

Full Length Research Paper

A new hybrid module for skin detector using fuzzy inference system structure and explicit rules

A. A. Zaidan¹, H. Abdul Karim¹, N. N. Ahmad¹, Gazi Mahabubul Alam^{2*} and B. B. Zaidan¹

¹Faculty of Engineering, Multimedia University, 63100 Cyberjaya, Selangor Darul Ehsan, Malaysia.

²Faculty of Education, University of Malaya, Kuala Lumpur, Malaysia.

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Skin detection is a popular image processing technique that has been applied in many areas such as video-surveillance, cyber-crime prosecution and face detection. It is also considered as one of the challenging problems in image processing. Despite being a well known technique to detect human appearance within image, it faces a fundamental problem when using colour as cue to detect skin. It is difficult to detect skin when the colour between the skin and the non skin within an image is similar. Therefore in this paper, a new hybrid module between explicit rules and fuzzy inference system structure, based on RGB colour space, is proposed to improve skin detection performance. Using the new hybrid module, we managed to increase the classification reliability when discriminating human skin. The new proposed skin detector depends on subtractive clustering technique, created and trained with training set of skin and non-skin pixels. The proposed system is tested on human images having upright frontal skin with any background. Our proposed system has achieved high detection rates of 87% classification and low false positives when compared with the existing methods.

Key words: Skin detector, fuzzy inference system structure, explicit rules.

INTRODUCTION

Skin detection has been used primitively in a wide variety of human-related image processing systems such as face recognition, lip reading, hand recognition, tracking and anti-spam system (Dargham et al., 2009). Nowadays, these applications are classified as security applications for they are very important to human life (Zaidan et al., 2010,a,b; Raad et al., 2010; Alanazi et al., 2010; Hmood et al., 2010). A skin detector should divide an image into two distinct classes, one representing skin regions and the other non-skin regions (Dargham et al., 2009).

Since human skin does not have a particular geometric shape, the only attributes that can be used for skin detection are texture and colour. So in this paper, we have presented colour as a feature of the skin detector. Most skin detection systems used by researchers are either a single-colour system or a single skin detection

module (Dargham et al., 2009). Skin colour modeling is a crucial task for several computer vision applications. There are problems, such as face detection in video, which are more likely to be solved if an efficient skin-colour model is constructed. Most potential applications of skin-colour model require robustness to significant variations in races, different lighting conditions, textures and other factors. Given the fact that, skin surface reflects light in a different way compared to other surfaces, we relied once again on data-mining techniques to define a skin colour model which enables the classification of image pixels into skin or non-skin (Hammami et al., 2003). An important step in the image classification process is colour segmentation of the image into homogeneous skin colour regions and non-skin colour regions, in a colour space that is relatively invariant to minor luminance changes.

The segmentation is used to localize and identify homogeneous regions in a picture by perceptual attributes which include the size, shape and texture and/or colour information. This operation is necessary for any image analysis, understanding and interpretation.

*Corresponding author. E-mail: gazi.alam@um.edu.my, gazimalamb@yahoo.com. Tel: + 603-7967 5077. Fax: + 603-7967 5010.

After segmenting out skin from images, the collection is useful for identifying faces, hand sign recognition and offensive content such as pornography. There are several strategies for segmenting images, which depend largely on the type of images to be processed and on a priori knowledge relative to the object features.

The methods can be roughly classified into several categories: contour-based methods, region-based methods and variational methods such as the global optimization approach that minimizes an energy function or some Bayesian criteria and active contours model. Kovac et al. (2003) presented a simple skin classifier through several heuristic rules. The main difficulty in achieving high recognition rates with this method is the need to find both good colour space and adequate decision rules empirically. On the other hand, there has been a method that uses machine learning algorithms, to find both suitable colour space and a simple decision rule that achieves high recognition rates (Gomez and Morales, 2002). The main problem faced by these methods is mentioned in the problem statement and the proposed way to solve this problem is stated in the research objectives. Given this, the importance of scientific research in practical applications of human life is mentioned in 'motivations'.

Motivations

Skin colour can generate many types of information about a person ranging from race, age, nationality, etc. However, the interpretation may not exactly be correct since life, history and culture are different for each person. Skin colour is very useful and helpful in detecting human existence from captured materials like still image photos and videos. Skin detection, a process which detects the pixels and regions having skin colour range in an image, has become a popular method in image processing. In the context of biometrics, skin detection is applied in facial recognition application. In such an application, detecting the skin colour pixels for human face or hands is accurate since the background image is normally controlled. For example, Sandeep and Rajagopalan (2002) used skin colour information for detecting human faces, in face recognition research where different colour ranges were collected from the Internet. Singh et al. (2003) also studied skin colour, based on three colour spaces, to create new skin colour based face detection, which is claimed to be more accurate in face recognition.

In video surveillance application, skin colour also plays an important role as it has been used in face detection in video analysis applications. For instance, Kam et al. (2006) studied the benefits of the skin colour feature, in his paper, to track the human face in his drowning detection system for outdoor public swimming pools. The application of skin detection in various fields shows its

popularity within image processing techniques. It is computationally effective and robust against rotation, scaling and partial occlusions. However, this skin colour modeling is not perfect, as there are still problems that need to be solved to achieve high accuracy for effective skin detection.

Problem statement

In this paper, our focus is on improving the reliability of skin detection. Skin detection algorithms have been used in many applications. Choosing skin colour as an element in detecting human existence is quite a simple and straight forward task, and in addition, skin colour has processing time advantage, since colour processing is faster compared to other features.

Still, it has several constraints since the skin colour representation, which has skin-like colour objects might be present in the image captured such as hair, soil, wooden materials, sand, drawings and animals. This is uncontrollable because the skin detection may contain errors and generate a false detection result and thus fails to identify the non-skin objects which have skin-like colour pixels.

Research objectives

Automatic skin detection is a component of various imaging applications such as face detection and tracking, content categorization, image enhancement, adaptive compression, etc. As mentioned previously in motivations, the colour-based methods have proven to be well suited for this task, but generally suffer from a type of false detection or non reliability of skin detector, as mentioned previously in the problem statement, which adversely influences the aforementioned tasks, namely the confident detection of hair regions as skin. This causes any skin detector to have much false detection in the background if the environment is not controlled. As such, we employed fuzzy system to overcome this problem (Bahari et al., 2009).

In the last decade, fuzzy system has been successfully applied in many different areas of engineering including automatic control, system identification and pattern recognition (Koutroumanidis et al., 2009; Nataraja et al., 2006). This research tries to achieve the following objectives:

- (1) To conduct a study in the literature of different skin detections and determine the strength of reliability and weaknesses of the products.
- (2) To design and implement a skin detector based on fuzzy inference system structure.
- (3) To implement a gathering approach based on fuzzy inference system structure and explicit rules that

overcomes the drawbacks of the available skin detections module.

