ESTEEM Academic Journal is jointly published by the Universiti Teknologi MARA, Pulau Pinang and UiTM Press, Universiti Teknologi MARA, 40450 Shah Alam, Selangor, Malaysia.

ESTEEM

Academic Journal UiTM Pulau Pinang

Volume 7, Number 1 | June 2011 | ISSN 1675-7939

Foreword

Alhamdulillah. First of all a big thank you and congratulations to the Editorial Board of ESTEEM Academic Journal of Universiti Teknologi MARA (UiTM), Pulau Pinang for their diligent work in producing this issue. I also would like to thank the academicians for their contributions and the reviewers for their meticulous vetting of the manuscripts. A special thanks to UiTM Press (Penerbit UiTM) for giving us this precious opportunity to publish this first issue of volume 7.

In this issue, we have compiled an array of seven interesting engineering research and technical based articles for your reading. Mazlan Mohamed, Rahim Atan and Mohd. Zulkifly Abdullah presents the simulation of three dimensional numerical analysis of heat and fluid flow through chip package. 3D model of chip packages is built using GAMBIT and simulated using FLUENT software. The authors had made comparison between three types of material in the term of junction temperature and found that the junction temperature of the nano-silver had the lowest junction temperature compared to epoxy and composite polymer. It was also found that the nano-silver had the highest value of thermal conductivity.

Solahuddin Yusuf Fadhlullah, Mohamad Adha Mohamad Idin and Mohd Halim Mohd Noor wrote an article that looks at Intrusion Detection System (IDS). In this study major and well known evasion techniques are exposed and discussed. Countermeasures are also mentioned and listed down in order to mitigate the threat of IDS evasion.

The third article written by Fairosidi Idrus et al. looked at the effect of wick structure and filling ratio to the vapour chamber performance in electronic cooling using an experimental method. The experimental results show that the rectangular wick structure gives the lowest thermal resistance and the wick structure with the working fluid and the boiling phenomenon is practically effective for a 45% fill ratio.

The article entitled "an introduction to e-ssc test kit as a new technique to characterize swelling and shrinkage potential of rock material" authored by Intan Shafika Saiful Bahri et al. A study was conducted to re-characterize the properties and behaviors of these weakly cemented rocks which were found to be very sensitive to moisture changes. A real time laboratory study determines the typical free swell and shrinkage behavior of the materials that potentially induced slope failures.

The fithth article by Rozaini Ramli and Intan Shafika Saiful Bahri examine on the determination of soil erodibility, k factor for sungai kurau soil series. The author concluded that *Tew* equation indicates the smallest error for RMSE and suggested to be the most applicable method for statistical determination of soil erodibility for Malaysian soil series.

Rizal Mat Jusoh, Sharifah Saliha Syed Bahrom and Saiful Fadzli Salian present the Skin Detection Using Color Component Subtraction and Texture Information. In this study the algorithm is tested on color images focusing on palm and face skin regions. The author concluded that the algorithm is able to achieve more than 90% of detection rate.

The last article is entitled effect of various sizes extraction of wood-wool on the properties of wood-wool cement board manufactured from kelampayan (*neolamarckia cadamba*). The authors, Mohd Azrizal Fauzi and Zakiah Ahmad found that the performance of WWCB is influenced by wood-wool size and density.

We do hope that you not only have an enjoyable time reading the articles but also find them useful. Thank you.

Soffian Noor Mat Saliah
Chief Editor
ESTEEM, Vol. 7, No. 1, 2011
(Engineering)

Skin Detection Using Color Component Subtraction and Texture Information

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ABSTRACT

This paper presents skin detection algorithm for detecting human skin regions in color images. The input color image in RGB format is converted into HSV format for color components subtraction. The value component minus hue component is applied for first stage of skin detection. The result of the subtraction is considered as skin region candidates. From the skin region candidates, rectangular box enclosing the regions are estimated. The texture features are also calculated for these skin candidates regions, where contrast and entropy are used. The features give acceptable separation between skin and non skin regions. These texture features are used to verify that the segmented blobs are skin regions. The algorithm is tested on color images focusing on palm and face skin regions. The results had shown that the algorithm is able to achieve more than 90% of detection rate.

