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Full Length Research Paper

Increase reliability for skin detector using backprobgation neural network and heuristic rules based on YCbCr

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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 unit-spam system. It is also considered as one of the most challenging problems in image processing. Despite being a well known technique in detecting human appearance within image, it faces several drawbacks when using colour as cue to detect skin. First, the difficulty is when the colour between skin and non skin within an image is similar. Second, the skin appearance of humans when exposed under different lighting condition adds the complexity to skin detection. Therefore, this paper proposed a new hybrid module for skin detector using backprobgation neural network and heuristic rules based on YCbCr with the purpose to improve the skin detection performance. Using the new hybrid module, the researcher managed to increase the classification reliability when discriminating human skin colour and regularize the problem when exposed to different lighting conditions. The new proposed skin detector depends on normalization technique to normalize the inputs and targets so that they fall in the interval [-1, 1] and trained with training set of skin and non-skin pixels. Using the techniques discriminates human for images having upright frontal skin with any background achieved high detection rates, scored an 88.5% classification and low false positives when comparing with the previous methods.

Key words: Skin detector, backprobgation neural network, explicit rules.

INTRODUCTION

According to (Dargham et al., 2009) skin detection is a process of detecting and reading coloured skin pixels and areas in the image or a video. Skin detection is a preprocessing step is reading and locating areas and boundaries of human skins including faces and other exposed areas. (Dargham et al., 2009) presented several computer programmers' that are designed for skin detection. The authors further stated that colour skin detector normally works by transforming the coloured pixels into coloured space and utilizes the skin classifier to label the pixels to skin or non-skin pixels (Jandaghi et al., 2010). (Yin et al., 2001) showed the ability of a skin classifier to define skin colour boundaries into decisions in the colour space where a set of skin-coloured pixels database was created prior detecting process. (Yin et al., 2001) stated that the main goal of the skin colour detection algorithm is to construct a rule that can differentiate (Steinberg, 2001) indicated that the main goal of skin colour detection is to build a ruling ability to differentiate between skin and non-skin pixels. The goal is accomplish by using a metric that measures the approximate distance between the colours pixel to the skin tone. (Albiol et al., 2001; Dargham et al., 2009) used skin colour modeling method to define the metric. Other literatures showed various methods in discriminating skin and non-skin coloured pixels. (Dargham et al., 2009) stated that the various skin discrimination methods can be grouped into three types of modeling; parametric, non-parametric and explicit skin cluster definition methods. (Liévin and Luthon, 2000) describes that parametric method uses colour values explicit rules. The advantage

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of the method are that it is easy to implement and inexpensive to compute. Parametric method advantage is that which is rigid and cannot handle skin detection complexity problem (that is, presents shadow, background and lighting). The non-parametric modeling utilizes the non-parametric skin-colour distributions. The method calculates an estimation of skin colour distribution from training data. The method does not produce an explicit skin colour model. All methods that uses skin distribution map (SMP) falls under non-parametric category. The SMP uses observed colours of skin discrete probability distribution. The advantage of non-parametric method is that it is fast. However, as stated by (Yin et al., 2001), it requires large storage space and relies heavily on the variability and selection of the training set (Diplaros and Gevers, 2004). Explicit cluster method uses parametric model for skin colour distributions and consists of Gaussian or mixture of Gaussians. The method uses a more compact skin representation and able to generalize and manipulate the training data built (Celeux et al., 2001; Sigal et al., 2004). (Celeux et al., 2001) shows that hue saturation chrominance space is an important element in explicit cluster method and introduced tint, saturation and lightness (TSL) as elements in modeling skin pixels samples compacted by Gaussian skin colour distribution method. (Tsumura et al., 2003) presented several strategies in segmenting images that depends extensively on the selection of the images to be process and information that make up the object selected. (Tsumura et al., 2003) further classified the methods as contour-based, region-based and variational methods such as the global optimization approach that minimizes an energy function or some Bayesian criteria; and active contours model. Peer et al. (2009) used a simple skin classifier with several Heuristic rules. However, this method requires the need to find good colour space and decision rule to achieve high recognition rates (Peer et al., 2009). To achieve high recognition rates, (Hammami et al., 2003) uses machine learning algorithms to find both suitable colour space and a simple decision rule. The research objectives section presents the problem statements and the proposed way to solve the problems.

Problem statement

Skin detection algorithms have been used in many applications. Choosing skin colour as a factor in detecting human existence is a quite simple and straight forward task and in addition, skin colour has the advantage in processing time since colour processing is faster compared to other features. Nevertheless, skin colour detection method has several constraints. One has to do with skin colour representation that is skin-like colour objects might that present in the image captured, for example, wood, leather, skin-coloured clothing, hair, sand, and etc. This causes any skin detector to have much false detection in the background if the environment is not controlled. Another challenge comes from the fact that the appearance of skin in an image depends heavily on the illumination conditions that involves illumination geometry and colour where the image was captured. Human has high sensitivity in identifying object colours in a wide range of illuminations, this is called colour constancy. Colour constancy is a mystery of perception. Therefore, an important challenge in skin detection is to represent the colour in a way that is invariant or at least insensitive to changes in illumination. The choice of the colour space affects greatly the performance of any skin detector and its sensitivity to change in illumination conditions. This paper takes the consideration of these factors in order to get robust skin detection model with high performance of reliability and elimination of false detection from new hybrid module.