(4) To evaluate the performance of the new skin detection module and compare it with the existing methods.

Research questions

Does implementing a new hybrid module using explicit rules and fuzzy inference system structure based on RGB colour space, improve the skin detection performance? Thus, this research tries to highlight and answer the following questions:

(1) According to (Chahir and Elmoataz, 2006; Chin, 2008; Hamid and Jemma, 2006), Takagi-Sugeno fuzzy inference system, fuzzy clustering method in most cases is only suitable for skin detector specified from fuzzy system techniques. The question is that is there any other fuzzy system technique that can be applied for better skin detection?

(2) There are many skin detector modules that can detect the skin with high rate, but are not reliable due to the fact that many pixels have the same skin-tone colours which is detected as skin, for example, skin-coloured clothing, background, etc (Chahir and Elmoataz, 2006). The question is: Is there any module for skin detector that can detect the skin pixels with high reliability and ability to differentiate skin from skin-coloured clothing?

(3) Fuzzy system cannot stand alone in the detection of skin (Hamid and Jemma, 2006). As such, the question is: Is it worthy to have hybrid approaches (that is, consists of fuzzy system and heuristic rules)?

Related work

The skin detection technique is delivered in many different ways and processes to achieve expected outcome depending on the system's objective. Based on previous works, the study proposes an idea that the skin detection method should be applied in soft computing environment, specifically on fuzzy system. Fuzzy system has been a subject of growing interest in recent years (Messaoudi et al., 2007) and it is considered to be appropriate to deal with the nature of uncertainty in system and human error (Ozcep et al., 2010). Chahir and Elmoataz (2006) proposed skin colour detection using fuzzy c-means (FCM).

FCM is the most popular fuzzy clustering algorithm (Karaboga and Ozturk, 2010) that applied the fuzzy clustering method (FCM) to perform skin detection based on decision rules in hybrid space. The author presented skin colour segmentation using the C-Mean algorithm. The algorithm segments the image into two classes: skin and non-skin regions, using neighborhood information to force the algorithm to create regions. Spatial data mining

method was adopted to be integrated with the segmentation method in identifying significant skin colour regions in an image.

The method achieved 96.1% classification rate, but is not reliable due to the fact that many pixels might have the same skin-tone colours which is detected as the skin, for example, skin-coloured clothing, background, etc. (Chin, 2008) has successfully evaluated the performance of fuzzy theory in classifying human and animal skin images. The fuzzy theory was also tested in classifying pornographic and non-pornographic images to verify the ability of fuzzy theory in filtering web content. Although the result is lower than the explicit method proposed in Kovac et al. (2003), it still achieved an accuracy of 75% in detecting human skin images and 83% in detecting animal skin images. They achieved an accuracy of 65% which is better, when compared with the method practiced by Kovac et al. (2003) which only has 21% accuracy when classifying porn and non-porn images. However, it is lower than the simulation result of Hamid and Jemma (2006) which uses Takagi-Sugeno fuzzy inference (TSFI) system.

MATERIALS AND METHODS

Skin detection framework

Basically, the framework of skin detection process can be divided into two phases. The first phase is referred to as the training phase and the second phase is referred to as the detection phase. These two phases are very important in building a functional and successful detection system. The first is the training or learning phase. It is a process used to study and learn the skin pixels sample from a group of collected skin images so that the detector is familiar with the skin colour pixels. At the same time, a skin model will be built from the comprehensive training data. According to Elgammal et al. (2009), the training phase involves several basic steps, which are referred to in Figure 1.

(i) Constructing a database that contains a collection of various patches of skin images, which typically consist of a wide range of skin-coloured patches from a variety of people with different illumination conditions.

(ii) Choose a suitable colour space.

(iii) Studying and learning the available parameters of the skin classifier.

In the detection phase, the skin pixels from a new image input will be identified based on the trained skin detector from the earlier training phases. Several tasks involved in detecting the pixels according to Elgammal et al. (2009), are shown in Figure 2.

(i) Translating / interpreting / converting the image into a similar colour space that was applied in the previous training phase.

(ii) Each pixel from the image is then classified into either skin pixel or non-skin pixel based on the skin classifier.

(iii) Typically, post processing is needed using morphology to impose spatial homogeneity on the detected regions.

RGB colour space

RGB colour space is the most commonly used colour space in digital images. It encodes colours as an additive combination of

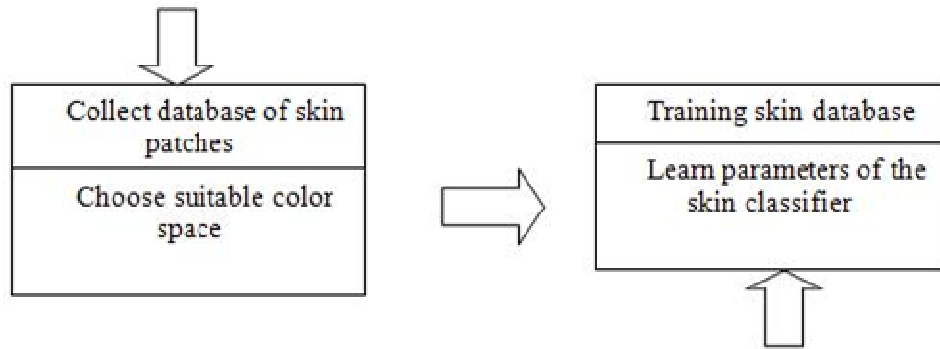


Figure 1. Training phases.

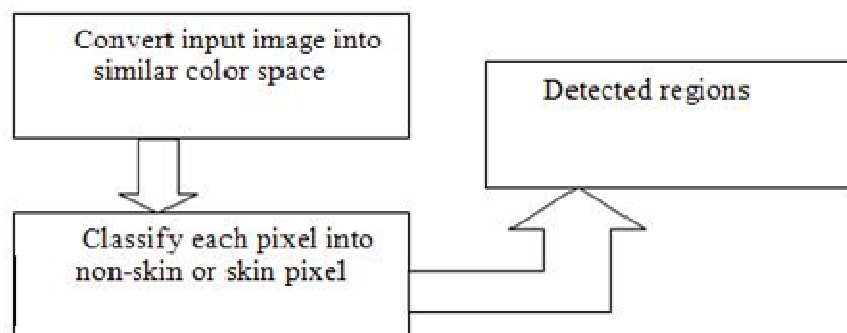


Figure 2. Detection phase.

three primary colours: red (R), green (G) and blue (B). One main advantage of the RGB space is its simplicity. However, it is not perceptually uniform, which means that distances in the RGB space do not linearly correspond to human perception. In addition, RGB colour space does not separate luminance and chrominance, and as such, the R, G and B components are highly correlated. The luminance of a given RGB pixel is a linear combination of the R, G and B values.