Keywords: *Texture, Color Space, Skin Detection, Color Components*

Introduction

Current technologies in home appliances are moving towards friendly interaction between devices and human. In detecting human skin, color is the main attribute in differentiating it with other parts of the body or background. Through observation skin color is the dominant

ISSN 1675-7939

and distinguishing feature compared to the others. Based on this consideration, skin detection process is looking for skin color in detecting human skin. Skin detection is mostly used in applications such as face detection/tracking, hand gesture detection, naked people detection and surveillance system. In hand gesture application, it is used to control or monitor a process or device based on command given by the user. Skin detection is very popular in detecting or tracking human body parts, such as face and hand.

The main issues with skin detection are the algorithm which should be able to cope with skin regions that may vary between two different consecutive images, variations in lighting conditions, complex background, objects with skin like color that appears in the same input image and people skin from different races.

The lighting conditions at indoor and outdoor are also critical issues for skin detection. These are the issues that are faced by the current researchers in skin detection area. This research is focusing on affords of increasing the detection rate of skin region detection. The detection rate is done by comparing the results of the proposed segmentation algorithm and manual segmentation. Skin detection is important because it is the primary step in gesture recognition, face recognition, face tracking and surveillance system. The sample images will be captured under the normal room lighting condition. Some sample images are collected from internet and online newspaper. The images are concentrated on the face and hand skin regions. This is because the HMI applications are using both of human body for interaction.

Based on the problems that have been identified, the objectives of this research are;

i. To develop an algorithm able to detect skin pixels (skin region) in color image. The method should be able to differentiate between skin and non-skin pixels with detection rate equal or greater than 90%.
ii. To test the performance of the developed algorithm on several color image samples taken from internet and captured images using webcam.

The input color image is captured from a color camera/webcam. The number of frames grabbed every second will depend on the total processing time and based on the skin detection algorithm. The processing step is done on static color image. The range of sample images taken is fixed at a distance of 100 cm.

Overview of Skin Detection by Others

Skin detection is a paramount process for human computer interface (HCI). Most of the research on skin detection is done on color image although some were done in grayscale image. Shin and Choi (2002) proposed skin detection method using color histogram and edge feature. Three types of edges constitute color distributions for the pixels. For each edge type, three distance measures are calculated. The proposed edge color histogram gave better results than traditional color histogram and edge histogram.

A method that combines color and edge features to differentiate skin and non-skin regions in color images is proposed by Phung, Bouzerdoum & Chai (2005). The presence of skin color pixels is detected by using bayesian model based on decision rule for minimum cost and nonparametric density estimation. The detected skin-color regions are then refined using homogeneity property of the human skin where edge information is put together. The bayesian skin color model achieved better results than other color models such as the piece-wise linear model, gaussian models and model based on multilayer perceptrons.

Kolsch and Turk (2004) performed frequency analysis-based method for instantaneous estimation for class separability without any training process in detecting skin pixels. An a priori estimate of detector performance based on frequency spectrum analysis and an estimate of the amount of grey level variation in the object's appearance is introduced. Although the method is very fast and accurate, it relies only on grey-level images. Meanwhile, Xu & Zhu (2006) presented a survey for color-based skin detection based on: i) color space selection ii) skin color modeling iii) illumination invariance and adaptation.

The survey found that color space transformation has no effect on the discrimination between skin and non-skin color regions. Dropping luminance component found worsens the discriminability significantly. Javier and Verschae (2004) used neighbourhood information for skin detection. A pixel is classified as skin if it has a probability of belonging to the skin class over a certain threshold, and as some of its neighbors, previously classified as belonging to the skin class, is similar to it.

This is implemented through a spatial diffusion process, starting from pixels with high skin probability (seeds). The proposed method has two steps; i) pixel-wise classification and ii) controlled diffusion. Sajdi, Najafi and Kasaei (2007) combined block-based classifier and a boosted pixel based for skin detection. The block based skin detector classifies image blocks using color and texture. A co-occurrence matrix describes spatial relationship among pixel intensities in an image and its probabilities (such as energy, entropy, contrast) are extracted to characterize skin texture. The block based method extracts a non-parametric skin model from training skin blocks and classifies it to skin or non-skin according to similarity measure. This method is capable of grouping similar skin color and works well on different skin types.

Texture

Texture refers to the properties held and sensations caused by the external surface of objects received through the sense of touch. Texture can also be termed as a pattern that has been scaled down where the basic elements that go on to make the pattern cannot be grouped (Haralick, Shanmugan & Dinstein, 1973). Texture is one of the meaningful approaches in describing a patch of interest. It can give three measures of properties such as smoothness, coarseness, and regularity.