Research objectives

Automatic skin detection is an essential component of various imaging applications, such as face detection, tracking and anti-spam system. Nowadays, these applications are classified as security applications for very important to human life (Zaidan et al., 2010; Zaidan et al., 2010a; Zaidan et al., 2010b; Raad et al., 2010; Alanazi et al., 2010; Hmood et al., 2010). 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 and the skin appearance of human under different lighting condition adds the complexity to skin detection as discussed in the problem statement. The combination of these weaknesses increases the background false detection if the environment is not controlled. This research tries to accomplish the following objectives:

(i) To conduct a study in the literature related to different skin detection methods and determine the strength, reliability and weaknesses of each methods.
(ii) To design and apply a skin detector method based on backprobgation neural network.
(iii) To implement a collective approach based on backprobgation neural network and explicit rules that overcomes the drawbacks of the current skin detection methods.
(iv) To compare the new skin detection module to the existing module.

Research questions

The study proposed an implementation of a new hybrid module between explicit rules and backprobgation neural network based on YCbCr colour space with the purpose to improve the skin detection performance. Thus, this research tries to highlight and answer the following questions:

(i) According to (Mohamed et al., 2008; Bao and Nhan, 2009) backprobgation neural network method is used mostly as classification for the target application after the skin detector method is completed. This leads to the first research question; can the backprobgation neural network method be applied on skin detector as segmentation method?
(ii) There are many skin detector method that can detect the skin with high rate, but it is not reliable due to the present of pixels that may have same skin-tone colours that is falsely detected as the skin, for example skin-coloured clothing, background, skin coloured materials, and etc (Chahir and Elmoataz, 2006). Thus, the second research question is formulated based on this fact; is there any module for skin detector that can detect the skin pixels with high reliability?
(iv) One of challenge comes from the fact that, the appearance of skin in an image depends on the illumination factors that involves illumination geometry and colour where the image was captured. The third research question states; is there any method for skin detector that able to detect the skin pixels without the influence of the illumination conditions?
(v) Neural system cannot stand alone to skin detector (Zakaria et al., 2009) the fourth research question states: is having a hybrid approaches (that is, consists of neural system and heuristic rules) worthy?

Related work

Chahir and Elmoataz (2006), stated that there are many methods and processes in skin detection. The methods depend on the systems objective and the type of objectives the system need to achieve. (Mohamed et al., 2008; Mohamed et al., 2007) proposed a method to detect skin in soft computing environment, specifically on neural system.

Mohamed et al. (2008) suggested a new algorithm for face detection using compressed domain. Their study used skin colour information of Cb and Cr colour space along with backprobgation neural network classifier, extracting features of DCT coefficient vector after segmentation. (Mohamed et al., 2008; Mohamed et al., 2007) divided face detection process into three stages; preprocessing segmentation, and classification using backprobgation neural networks. (Mohamed et al., 2008; Mohamed et al., 2007) studies use tested dataset of upright frontal colour face images from the internet and the studies showed high detection rate.

(Hashem, 2009) proposed a new face detection method that combines skin face detection using HSV colour space and the back propagation neural network methods to achieve better detection rate. The second proposed method involves the neural network that only detected the face of the person instead of the whole exposed skin of the human/ images. This method saves the search time and the search space. The new system is designed to read the frontal faces in colour images with all kind of backgrounds simple or complex). The skin colour algorithm does not work in all cases. According to (Hashem, 2009), the skin colour algorithm will not work when the non-skin colour resembles skin colour. In this case the algorithm cannot differentiate and draw boundaries between the two materials. The algorithm will read the two skin regions as one because the false skin pixels will form a connecting between the two regions. (Hashem, 2009) study used texture skin to draw the boundary between the skin and non-skin. The skin detector will give the edge information crucial for differentiation. The false pixels will have high gradient since the pixels are at the boundary of the face. The study shows 91.43% detection ratio even the colour of the clothes has the same colour of the skin. The method is able to isolate the pixels.

Other part of the body like the eye and the mouth often considered as skin. This study discusses the weakness of the skin detector methods and proposes a new method that will help in increasing the reliability of the method.

(Peer et al, 2009) combined specific pre-processing techniques and neural network power to mitigate the problems associated with skin detector. The researchers divide the images into segments based don skin characteristics and add specialized techniques to match the mouth and lips colour exactly. The process of classifying the images through neural network is faster and according to the researchers the estimated runtime method increased considerably. Efficiency is increased to about 85.5%.

However, (Peer et al, 2009) study was not able to resolve the problem associated with light conditions and the colour of the backgrounds such as skin like environment. The method also unable to produce correct ratio of not more than 90% and produces the effects of detection positions. (Peer et al., 2009) detection method was not able to detect skin mouth in faces image that have dense beard, moustache, sunglasses, and colour like skin. Two methods of data fusion were used in (Dargham et al., 2009) study to improve the skin detection performances. The first data fusion method combines the two chrominance components from the same colour space and the second method fuses the outputs of the two combined skin detection methods, each results was based on a different colour space platform. (Dargham et al., 2009) study used colour spaces of the normalized red, green, blue (RGB) colour space, referred to as pixel intensity normalization. The researchers also proposed new method call for maximum intensity normalization in obtaining the R, G, and B components of the normalized RGB colour space. The researchers used the multilayer perception (MLP) neural network and histogram thresholding for skin detection. Skin colour and neural network were also used in (Zakaria et al., 2009) study to detect multiface skins. The study conducted an experimental investigation of skin colour and neural network in order to produce feasibility study. Zakaria et al., 2009 showed better results when using skin colour and neural network combination compared to using skin colour and template combination. The combination method produced face image detection accuracy of 75% and more. Dargham et al. (2009), Peer et al. (2009) and Zakaria (2009) studies produced high detection rate of more than 70%. But, the methods have been criticized for their reliability due to the inability of the detector to differentiate fully pixels that have same skin tone or colour. Skin-coloured clothing, skin colour materials, background, and etc. present challenges in detecting true skin. Moreover, the skins were still affected by lighting and its variables.