Therefore, changing the luminance of a given skin patch affects all the R, G and B components. The skin colour cluster is extended in the space to reflect the different illumination intensities in the patches. Similarly, the skin colour clusters for patches from different races will be located at different locations in the RGB colour space. Despite these fundamental limitations, RGB is extensively used in skin detection literature because of its simplicity. For example, RGB is used by Jones and Rehg (2002) and it yielded a quite satisfying performance.

System overview

Our proposed skin detection system using fuzzy inference system structure and heuristic rules is shown in Figure 3. First, we had to prepare the image database. To do that, we gathered 200 human skin images from the internet and manually cropped them. This process is to remove the non-skin pixels from the image; thus, we used Adobe photoshop to complete this task. Figure 4 is an example of an image that has been cropped. The cropped image database together with the original image (before cropping) database are the image databases that are going to be used in our

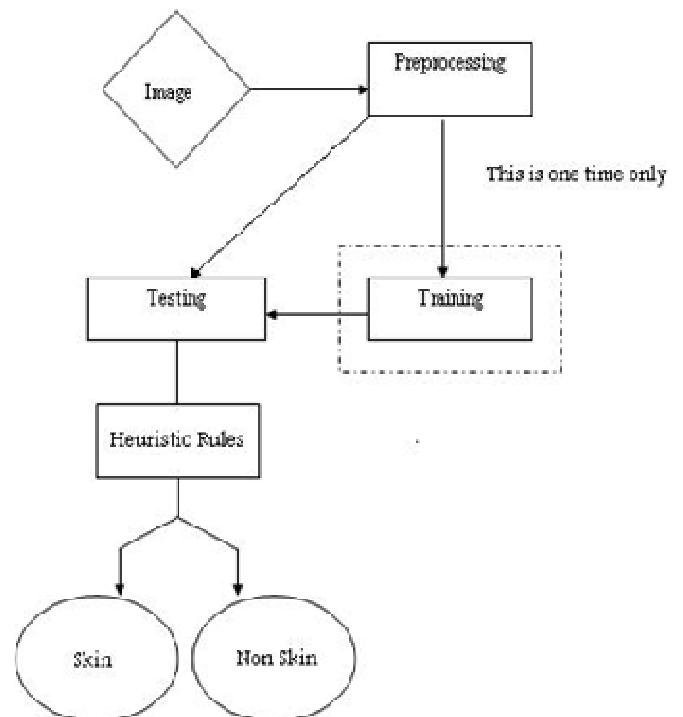


Figure 3. Main structure of the proposed method.

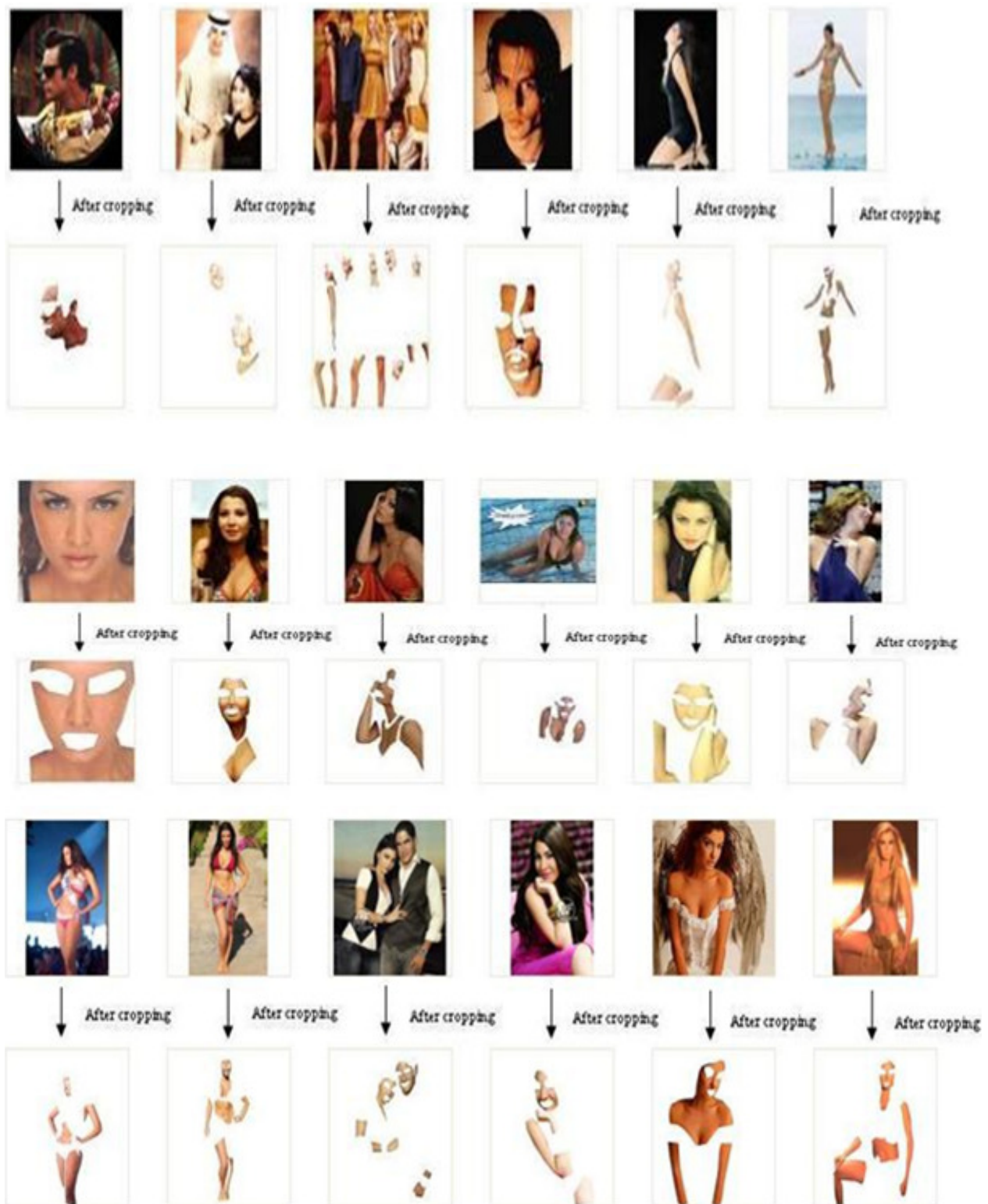


Figure 4. An example of cropped images (without non-skin pixels) from the original image.