In segmenting texture, several techniques are used such as gabor filter or bank of gabor filters (David & Jernigan, 2000; Anil K. Jain & Farshid, 1990), local binary pattern (LBP) (Liao, Max & Albert, 2009), (Hui, Runsheng & Cheng, 2008), (Timo, Pietikaeinen & Maenpaea, 2002), (Timo, Abdenour & Pietikainen, 2006), (Xiangjian et al., 2007), wavelet (Michael, 1995), (Arivazhagan & Ganesan, 2003), (Bashar, Matsumoto & Ohnishi, 2003), gray level co-occurrence matrices (GLCM) (Christoph, 2004), moments (Mihran, 1992), (Qaiser & Hussain, 2003) and clustering (Hammouche, Diaf & Postaire, 2006), (Scarpa & Haindl, 2006).

Haralick, Shanmugan and Dinstein (1973) developing a set of features for classifying pictorial data based on graytone spatial dependencies. Two kinds of decision rules are used; convex polyhedra and min-max. Textural features set are based on statistics which summarize the relative frequency distribution. Meanwhile, (Ma & Manjunath, 1996) addresses on feature extraction and similarity search where a simple hybrid neural network algorithm is used to learn the similarity by simple clustering in the texture feature space. Texture analysis utilizes gabor wavelet.

Liao, Max and Albert (2009) proposed a method to extract image features for texture segmentation which is robust to image rotation, less sensitive to histogram equalization and noise. It comprises of two sets of features: dominant local binary patterns (DLBP) in a texture image and the supplementary features extracted by using the circularly symmetric Gabor filter responses.

Meanwhile, Randen & Husoy (1999) reviewed most of the famous filtering methods to texture feature extraction and performed comparative study. Filtering approaches included are Laws masks, ring filters, dyadic Gabor filter banks, wavelet transforms, wavelet packets and wavelet frames, quadrature mirror filters, discrete cosine transform, eigenfilters, optimized Gabor filters, linear predictors, and optimized finite impulse response filters. The local energy of the filter responses are treated as the features.

David (2002) studied the ability of co-occurrence probability statistics to classify natural textures based on grey level quantization. Many of the statistical results show a decrease in classification with increasing grey levels, but some retain classification accuracy. None of the individual statistics shows increasing classification accuracy throughout all grey levels. Correlation analysis is used to rationalize a preferred subset of statistics.

The preferred statistics set (contrast, correlation, and entropy) is demonstrated to be an improvement over using single statistics or using the entire set of statistics. Instead of using normal local features, (Michael, 1995) characterized texture properties at multiple scales using the wavelet transform. The analysis uses an overcomplete wavelet decomposition, which yields a description that is translation invariant. Results based on testing done on 12 Brodatz textures shown that the discrete wavelet frame (DWF) method gave better segmentation than standard wavelet transform feature extraction.

Proposed Methodology

This section explained the approaches used for skin detection in color image. The proposed method consists of two main steps which are subtraction of HSV color component and texture features measurement.

HSV Subtraction

Based on the testing done hue component minus value component gives the best result for skin region segmentation. Figure 1 shows the HSV subtraction. The input color image in RGB format is first converted into HSV format and then HSV color component subtraction is done.

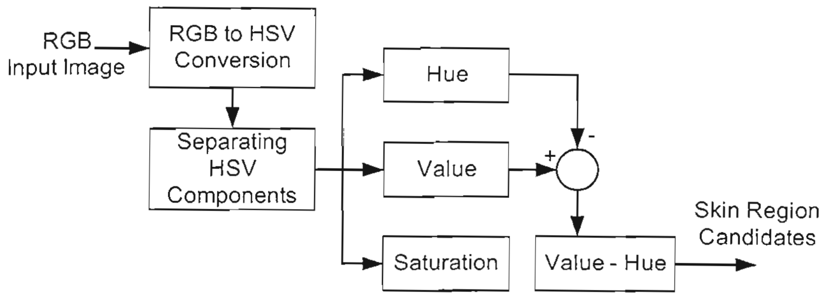


Figure 1: Separating HSV Components and Subtraction Process

The output of the subtraction is candidate of skin regions. These candidate skin regions normally have blob shapes. The rectangles of these blobs are estimated in order to calculate the texture features. The rectangular box is used to reduce the processing time as compared to blob area itself.

Skin Detection Evaluation

Figure 2 shows skin detection evaluation process. The skin detection rate is calculated using manual method where input image, Fig. 2(a) subtract the detected skin regions image, Fig. 2(b) region B. Region C is considered as undetected skin region. The residue of the subtraction, Fig. 2(b) region C, is treated as error and if the error is less than 10 percents meaning that the detection rate is greater than 90 percent. The calculation is based on the total number of pixels of skin and non-skin regions.