MATERIALS AND METHODS

Skin detection framework

There are two phases in skin detection process according to (Dargham et al., 2009); the training phase and the detection phase.

Training a skin detector involves three basic steps (Elgammal et al., 2009):

1. Creating database of various images skin patches that contains skin-coloured patches under different lighting conditions and background.
2. Choosing and matching suitable colour space for the images
3. Learning the parameters of a skin classifier.

The training for the skin detector to detect images or video frame involves giving a trained skin detector. Identifying skin pixels in a given image or video frame involves (Elgammal et al., 2009):

1. Converting the image into the same colour space that was used in the training phase.
2. Classifying each pixel using the skin classifier to either a skin or non-skin.
3. Imposing spatial homogeneity on the detected regions in the post processing step using morphology.

Elgammal et al. (2009) skin colour plays an important role occupying the colour space that can be either compact or scattered in the space. The space is referred to as skin colour cluster. The skin classifier is classified in a one-class or two-class classification problem. All images pixels are classified and labeled. In skin colour classification, true positives are defines as when skin pixels are read by classifier correctly as skin. True negatives are non-skin pixels that the classifier correctly labels as non-skin. Errors are when classifiers wrongly label the non-skin pixel as skin or a skin pixel as a non-skin (Hashem, 2009). The former type of errors is referred to as false positives (false detections) while the later is false negatives. A good classifier should have low false positive and false negative rates (Elgammal et al, 2009). As in any classification problem, there is a tradeoff between false positives and false negatives. The more loose the class boundary, the less the false negatives and the more the false positives. The tighter the class boundary, the more the false negatives and the less the false positives (Singh et al., 2003). The same applies to skin detection. This makes the choice of the colour space extremely important in skin detection. The colour needs to be represented in a colour space where the skin class is most compact in order to be able to tightly model the skin class. The choice of the colour space directly affects the kind of classifier that should be used (Elgammal et al., 2009; Singh et al., 2003).

YCbCr colour space

(Singh et al., 2003) stated that the human skin colour has a restricted range of hues and is not deeply saturated, since the appearance of skin is formed by a combination of blood (red) and melanin (brown, yellow). Therefore, the human skin colour does not fall randomly in a given colour space, but clustered at a small area in the colour space. But it is not the same for all the colour spaces. Variety of colour spaces has been used in skin detection literature with the aim of finding a colour space where the skin colour is invariant to illumination conditions (Elgammal et al., 2009). The appearance of skin in an image depends on the illumination factors such as illumination geometry and colour where the image initially was captured. Human eyes are highly responsive in identifying coloured object in a wide range of illuminations. This ability is called colour constancy. According to (Elgammal et al., 2009), colour constancy is a mystery of perception. Therefore, the important challenge in skin detection is to represent the colour in a way that is invariant or not affected to the changes of illumination factors. The choice of the colour space affects greatly the performance of any skin detector, and is sensitive to changes in the illumination conditions (Elgammal et al., 2009). The choice affects the shape of the skin class, the detection process, and the selection of the colour space that will be used in skin colour modeling. Bao and Nhan (2009) stated that different people have different skin colour appearance, but these differences lie mostly in the colour intensity not in the colour itself. That is why many skin detection methods disregard the luminance component factor of the colour space. Dropping the luminance component factor achieves two important goals; first the model will be independent of the differences in skin appearance that may arise from the difference in human race, or the difference in the lighting of the image; second the colour space dimensions will be reduced so the calculations would be easier (Bao and Nhan, 2009). The paper used YCbCr colour spaces. A skin colour model is created in the level of YCbCr colour space. The reason for choosing chrolninance blue and chrolninance red (Cb and Cr) colour space instead of YCbCr is to eliminate the affect of illumination changes by using Y component (Bao and Nhan, 2009). Classification using only pixel chrominance Cb and Cr (pure colour) skin segmentation may become more robust to lighting variations if pixel luminance is discarded. The classification is also to narrow the search and speed up the calculation in detecting the skin face regions.

