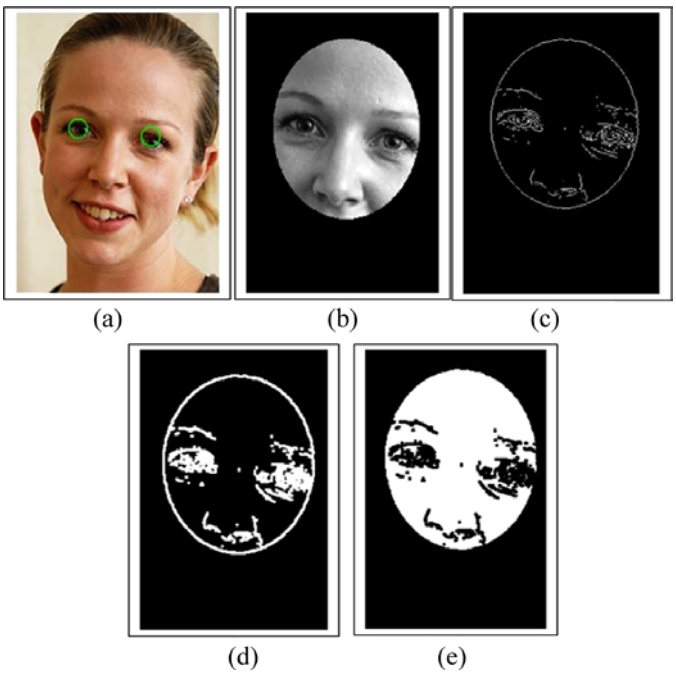


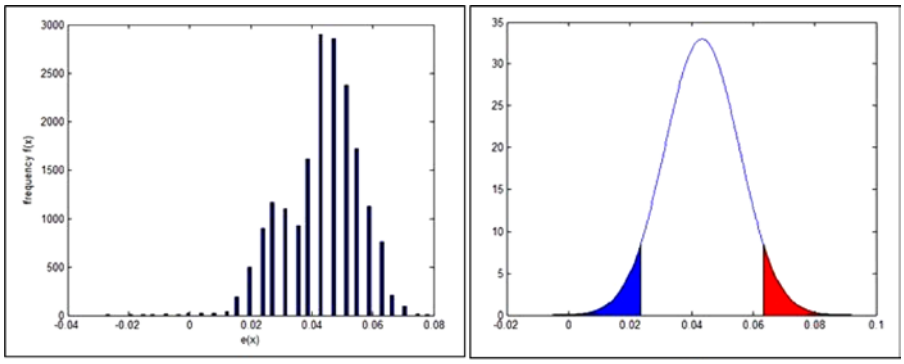
Figure 6(d). Finally the calculated non-smooth region is subtracted from the face region and smooth region is obtained, see Figure 6(e). Finally, the values from $e(x)$ which correspond to the detected smooth region are considered for the dynamic threshold calculation. For simplicity we assume those correspondence $e(x)$ values stored in array SR. Figure 7(a) shows the frequency distribution of SR.

Figure 6 (a)–(e) represent eye detection, face region, edge detection, dilated image and smooth region respectively (see online version for colours)



Even though the dilation operation is applied, there is no guarantee that 100% of the non-smooth regions are removed properly. Therefore a two-sided 95% confidence interval of a normal distribution, $\mathcal{N}(\mu, \sigma^2)$, is fitted on SR to generate the dynamic threshold, see Figure 7(b). Here μ and σ are mean and standard deviation of SR and the lower and upper boundaries of the dynamic threshold values calculated based on the confidence interval of normal distribution. Based on these calculated dynamic threshold values each and every pixel in the colour image

Figure 7 (a) and (b) represent the frequency and normal distribution with 95% confidence interval respectively (see online version for colours)



(a) (b)

is classified as skin and non-skin. When more than one face region are detected in the image, each region is used to construct a dynamic threshold, and each threshold is used to perform skin tone detection on the whole image. The final result is a logical OR combination of each of the detected regions obtained respectively with each dynamic threshold. The next section shows some experimental results using our dynamic threshold approach.