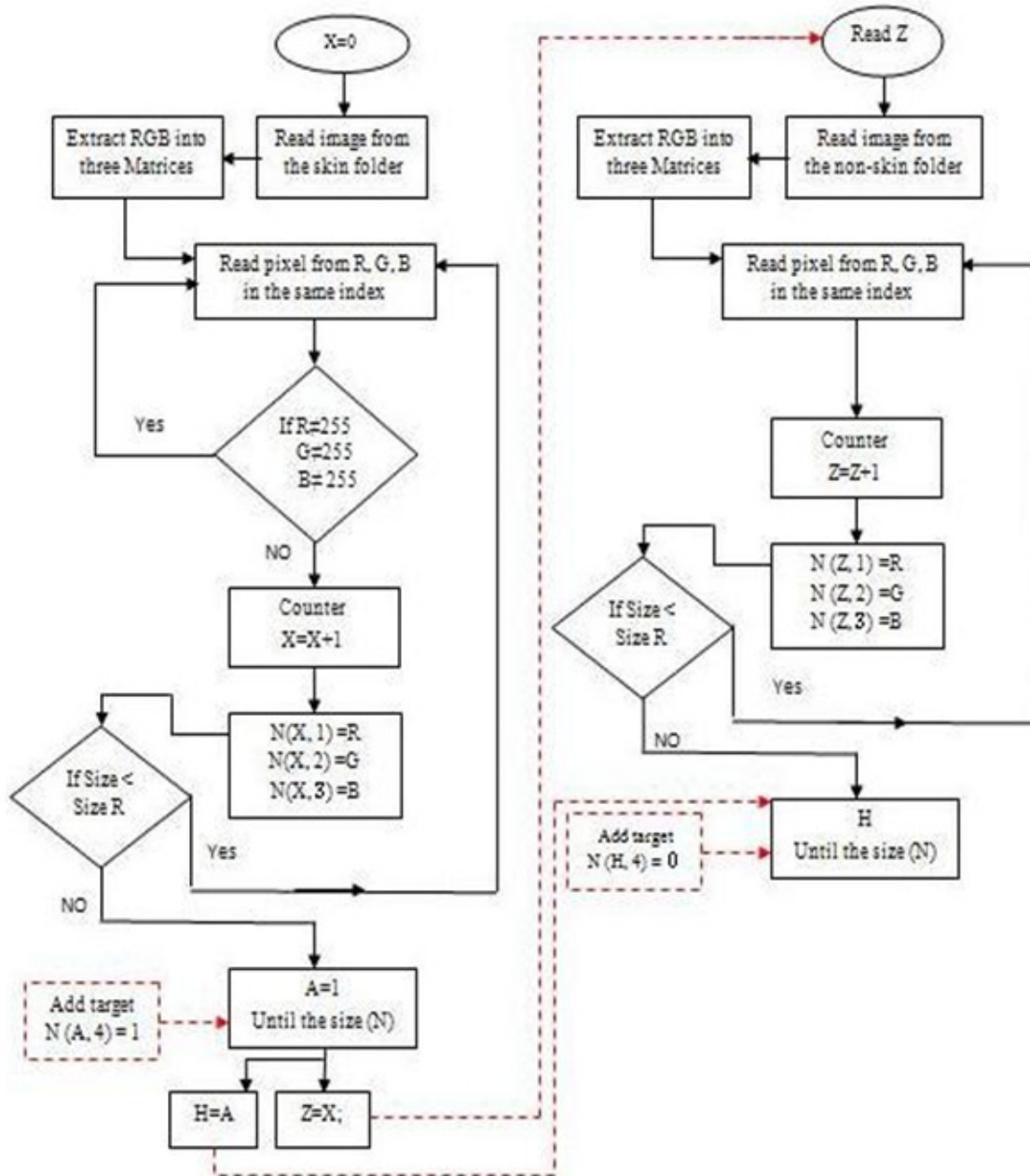


Figure 5. Flowchart of the pre-processing phase.

fuzzy skin detection, while the output from the fuzzy detector will be taken as the input for heuristic rules, which will be the second stage.

In this paper, we used 6000 pixels of various skin tones and 6000 pixels from tones that is non skin. These are taken for the training process. In the testing process, given the inputs of new function within two parameters, one of these parameters is the output from fuzzy system and the other is the original image that is required from this system (as segment of the skin pixels, on the basis of pixels' positions), which is similar to the original picture. The results from fuzzy system will be passed through all pixels on the threshold that is 0.3. This threshold was chosen based on the experiences that the researchers had previously at the stages of building the

program, and also, for taking the resulting image as skin extract to be entered as input into the rules that would be mentioned later on. Using these heretical rules, the researchers can filter the image of pixels as skin, which is the output of the fuzzy system, and consider it as non skin and as such, call it skin-like. The proposed method consists of four important phases, that is, pre-processing, training, testing and heuristic rules.

Pre-processing phase

Figure 5 shows a flowchart of the pre-processing phase which consists of three main steps:

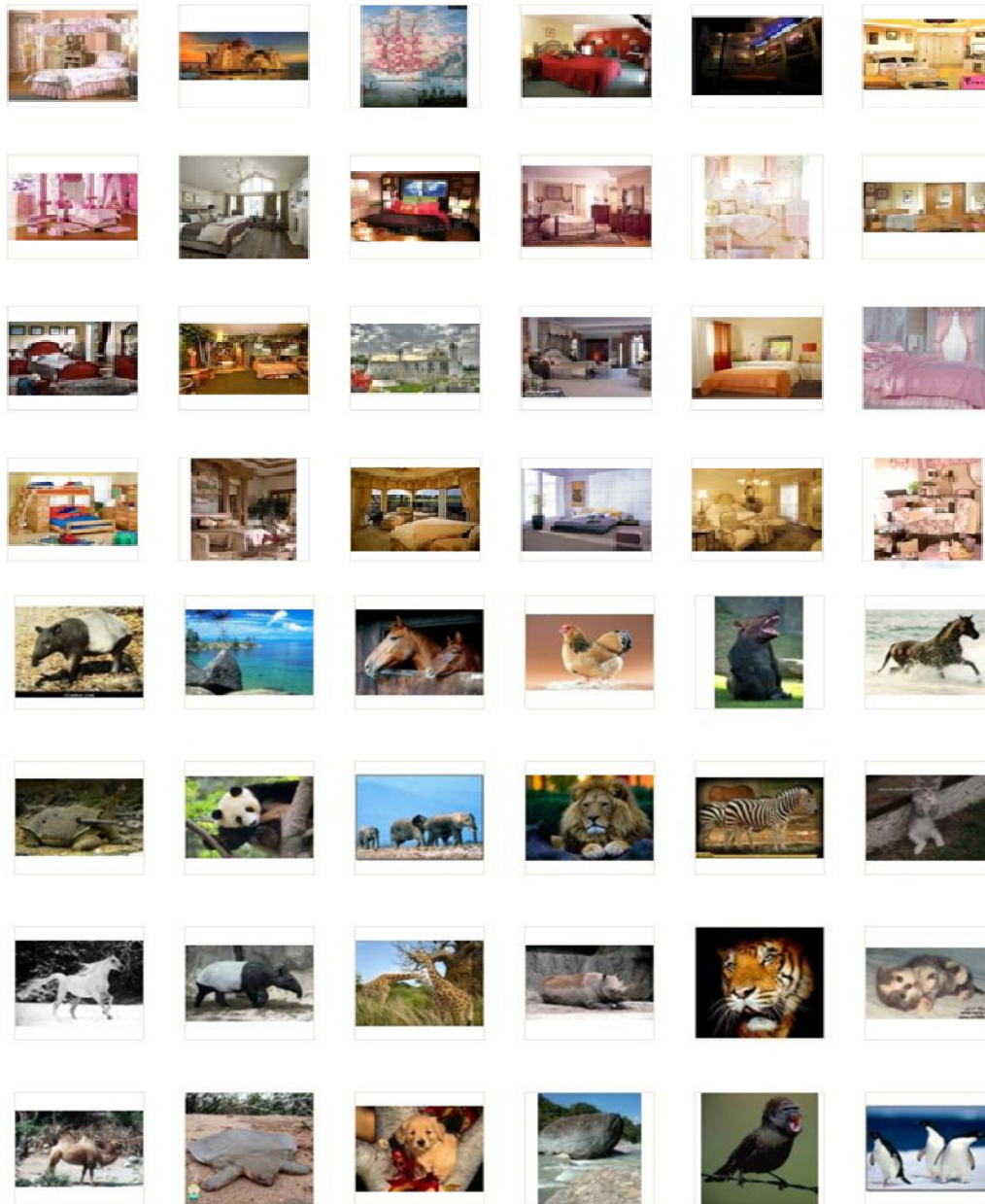


Figure 6. Sample of non-skin pictures used for training.

Step 1: Extracting the image features which is the RGB colour information.

Step 2: Converting each R, G and B matrix into vector and combine the vectors as one array.

Step 3: Adding another vector which include the target. However, 1 indicates non skin and 0 indicates skin.

The steps are repeated for 200 original images and 200 cropped images. Only then will the collected data set be ready to be imported to the fuzzy system.

Training phase

This training phase is performed only once in the first stage to

generate fuzzy inference system structure from data, using subtractive clustering. The purpose of preparing this phase is to train the fuzzy system to create rules. The most important things in this phase are how accurate the data set is, so that the fuzzy rules cover a wide range of skin colour. They have two data sets for training phase which can be classified as non-skin and skin images.

Non-skin images database

The non-skin picture database consists of 200 images that were collected from the internet. All pixels of the pictures will be considered in the training for practical work. Figure 6 shows an example of sample of non-skin pictures that were used for training.

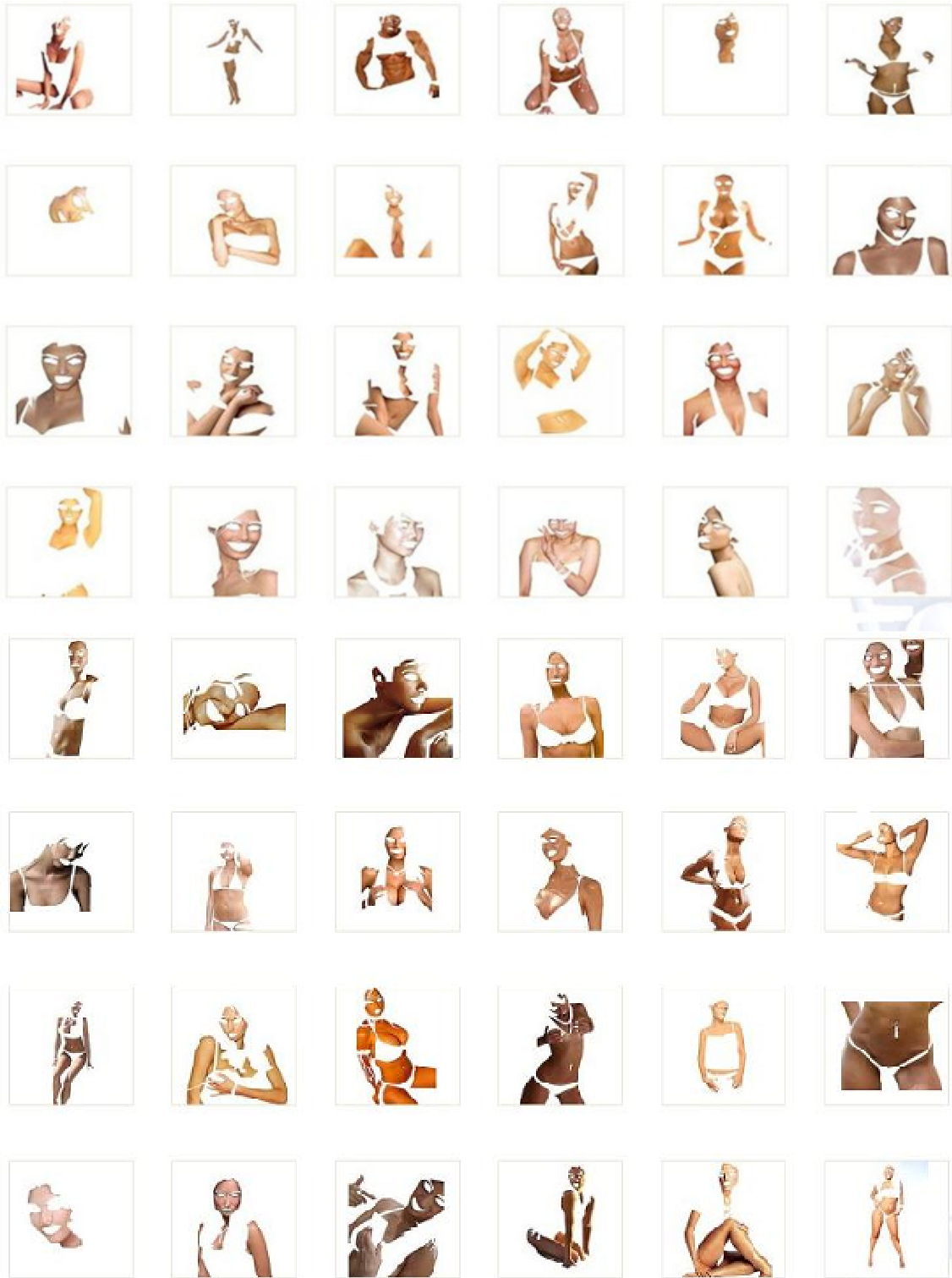


Figure 7. Samples of skin pictures used for training.