System overview

The study proposed skin detection system using backprobgation neural network and heuristic rules and is shown in Figure 1. Firstly, the researchers have to prepare the image database. To do that, the researcher gathers 200 human skin images from the Internet and manually cropped them. The process is to remove the non-skin pixels from the image. The researcher used Adobe Photoshop to complete this task. Figure 2 is an example of image that has been cropped. The cropped image database together with the original image (before cropping) database are the image databases that are

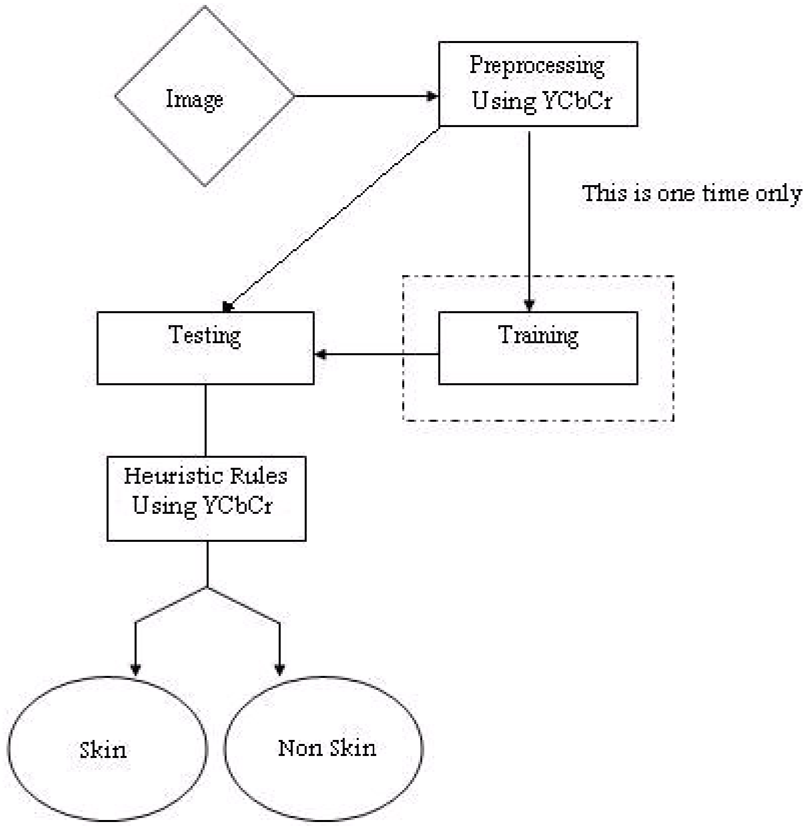

Figure 1. Main structure of the proposed method.

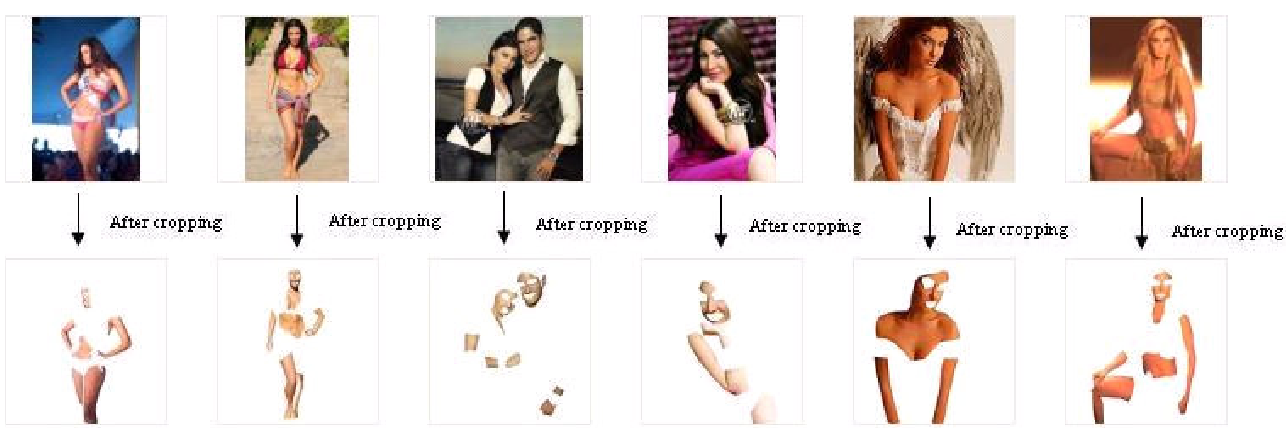

Figure 2. Examples of cropped images (without non-skin pixels) from the original images.

going to be used in the study neural skin detection and the output from the neural detector will be taken as the input for heuristic rules as the second stage. In this paper the study uses 6000 pixels of all tone skin and 6000 pixels from non skin pixels for the training. In the testing process, given the inputs of new function within two parameters; one of these parameter as the output from neural system and the other is the image which is the original image that is required from this system as segment of the skin pixel. On the basis of positions of pixels as matching with the original picture and the results of neural system, the study passes all pixels on the threshold that is 0.6 and above. The threshold was chosen based on the researches that have been conducted at the stages of building the program, taking the result image as skin extract and entering the results as an input to the rules. Using this heretical rules the researcher able to filter the image of pixels which is the output from neural system as skin and considered as non skin and call it skin-like. The proposed method achieved high reliability (88.5%) skin detection rate. The system has been implemented by using Matlab.

The new skin detector using backprobgation neural network and heuristic rules consist of four important phases, that is, pre-processing, training, testing and heuristic rules.

Pre-processing phase

In this important part of how we offer your paper, arrange the data before introduction to the machine learning (backprobgation neural network) Where you review in this part a new way to arrange the data pixels who is take each pixel from the image and turn them into YCbCr colour space and there neglect Y and take only the CbCr. After completing all the pixels of the first image under the target 1 we take the second picture in the same target and so on until we've all forms of skin the program runs automatically on the non skin images folder in the same process under the target-1. Until the finished all the images inside the folder. In the conclusion we found the same matrix content the skin pixels within the target 1and then non skin pixels within the target 1. Figure 3. Shows the flowchart of pre-processing phase consisting of three main steps:

Step 1: Extracting the image features that is, the YCbCr colour information.
Step 2: Converting each Cb and Cr matrix into vectors and combine the vectors as one array.
Step 3: Add another vector which include the target 1 that indicates as non skin or -1 indicates as skin.