4 Skin tone detection: results and discussion

To carry out skin tone detection, a set of images was downloaded from Google. These random images may have been captured with a range of different cameras using different colour enhancement and under different illumination. The method of Cheddad et al. (2009a) and our proposed method are applied and Figure 8 shows a sample of results obtained for three images. From the above results it can be argued that our dynamic threshold method can optimally discriminate skin from non-skin, even when non-skin colour is more similar to skin colour, than given in Cheddad et al. (2009a).

Figure 8 shows that Cheddad et al.'s method detected human skin and also detected many non-skin objects as skin. But if we further analyse Figure 9 then we can see that Cheddad et al.'s method failed to detect most of the skin area. Therefore as we discussed previously in this paper about the drawback of fixed threshold methods, Cheddad et al.'s method also searches for certain range of skin colours. We can conclude that our method is more robust for any skin colour as the algorithm learns dynamic threshold values instantly from the current image, more results can be found in Figures 10 and 11.

In addition to the arbitrary still images from the internet, we tested the algorithm on a larger benchmark, i.e., image frames from the video '14.avi' of PRIP Skin-Database(http://www.prip.tuwien.ac.at/people/julian/skin-detection/skin-database.rar). This database includes the ground truth data as well. Figure 12 shows some frame samples, the ground truth, skin tone detection based on our proposed method and skin tone detection based on Cheddad et al.'s method.

Figure 8 Columns (a)–(c) represent random images from google, skin tone detection using Cheddad et al. (2009a) and our methods respectively (see online version for colours)

Figure 9 (a)–(c) represent a random image from google, skin tone detection using Cheddad et al. (2009a) and our methods respectively. In this experiment, our method instantly learned a threshold $[-0.0041, 0.0332]$ and Cheddad's fixed threshold $[0.02511, 0.1177]$ (see online version for colours)

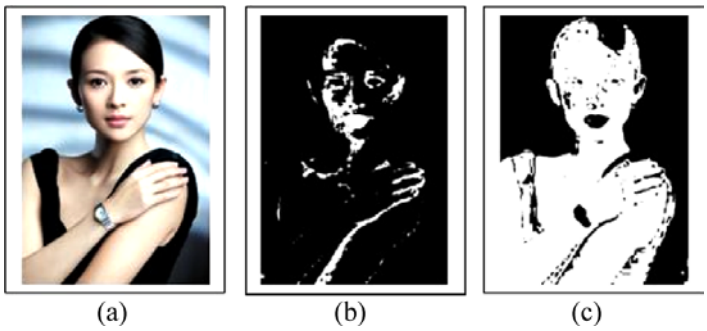
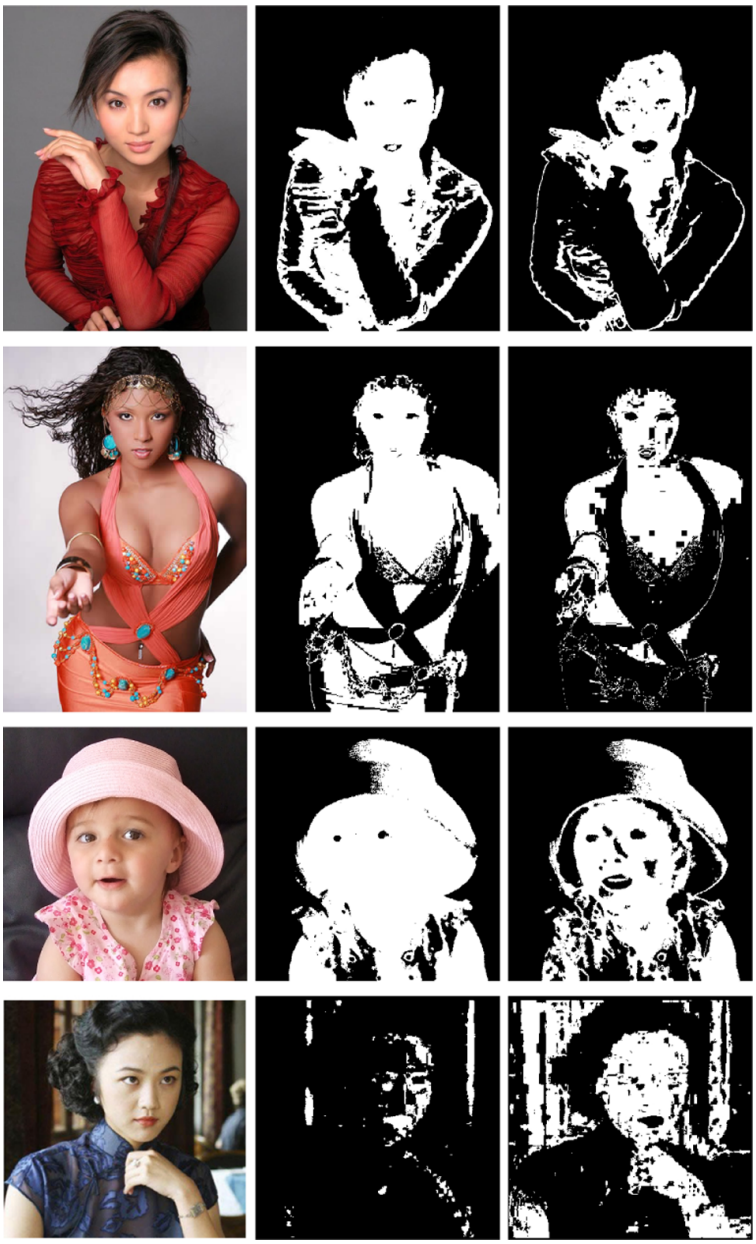