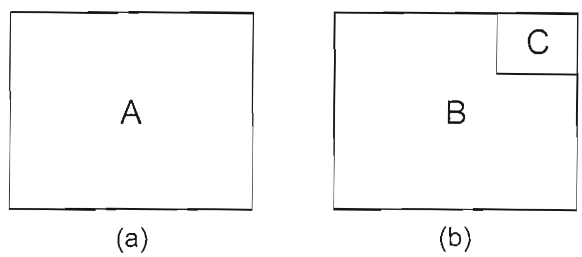


Figure 2: Skin Detection Rate Calculation

Statistical Texture Measurement

The final step in verifying the candidates' skin regions is by implementing the statistical texture features measured on those regions. As proposed by Haralick, Shanmugan and Dinstein (1973) the preferred statistics or the statistical measures that give high dissimilarity measures, in this case between skin and non-skin regions are contrast, correlation and entropy. All three texture information is contained in the gray-tone spatial-dependence matrices. Hence, all the textural features are extracted from these gray-tone spatial-dependence matrices. The following equations define the features;

Notation:

- *P(i, j)* - (i,j) th entry in a normalized gray-tone spatial-dependence matrix, = P(i,j)/R.
- N_g - Number of distinct gray levels in the quantized image.
- *R* - The number of neighboring resolution pairs

$$Contrast = \sum_{n=0}^{Ng-1} n^2 \left\{ \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} p(i,j) \right\} \quad (1)$$

$$Entropy = -\sum_i \sum_j p(i,j) \log(p(i,j)) \quad (2)$$

$$Correlation = \frac{\sum_i \sum_j (i,j) p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \quad (3)$$

Where μ_x, μ_y, σ_x and σ_y are the means and standard deviations of the marginal distributions associated with *P(i,j)/R*, and *R* is a normalizing constant.

Figure 3 shows overall system of the proposed skin detection. The system is divided into three main parts: (i) HSV color space conversion and subtraction (ii) Skin candidates' rectangular box estimation, and (iii) Texture features measurement.

The method begins with the color input image in RGB format being converted into HSV format. Then color subtraction of HSV components is done to get the blob of candidates' skin regions. The rectangular boxes of the blobs are estimated where these rectangular boxes are used

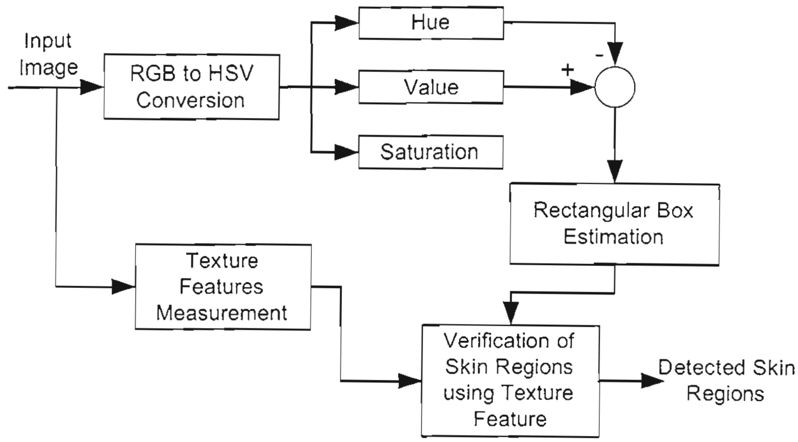


Figure 3: Block Diagram of the Proposed Skin Detection Method

as the basis for texture features measurement. The results from color component subtraction and texture features measurement are verified where the final result of both process is the detected skin regions.

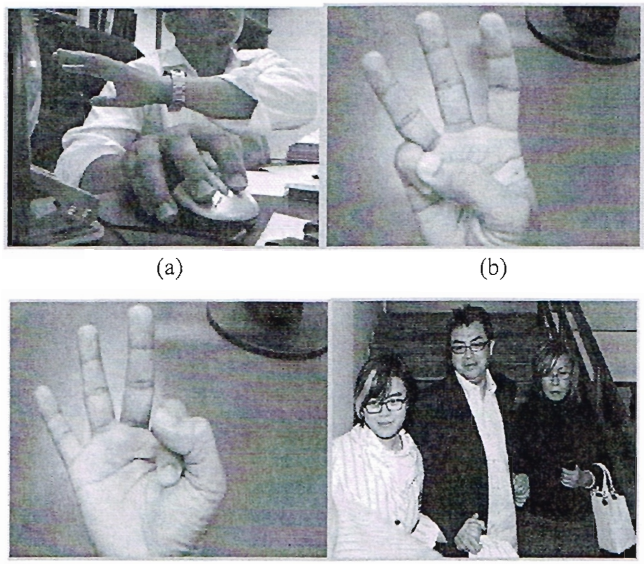
Results and Discussion

This section explained the results of the proposed skin detection method on color image. The results will cover on HSV color component subtraction, and texture features measurement.