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

Training phase

This training phase is performed only once in the first stage to generate neural system from data using normalization technique. The purpose of this phase is to train the neural system to be able to differentiate the skin dataset and non skin dataset. The most important things in this phase are how accurate the data set is so that the neural trained data covers a wide range of skin colour in both part of skin and non-skin. The two data sets for training phase can be classified as non-skin images and skin images.

(i) Non-skin images database

The non-skin picture database consists of 200 images the researcher collected from the internet. All pixels of the pictures will be considered in the methods of the study. Figure 4 shows an example of sample of non-skin pictures used for training.

(ii) Skin images database

The skin picture database consists of 200 images that were collected from the internet. Not all pixels of the pictures will be considered from these images. The researchers used just skin pixels and neglect the white colour pixels in the training. Figure 5 shows few examples of the skin sample with different body forms with various human skin without any noise used for the training phase.

(iii) Neural network method

Neural network has been used successfully in many skin detection systems (Zakaria et al., 2009). Neural network has been a subject of growing interest in recent years (Messaoudi et al., 2007). Also the neural network is considered to be appropriate to deal with the nature of uncertainty in system and human error (Ozcep et al., 2010). The system has been applied in area of pattern recognitions that look into recognizing optical character, object, driving autonomous robot (Celik, 2010; Gencel, 2009). The system has many advantages including the feasibility of training the system that able to capture the complex class conditional density of face patterns. The researchers further emphasized that using neural network can produce high accuracy in detecting face that has been shown in (Rowley, 1999). The system also has few disadvantages as stated by Zakaria et al. (2009); the neural network needs more processing time compared to the other methods such as fuzzy system (Bahari et al., 2009; Ardil and Sandhu, 2010) or Baysian method. Artificial neural networks (ANNs) are massively parallel systems composed of many processing elements connected by links of variable weights (Yenigün et al, 2010). The back-propagation training algorithm is the most frequently used neural network methods and is the method used in this paper (Pradhan and Lee, 2009). The back-propagation training algorithm is trained using a set of examples of associated input and output values (Pradhan and Lee, 2009).

In the proposed method, the weakness is that the back-propagation nural network, has to be optimized (number of layers, number of nodes, threshold, training algorithm etc.) to get the best performance (Zakaria et al., 2009). In the study neural network model consists of three layers (1- inputs, 2-hidden and 3-output). Figure 6 below shows the neural network architecture of back propagation neural network with four neurons in the hidden layer and one neuron in the output layer for segmentation task.

Training steps

The training steps consist of nine important steps:

1. Loading the data which are prepared from preprocessing and the data are then saved in the mat file.
2. Processing row 1 to 6000, columns 1 to 2 as input (1:6000, 1:2);
3. Processing row 6000, starting from 10th column as targets (1:6000, 10);
4. Normalizing the premnmx that involves preprocessing the data so that the minimum is -1 and the maximum is 1.

Syntax:[pn,mip,maxp,tn,mint,maxt]=premnmx(p,t).

Normalizing the inputs and targets so that they fall in the interval [-1, 1]

1. Using the train Fcn =”trainb’ algorithm for training.
2. Using the function (minmax (pn), [4 1], {'tansig','purelin'},'trainlm') for training;
(i) Minmax (p) is used for large data to defend the min and the max for the vector.
(ii) (Trainlm) creates a neural network of one hidden layer with 4 neurons and Levenberg-Marquardt backpropagation.
(iii) {'tansig', 'purelin'}, (tansig); a non linear function using between