Figure 13 shows the graphical performance analysis of the proposed method against Cheddad et al.'s method. In Figure 13, skin pixels represents the number of classified skin tone pixels from ground truth. Detection represents the number of classified skin tone pixels using our proposed and Cheddad et al.'s experiments. False positive and false negative based classified number of pixels also shown in Figure 13.

Figure 10 Columns from left to right represent random images from google, skin tone detection using Cheddad et al. (2009a) and our methods respectively (see online version for colours)



In our experiments, false positive means that result shows that a pixel represents 'Skin' colour, but in reality, it does not. False negative means that result shows that a pixel does not represents 'Skin' colour, but in reality, it does.

We also tested the algorithm with another video '13.avi' of PRIP Skin-Database (http://www.prip. tuwien.ac.at/people/julian/skin-detection/skin-database.rar), see

Figure 11 Columns from left to right represent random images from google, skin tone detection using Cheddad et al. (2009a) and our methods respectively (see online version for colours)

Figure 12 Rows (a)–(d) represent sample frames, ground truth data, results using proposed method and Cheddad et al.'s method respectively (see online version for colours)

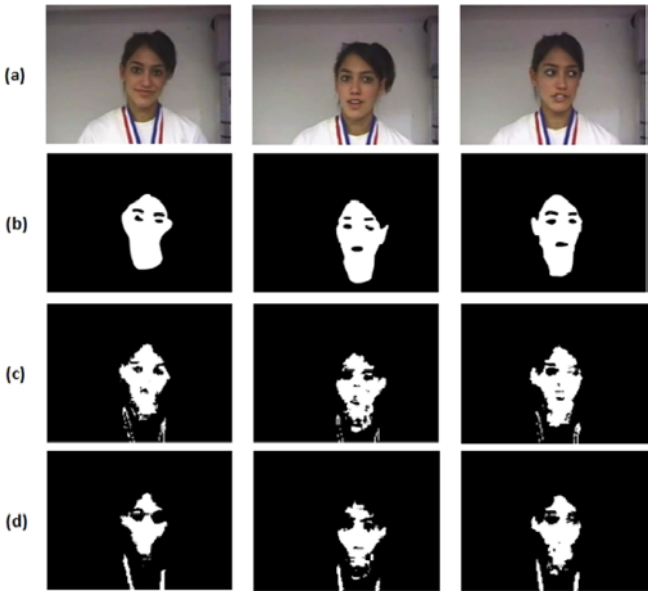


Figure 13 Top and bottom rows represent sample frames and ground truths respectively