Skin images database

The skin picture database consists of 200 images which were collected from the internet. Not all pixels of the pictures will be used

in the training. We will use the skin pixels only and neglect the white colour pixels in the practical work. Figure 7 shows an example of the skin pictures' sample within different body from human skin and without any noise used for the training phase.

Fuzzy inference system structure using subtractive clustering data

A fuzzy inference system (FIS) is a way of mapping an input space to an output space using fuzzy logic (Ardil and Sandhu, 2010). Fuzzy inference system structure is a remarkably convenient method that handles the concept of partial truth, in which the true values could be a continuum of value between 0 and 1. This is because the truth of any statement becomes a matter of degree in fuzzy inference system structure. Fuzzy set that is set with clearly defined boundaries can contain elements whose membership is partly in degrees. For instance, instead of assigning 'true' with the value of 1 and 'false' with the value of 0, fuzzy inference system structure also allows it in between values such as 0.3 and 0.895. Genfis 2 generates a Sugeno-type fuzzy inference system (FIS) structure with a function in the fuzzy system; whereas the most important stage is determining the membership degree of the input/output variables (Bektas and Ozgan, 2010).

It used subtractive clustering and requires separate sets of input and output data as input arguments. When there is only one output (Genfis 2), it may be used to generate an initial FIS for training set. Genfis 2 accomplishes this by extracting a set of rules that models the data behaviour. The rule extraction method first uses the subclust function to determine the number of rules and antecedent membership functions and then uses linear least squares estimation to determine each rule's consequent equations. This function returns a FIS structure that contains a set of fuzzy rules to cover the feature space, on the grounds that the fuzzy system uses rules to describe the system of interest (Mirbagheri, 2010).

TESTING PHASE

In this phase, fuzzy classification technique is used where fuzzy classifier is proposed to overcome the fuzziness problem of skin detection. Fuzzy classifier offers a means for working with indistinct features, that is, pixel skin or non skin (Jandaghi et al., 2010). In this phase also, the fuzzy rule will classify the image either to skin cluster or non-skin cluster. This testing phase is performed for several times. To perform fuzzy inference calculations, evalfis function is used. Output = evalfis (input, fismat). Evalfis function has the following arguments:

Input: A number or matrix specifying input values. If input is an M-by-N matrix, where N is the number of input variables, then evalfis takes each row of input as an input vector and returns the M-by-L matrix to the variable output, where each row is an output vector and L is the number of output variables.

Fismat: A FIS structure to be evaluated.

Heuristic rules phase

This is one of the easiest methods as it explicitly defines skin colour boundaries in different colour spaces. Different ranges of thresholds are defined according to each colour space component as the image pixels that fall between the pre-defined ranges are considered as skin pixels. A performance comparison of three different colour spaces YCbCr, HSV and RGB based on explicitly defined skin region has been stated by Phung et al. (2005). The advantage of this method is obviously its simplicity, which avoids attempting too complex rules to prevent overfilling data. However, it is also important to select a good colour space and suitable decision rules to achieve high recognition rate.

The application of this method can be seen in Gomez and Morales, (2002), Phung et al. (2005), Girgis et al. (2007) and Kovac et al. (2003). An example of explicitly defined skin region is carried out in Kovac et al. (2003). In this paper, the heuristic rules have

been inferred by using the photoshop, where researchers used images that contain only skin. The images were measured in the proportion of the red, green and blue colours for each pixel which is selected on this basis. Therefore, inferring to these rules, the different ratios for the different pixels used logical operations as condition. If the condition is met, the pixel refers to the skin; otherwise the pixel refers to the non skin. The study concludes that, these rules have helped the researchers to increase the reliability of the proposed skin detector. The proposed heuristic rules are as follows:

The skin colour at uniform daylight illumination.

Rule 1: The RGB components must not be close to each other (grayness elimination).

$R > 95$ and $G > 40$ and $B > 20$ and $\max\{R, G, B\} - \min\{R, G, B\} > 15$ and

Rule 2: The R and G components must not be close to each other when we are dealing with fair complexion.

$|R - G| > 15$ and

Rule 3: The R component must be the greatest one because the skin is created by a combination of blood (R) and melanin (yellow and brown).

$R > G$ and $R > B$ or

The skin colour under flashlight or daylight lateral illumination

Rule 4:

$R > 220$ and $G > 210$ and $B > 170$ and

Rule 5: R and G components must be close to each other

$|R - G| \leq 15$ and

Rule 6: B component must be the smallest component

$R > B$ and $G > B$

RESULTS AND DISCUSSION

Based on the first test, and to answer the second research question, the researchers found that the skin-like colour increases the rate of false positive and false negative and thus reduces the true positive. In other words, the skin detector is not reliable. To overcome this wide range of skin and non skin colour issue for this module, the studies conclude that two basic things must be done. Firstly, the study has to collect more than 200 images having a variety of skin colour and used these images for the training phase of skin part, to train the system to different types of skin pixels in order to avoid overlap as much as possible. An example of the skin data set is shown in Figure 8. There are some limitations that we faced daily in that the data which were used in this system were not available in the internet, and as such, they are images that contained skin only data which were used for the training process.

It is noteworthy that we segmented these images (from the internet that contain skin) manually using photoshop and this action took a lot of time. However, it took us about a month and a half to be able to segment the skin only from the daily 200 images skin part of the training. Secondly, in selecting the models of the images displayed in the Figure 9, the researchers have seen that using too many different tons of gray coloured images in the training phase of non skin part will help us. The question that arises at this stage is: why is the focus on the gray colour so particular Figure 10a? Because this

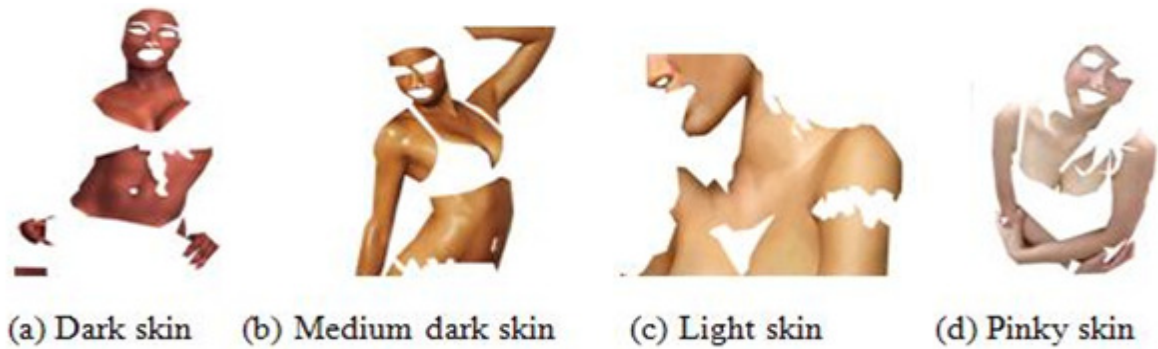


Figure 8. Samples of skin colour in the study's data set.