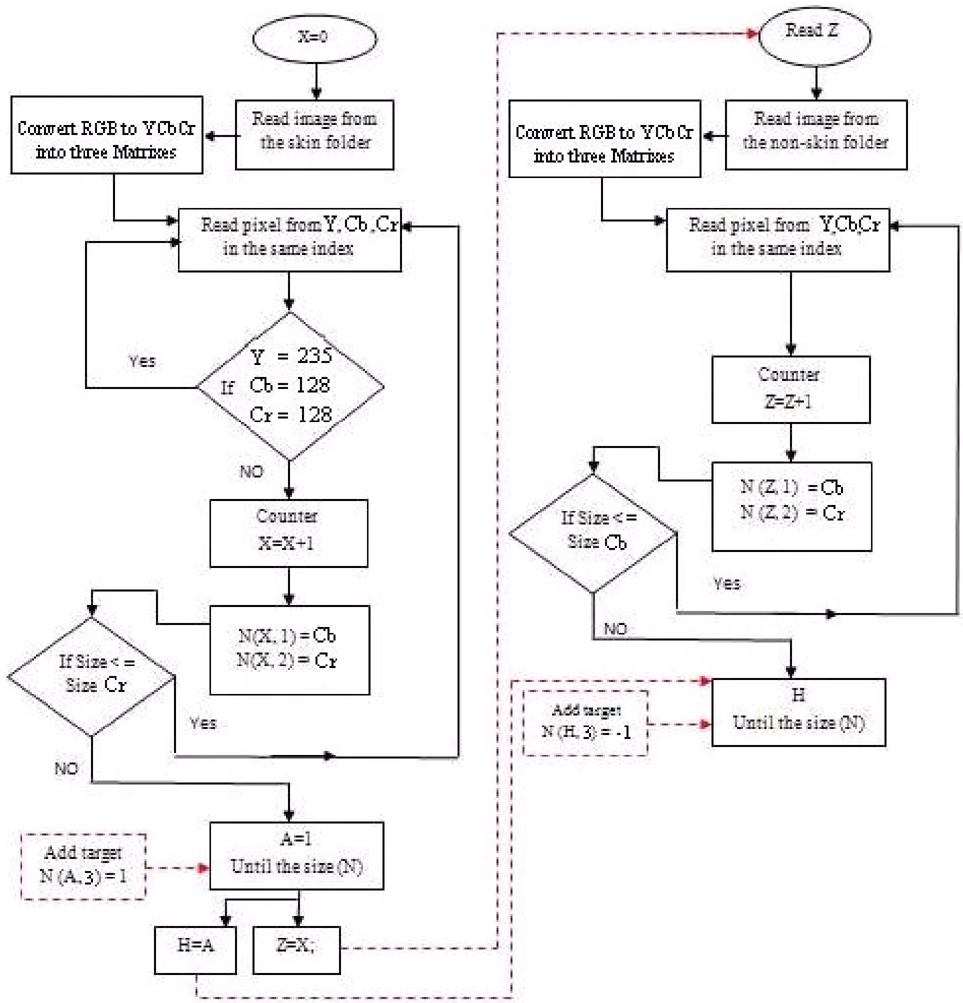

Figure 3. Flow chart of pre-processing phase.

the inputs and hidden layer because they have processing and there is no relation between the input and the hidden layer, then using (purelin) liner function between the hidden and output layers because no other processing in this area can just transfer the output, this nonlinear function help the study to reduce the time for neural process.
(iv) The process consists of four neurons in one hidden layer [4, 1].
3. The number of training is 150, the time between status reports of the training function is 100, the learning rate is 0.30, and the momentum is 0.6.
4. The weight for this network is initialized at net=init (net).
5. For batch training, the study used the training function (net, pn, tn); as starter for the training.

While in the case of reducible performance, the neural network shows more stability where errors were decrease smoothly with iteration number equal to 150, as shown in Figure 7. The study found that the data trained until the error is fixed. Also the performance of BPNN was also measured using regression analysis between the network outputs (Y) and the targets (T). The regression analysis shows that the relation between Y and T is close, and the correlation coefficient R is equal to 0. 90891. Figure 8 shows a good fit between the network output and the target where the correlation coefficient R is equal to 0. 90891.

Testing phase

Testing steps

The testing steps involve:

1. Loading the data which are prepared from preprocessing for testing set that are saved in the mat file.
2. a===== must be the same dimension as p From row 1 to row 6000, columns 1 to 2 from test data set.