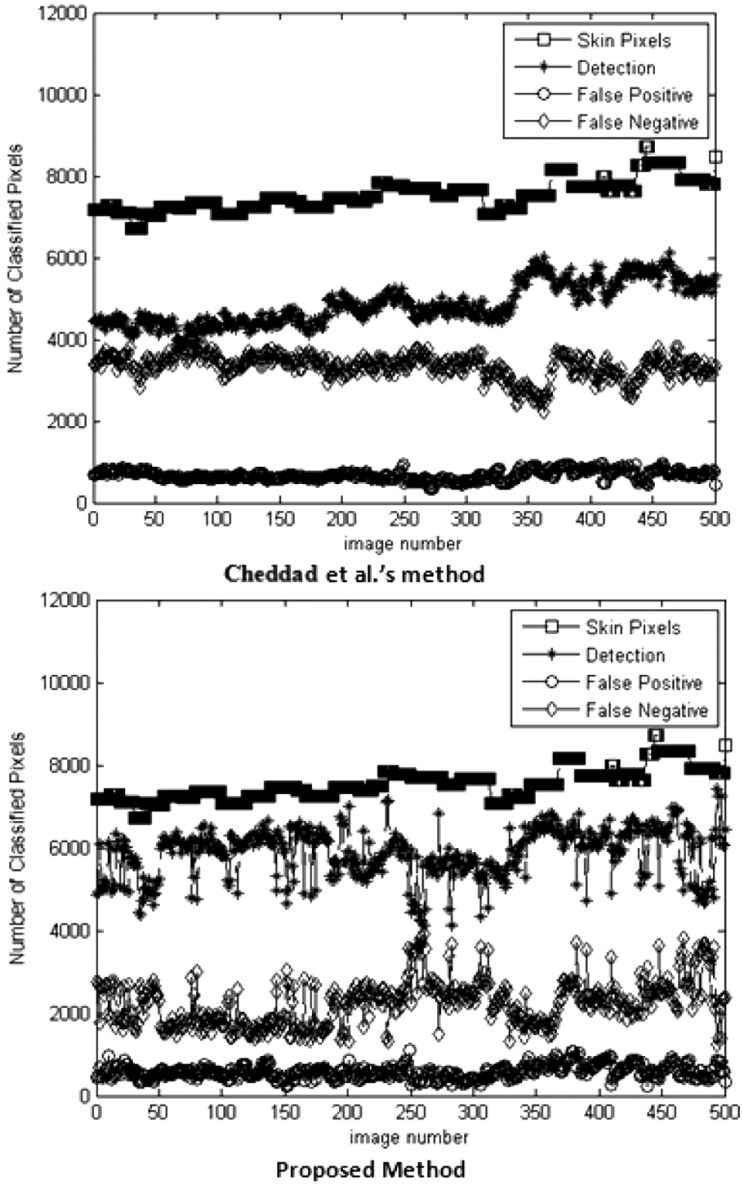


Figure 14 shows some frame samples, the ground truth, skin tone detection based on our proposed method and skin tone detection based on Abbas et al.'s method.

Figure 15 shows the graphical performance analysis of the proposed method against Cheddad et al.'s method.