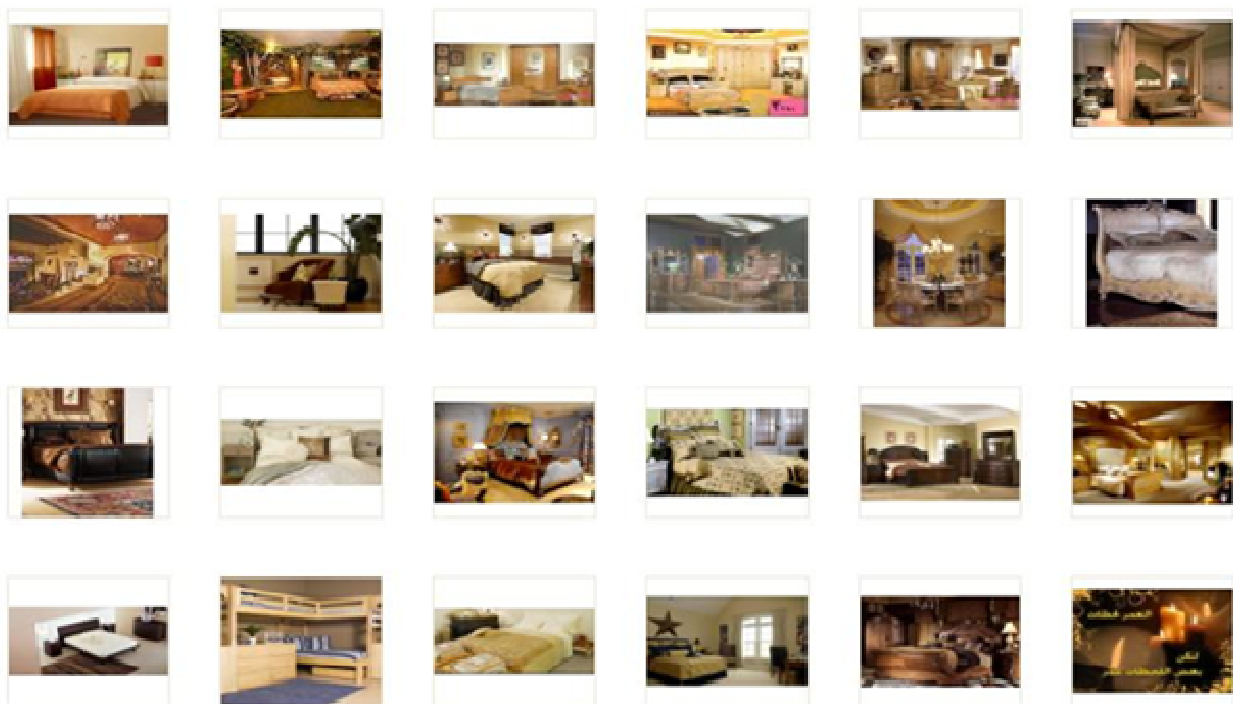


Figure 9. Samples of non skin colour in the study's data set for gray colour.

colour works similarly with skin colour, they were trained with a large number of images that contain the colour gray, but it is non skin. Therefore, it can be obtained on efficient module with high reliability for skin detector. As mentioned earlier in the overview system, this proposed system consists of two basic parts: the fuzzy inference system structure and heuristic rules base on RGB. In results and discussion, the study presented the results of fuzzy inference system structure alone to answer the first research question. The study found that the fuzzy inference system structure alone is not enough to give the results of high accuracy and high reliability as shown in Figure 10b, whereas the researchers note that the fuzzy inference system structure detected the skin pixel and also detected the non-skin pixels. Hence, the

researchers conclude that the fuzzy inference system structure alone in this proposed system will result in a lot of skin-like colour.

In other words, the skin detector is not reliable. The aim of the new heuristic rules in this system is to remedy this problem, which has a backing from the fuzzy inference system structure, and as such, we proposed the heuristic rules to pass the output of the fuzzy inference system structure to other rules. These heuristic rules have been developed to remove the non-skin pixel which resulted from the fuzzy inference system structure as the skin (Figure 10C) and which refers to the third research question posed. The hybrid module for skin detector, using fuzzy inference system structure and explicit rules are considered as adequate and efficient to detect the



Figure 10. The results from the proposed system. (A) The original image (B) the results from the fuzzy system and (C) the results from the hybrid method.

skin pixels with high accuracy. Our proposed system has achieved high detection rates of 87% classification as can be seen in Figure 12.

Although we discussed the problem of skin-like and proposed a new hybrid module as solution, nevertheless, some pixels still have problem and the study was unable