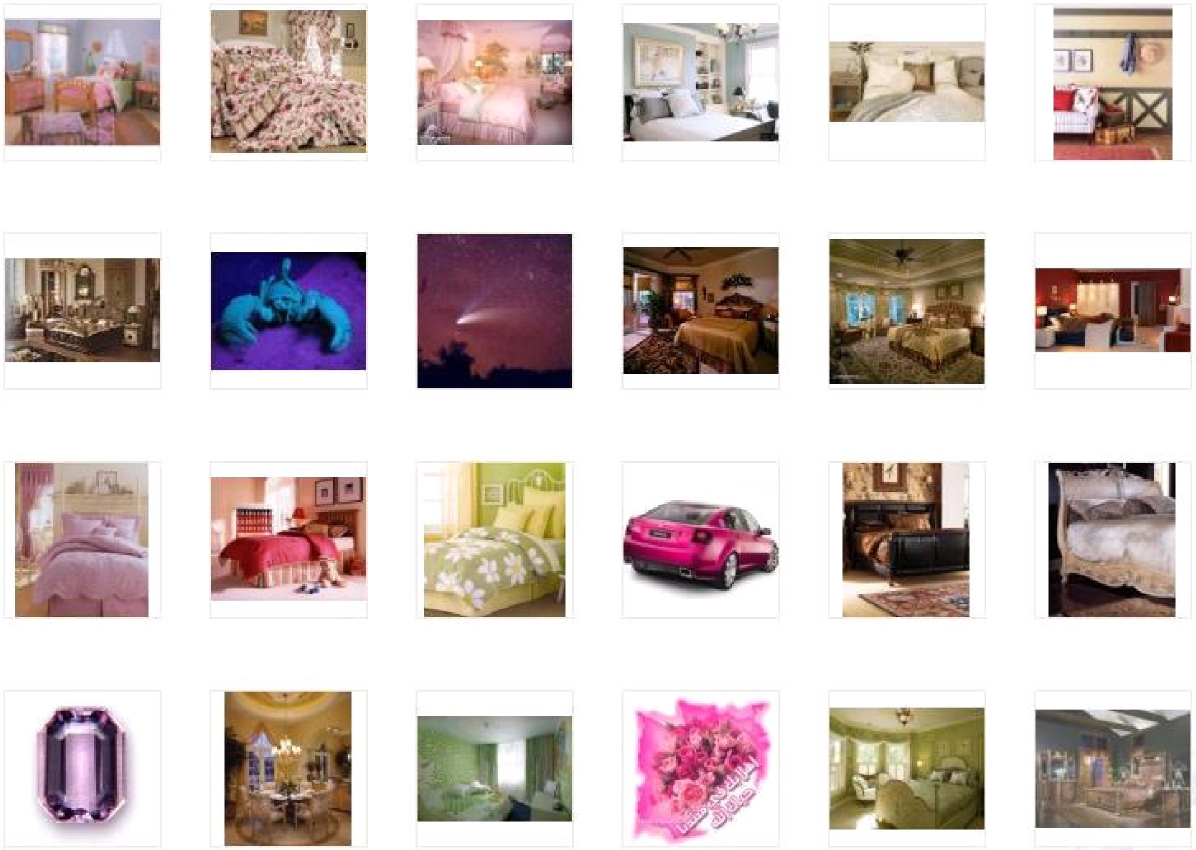

Figure 4. Samples of non-skin pictures used for training.

3. s===== from 1 to 6000 rows, from 10th column test data set.
4. Preprocessing the data using the premnmx so that the minimum interval is -1 and the maximum interval is [an, mina, maxa, sn, mins, maxs] =premnmx (a', s') and normalizing the inputs and targets so that they fall in the interval [-1, 1].
5. Starting the test using yn = sim(net, an) in the training
6. Converting the output (yn) back to the original scale including the following command. Postmnmx (yn', mins, maxs).

Determining appropriate threshold value

In determining the appropriate threshold value, (Zakaria et al., 2009) used the appropriate threshold value to match the suitable proposed method (Threshold versus total skin detection).The researchers used different images human for testing. The researchers concluded that the best threshold value is 0.6. The value was taken as it is not too rigid and not too loose for skin detection system.

Heuristic rules phase

The heuristic rules has been inferred by using the photoshop using images that contain only the skin and was measured using the proportion Cb and Cr colour for each pixel which is selected on this basis and neglected the Y matrix because in Y matrix contains lighting effects of the colour space. Therefore, the study has used these rules from these different ratios of the different pixels using 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 study to increase the reliability of the proposed skin detector. The implementation for these proposed heuristic rules are as follows:

If (Not Equal (Cr > 132)) And
If (Not Equal (Cr < 173)) And
If (Not Equal (Cb > 76)) And
If (Not Equal (Cb < 126))

RESULTS AND DISCUSSION

Peer et al. (2009), Tsumura et al. (2003) and Zakaria et al. (2009) repeatedly stated in their studies that neural