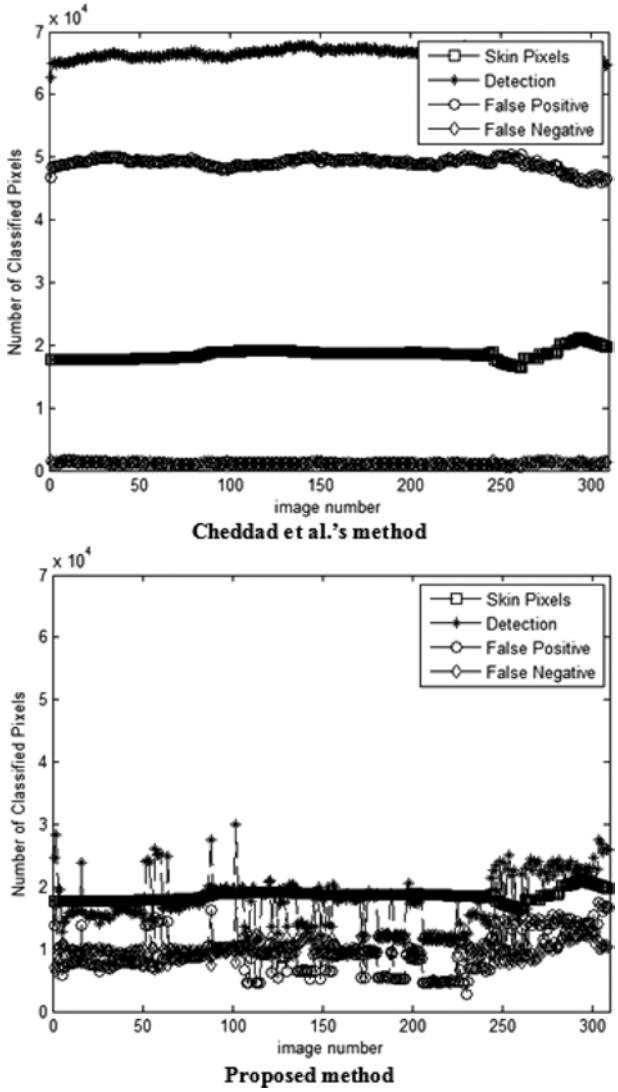
As can be seen, the proposed method is by far the most efficient in that it preserves lower rates for the dual false ratios while securing a high detection rate than Cheddad et al.'s method.

Figure 14 Rows (a)–(d) represent sample frames, ground truth data, results using proposed method and results from Cheddad et al.'s method respectively (see online version for colours)

5 Conclusion and future works

The proposed skin tone detection technique performs better than the fixed threshold skin tone detection proposed previously (Cheddad et al., 2009a). The proposed method is robust to imaging conditions and not biased by human ethnicity. Two main drawbacks with fixed threshold classification outlined in this paper are solved by our novel dynamic skin tone detection technique. However, thresholding techniques are not sufficient to get satisfying classification results sometimes because of its simplicity. Some recent methods such as region growing and merging, Ning et al. (2010), and active contour models, (Zhang et al., 2010a, 2010b), proved their effectiveness on image segmentation. Therefore as future direction, we would like to investigate best segmentation method that can be used to improve the skin tone detection performance.

Figure 15 Top and bottom rows represent sample frames and ground truths respectively



Also, it is noted that if there are no eyes detected in the image then our method can not be applied to skin tone detection problems. The elliptical mask model used in this paper is based on the frontal face. So it may not be robust for photos which are taken from other angles. Therefore we plan to apply an 'elastic' mask model in our future work to solve this problem.

Acknowledgements

This Project was partially funded by Invest Northern Ireland under the Proof of Concept Scheme.

References

Berens, J. and Finlayson, G.D. (2000) 'Log-opponent chromaticity coding of colour space', *Proceedings of IEEE ICPR*, Barcelona, Spain, pp.206–211.

Chai, D. and Ngan, K.N. (1999) 'Face segmentation using skin-color map in videophone applications', *IEEE Trans. Circuits Syst. Video Technol.*, Vol. 9, No. 4, pp.551–564.

Cheddad, A., Condell, J.V., Curran, K.J. and McKevitt, P. (2009a) 'A new colour space for skin tone detection', *Proceedings of The IEEE International Conference on Image Processing (ICIP)*, Cairo, Egypt, pp.7–11.