HSV Color Subtraction

The testing of the proposed algorithm is done with four sample images in Figure 4.

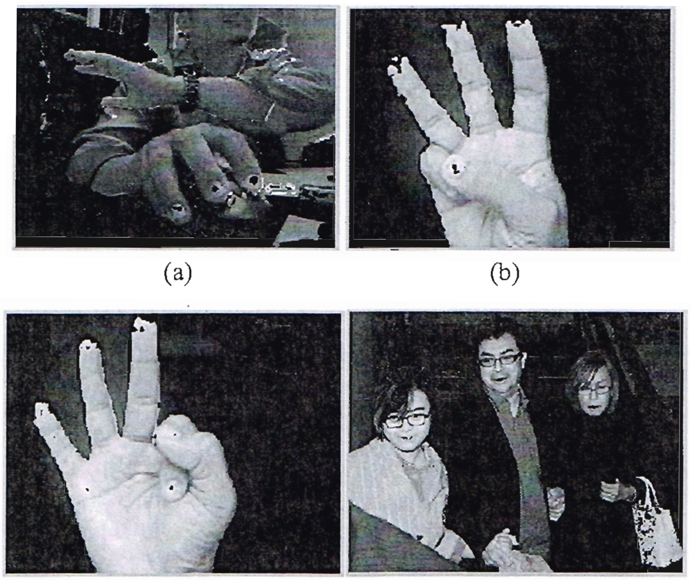
The algorithm of the proposed method starts with HSV components subtraction. The results of the testing are shown in Figure 5. Figure 5 (b) and (c) shown acceptable separation skin and non-skin regions compared to Figure 5 (a) and (d). This is because Figure 5(a) and Figure 5(d) consist of many background cluttered that may affect the segmentation of skin regions.



(a) (b)

(c) (d)

Figure 4: Input Images in RGB Format



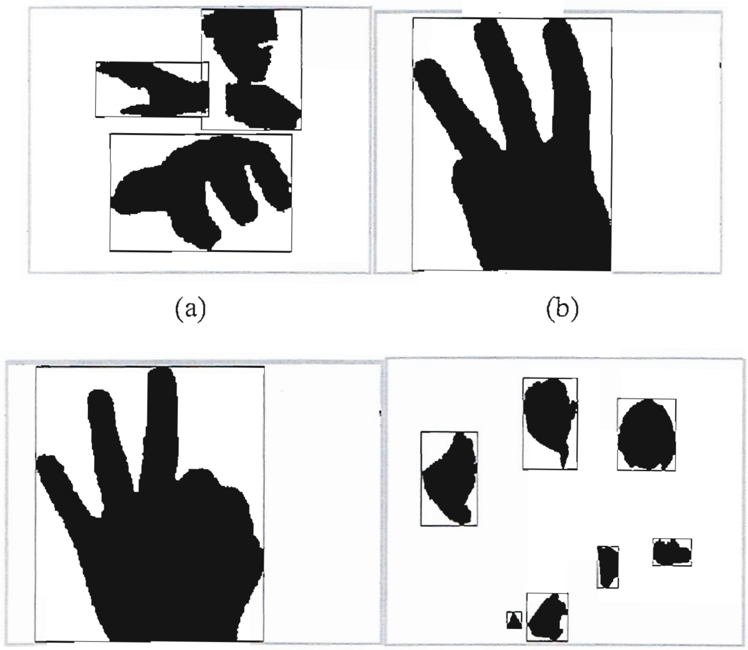
(a) (b)

(c) (d)

Figure 5: The Results of Value Component Minus Hue Component

Texture Measurement

The estimated rectangular box as in Figure 6 is used for texture features extraction process. This texture is useful since the sample images are classified as short distance captured images and their textures are still available. Hand palm texture can be seen clearly in Figure 4(b) and Figure 4(c). This texture feature is significant in separating skin and non-skin regions. Table 1 to Table 4 show the statistical texture features for the sample images.