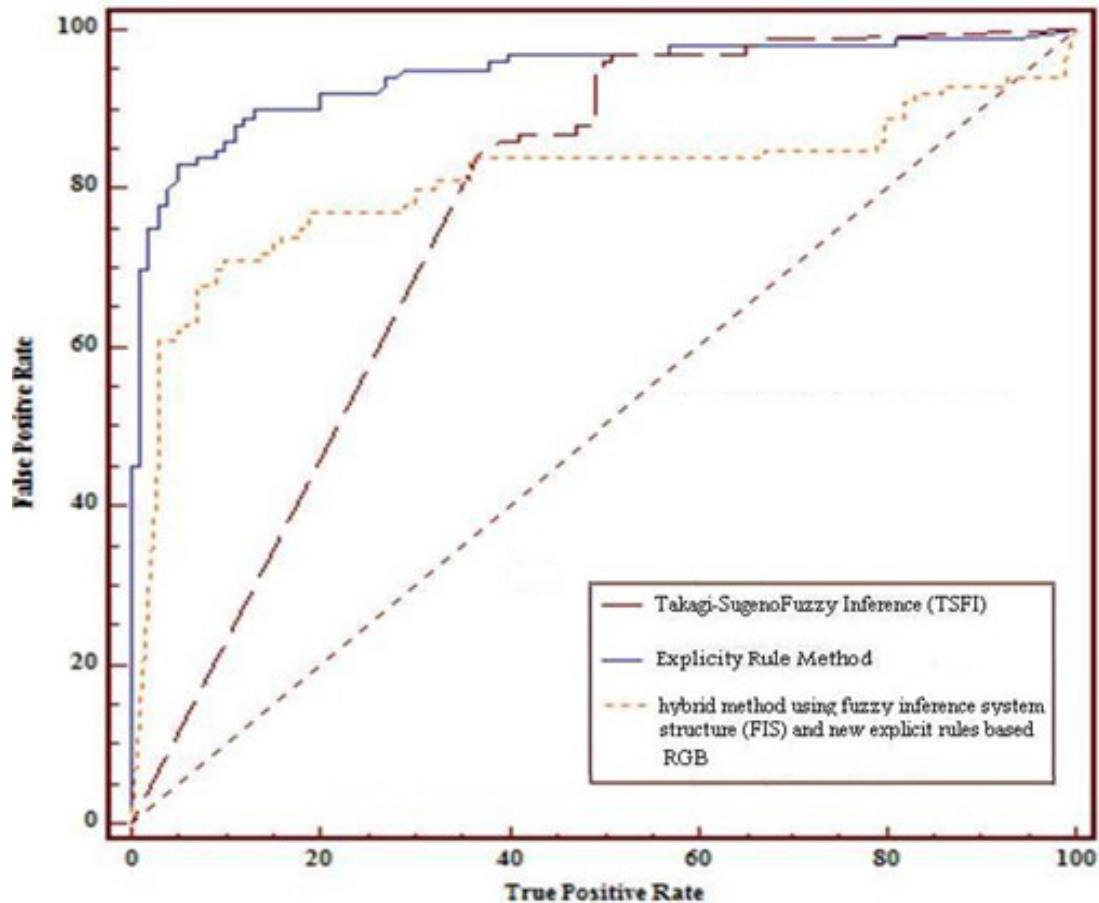


Figure 11. ROC comparison of human skin images classification methods.

to solve the problem radically as shown in Figure 10C. The reason, as to why the study uses the fuzzy system for the first stage of the proposed system, was a solution for making a decision (Nuhodzic et al., 2010), in that the output image from the fuzzy system contains some pixels that are not skin, but were detected as skin. However, the images extracted from the fuzzy system enters as input into the heretical rules to filter the image of pixels, and as such, the output from these rules in some pixels as skin were considered as non skin. Moreover, the researchers conclude that the method is still not reliable radically, and future study must be conducted to resolve this problem. The study suggests that in a future research, other features addition to the colour feature should be adopted for fuzzy system to produce better results than what is used now.

Comparison of result

The study classification results will be compared to the simulation result of explicitly defined rules' skin region (Kovac et al., 2003) and Takagi-Sugeno fuzzy inference

(TSFI) (Hamid and Jemma, 2006). This will be followed by accuracy rates comparison.

Comparison on skin classification rate between Takagi-Sugeno fuzzy inference, explicitly defined skin region and the proposed method

Here, the result of human skin classification for the proposed method is compared with the simulation result based on the method stated by Kovac et al. (2003) and Hamid and Jemma (2006). Figure 11 shows the comparison of ROC curves for the three different methods. It is observed that that the performance of our proposed (fuzzy-explicitly) classification method is better than that of Kovac et al. (2003), but worse than that of Hamid and Jemma (2006). The value of the area under ROC curve for the explicit rule method is 0.943, while the value of the area under ROC curve for TSFI method is 0.764. However, the area difference between the proposed method and the TSFI method is 0.0435, while the difference of the area between our proposed method and the explicit rule method is 0.135.

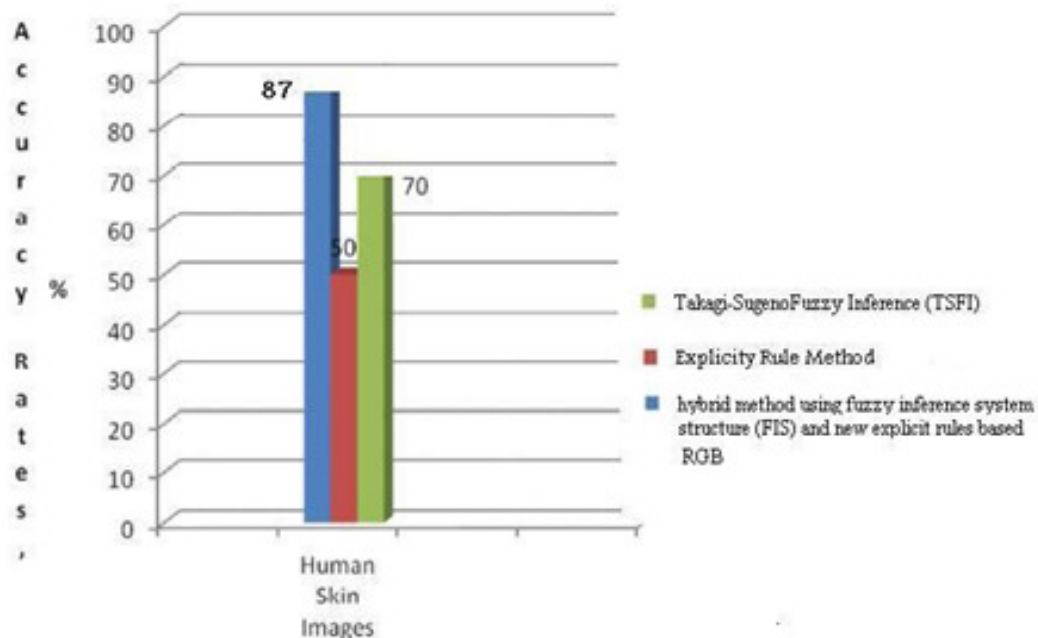


Figure 12. Comparison of accuracy rates between the study's proposed method, explicitly defined skin region and Takagi Sugeno fuzzy inference.

Accuracy rates comparison between the study's proposed method, explicitly defined skin region and Takagi-Sugeno fuzzy inference on human skin images

Based on Figure 12, the accuracy of the study's proposed method is the best when compared to the other two methods. It achieved an accuracy rate of 87%, that is, higher by 27 and 17% to the explicitly defined skin region and TSFI, respectively.

Conclusion

The study applied the hybrid method, incorporating the explicit rules and fuzzy inference system structure method, to perform skin detection based on RGB colour space. The researchers considered the results as satisfactory because firstly, the modification for the classical use of fuzzy inference system structure in skin detection is tested only on the skin candidate pixel for skin, thus the search space is reduced. After that, the author has used the explicit rule as a filter to the image after applying the fuzzy method to achieve better performances. Secondly, the researchers realized that the skin-like colour increase the rate of false positive and false negative, and thus reduce the true positive. In other words, the skin detector is not reliable.

To overcome this wide range of skin colour issue, the researchers have collected more than 200 images having a variety of skin colour. After updating the dataset with a

wider range of skin colour, the results are more reliable. The results of the study suggest that skin colour is a more powerful cue for detecting people in unconstrained imagery. The study solution showed its effectiveness of 87% classification rate. This technique will be improved by considering different illumination level. Then, different features such as texture should also be considered in future work. By using texture, the human object can be extracted from the images which can filter other unwanted 'noise' and the homogeneity region of skin found within the images. With the combination of colour and texture, it is believed that a better classification performance can be achieved.

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