Cheddad, A., Condell, J.V., Curran, K.J. and McKevitt, P. (2009b) 'A skin tone detection algorithm for an adaptive approach to steganography', *Elsevier – Journal of Signal Processing*, Vol. 89, No. 12, pp.2465–2478.

Dai, Y. and Nakano, Y. (1996) 'Face-texture model based on SGLD and its application in face detection in a color scene', *Pattern Recognition*, Vol. 29, No. 6, pp.1007–1017.

Elgammal, A., Muang, C. and Hu, D. (2010) 'Skin Detection – a short tutorial', *Encyclopaedia of Biometrics*, R.U., Department of Computer Science, Piscataway, NJ, USA, Springer-Verlag, Berlin, Heidelberg, Vol. 2, No. 5, pp.1–10.

Fasel, I., Fortenberry, B. and Movellan, J.R. (2005) 'A generative framework for real time object detection and classification', *CVIU*, Vol. 98, No. 1, pp.182–210.

Gonzalez, R.C. and Woods, R.E. (2008) *Digital Image Processing*, 3rd ed., Prentice-Hall, Upper Saddle River, NJ.

Hsu, R.L., Abdel-Mottaleb, M. and Jain, A.K. (2002) 'Face detection in color images', *IEEE Trans. PAMI*, Vol. 24, No. 5, pp.696–702.

Kakumanu, P., Makrogiannis, S. and Bourbakis, N. (2007) 'A survey of skin-color modeling and detection methods', *Pattern Recognition*, Vol. 40, No. 3, pp.1106–1122.

Kovac, J., Peer, P. and Solina, F. (2003) 'Human skin colour clustering for face detection', *Proc. of International Conference on Computer as a Tool*, Ljubljana, Slovenia, pp.144–148.

Ning, J., Zhang, L., Zhang, D. and Wu, C. (2010) 'Interactive image segmentation by maximal similarity based region merging', *Pattern Recognition*, Vol. 43, pp.445–456.

Paul, B., Zhang, L. and Wu, X. (2005) 'Canny edge detection enhancement by scale multiplication', *IEEE Trans. Pattern Anal. Machine Intell.*, Vol. 27, pp.1485–1490.

Phung, S.L., Chai, D. and Bouzerdoum, A. (2005) 'Adaptive skin segmentation in color images', *IEEE International Conference on ASSP*, Hong Kong, pp.182–210.

Sezgin, M. and Sankur, B. (2004) 'Survey over image thresholding techniques and quantitative performance evaluation', *J. Electron. Imaging*, Vol. 13, pp.146–165.

Sobottka, K. and Pitas, I. (1998) 'A novel method for automatic face segmentation, facial feature extraction and tracking', *Signal Process. Image Communication*, Vol. 12, No. 3, pp.263–281.

Verma, A., Liu, C. and Jia, J. (2011) 'New colour SIFT descriptors for image classification with applications to biometrics', *International Journal of Biometrics (IJBM)*, Vol. 3, pp.56–75.

Wang, Y. and Yuan, B. (2001) 'A novel approach for human face detection from color images under complex background', *Pattern Recognition*, Vol. 34, pp.1983–1992.

Zhang, L. and Paul, B. (2002) 'Edge detection by scale multiplication in wavelet domain', *Pattern Recognition Letters*, Vol. 23, pp.1771–1784.

Zheng., Q., Zhang, M. and Wang, W. (2004) 'A hybrid approach to detect adult web smages', *PCM*, Vol. 2, pp.609–616.

Zhang, K.H., Zhang, L., Song, H.H. and Zhou, W. (2010a) 'Active contours with selective local or global segmentation: a new formulation and level set method', *Image Vision Computing*, Vol. 28, pp.668–676.

Zhang, K.H., Song, H.H. and Zhang, L. (2010b), 'Active contours driven by local image fitting energy', *Pattern Recognition*, Vol. 43, pp.1199–1206.

Website

http://www.prip.tuwien.ac.at/people/julian/skin-detection/skin-database.rar