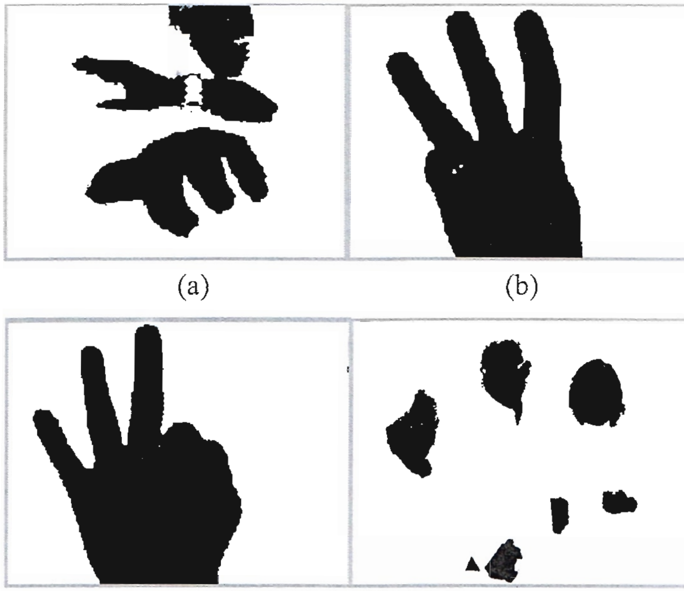


(a) (b)

(c) (d)

Figure 6: The Rectangular Box Estimation of the Skin Blobs Candidates

Figure 7 shows the detected skin regions. For all four sample images the thresholding process gives acceptable skin detection and separation of non skin regions especially for Figure 7(a).



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

Figure 7: The Detected Skin Regions

Table 1: Texture Features for First Sample Image

Features\ Image					
Contrast	65.09	54.46	65.7	57.79	19.67
Entropy	7.69	7.24	7.34	7.52	6.22

Table 1 shows texture features for the first sample image. Image in the first column is the original sample and the next column is the sub-image that has been cropped for texture feature calculation. The last column image is the background that does not contain the skin region. The contrast value for the skin region varies from **65.09** to **57.79**, meanwhile the entropy varies from **7.69** to **7.52**. The contrast and entropy values for non-skin region show a great difference when compared to skin region.

Table 2: Texture Features for Second Sample Image

Features\ Image				
Contrast	44.09	32.39	29.87	6.65
Entropy	7.28	7.0	6.59	4.67

Table 2 shows the texture of hand palm with two fingers being folded. First column image is the original size sample image and the next three are the sub-images. The contrast and entropy vary from **29.87** to **44.09** and from **6.59** to **7.28**, respectively for skin regions. Meanwhile the non-skin region give contrast and entropy **6.65** and **4.67** respectively, which is quite a big difference when compared to skin regions.

Table 3: Texture Features for Third Sample Image

Features\ Image				
Contrast	47.9	37.48	34.32	34.15
Entropy	7.31	7.11	6.74	5.92

Table 3 shows the texture features calculation results for hand palm with two fingers being folded but different fingers compared to Table 2. Entropy feature gives robust separation between skin and non-skin regions, but contrast gives no big difference between skin and non skin regions.

Table 4: Texture Features for Forth Sample Image

Features\ Image						
Contrast	82.14	71.42	46.19	73.95	48.15	36.2
Entropy	7.56	7.72	7.34	7.86	6.62	6.31

Table 4 shows the contrast and entropy for the fourth sample image. Again, for this sample contrast does not give acceptable separation between skin and non-skin regions. However, entropy still gives good skin and non-skin regions separation.

Conclusion

This article presents a skin detection method using HSV color components subtraction and texture features measurement. The Value component minus Hue component of HSV color space is applied. The proposed skin detection method is focused on detecting hand palm and face skin regions. The method can detect skin accurately on the four test color images. The detection rate for the skin regions is more than 90 % of total skin regions of an image. The results also show that the proposed method is fairly robust on the shiny surfaces and complex background.

Future Works

Future works will focus on common features on the face such as dark color lip, nail, and wristwatch. These features sometimes fail to be detected as skin region by using normal skin detection algorithm. Another important issue is brown colored hair since it has become at common trend nowadays. Major axis calculation also could be used instead of minimum and maximum of left to right and top to bottom rectangular box estimation. Formulating new color space for skin detection is also a promising future.

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