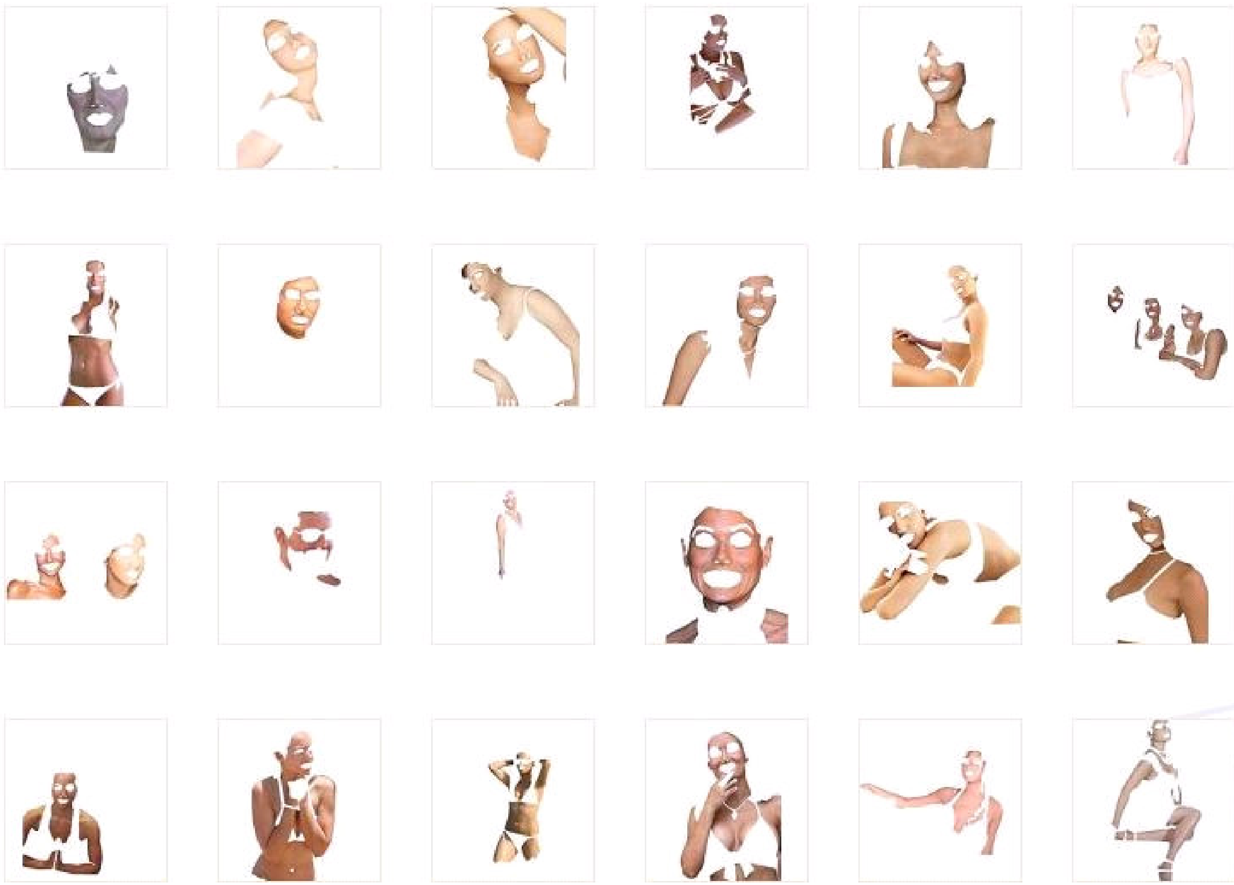

Figure 5. Samples of skin pictures used for training.

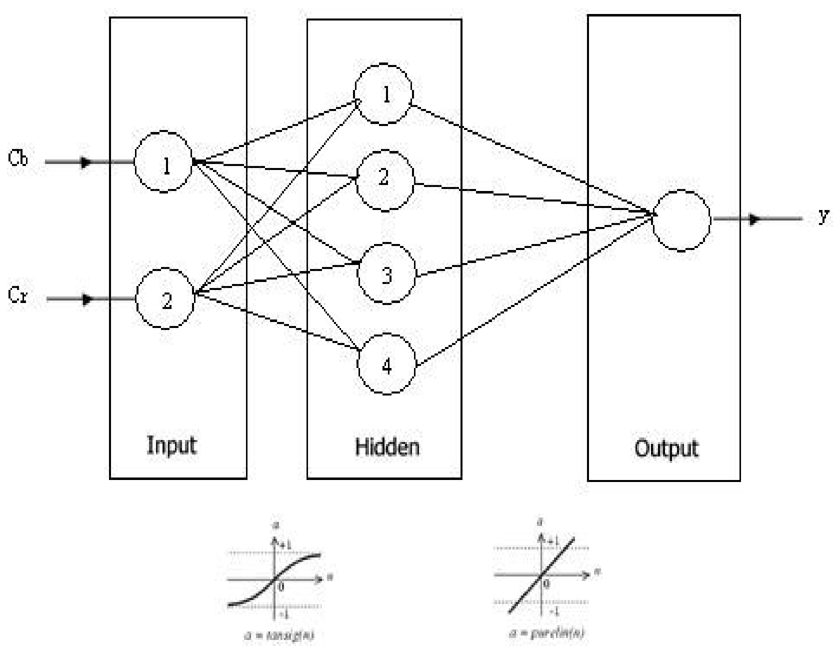

Figure 6. Neural network architecture.

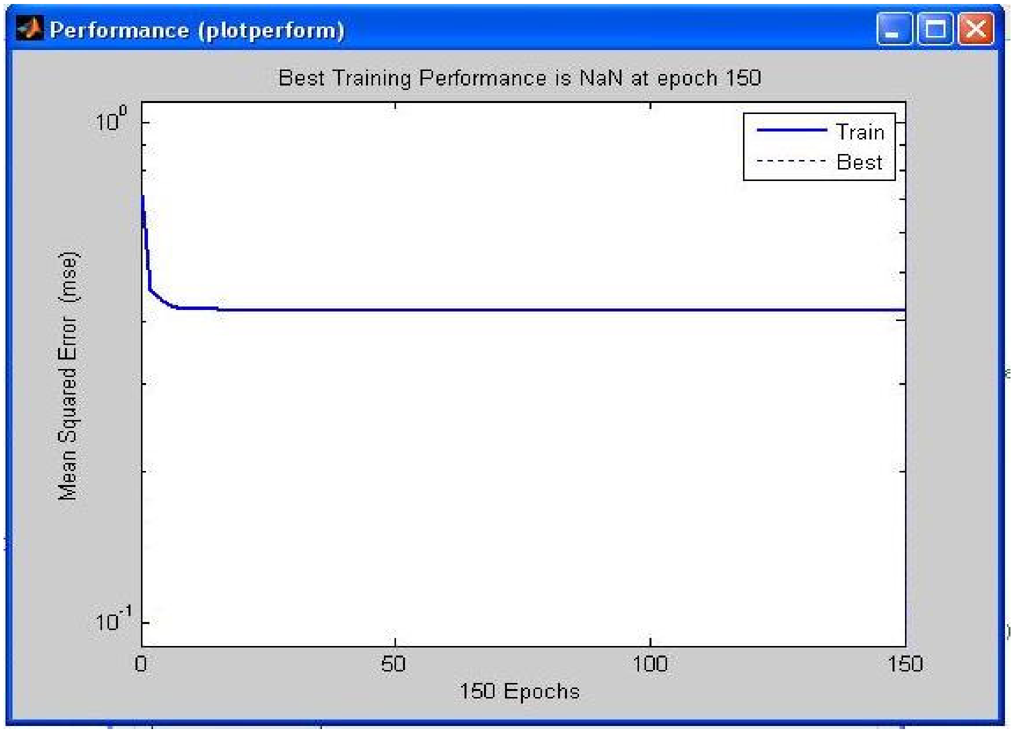

Figure 7. Error characteristics during training to reduce BPNN.

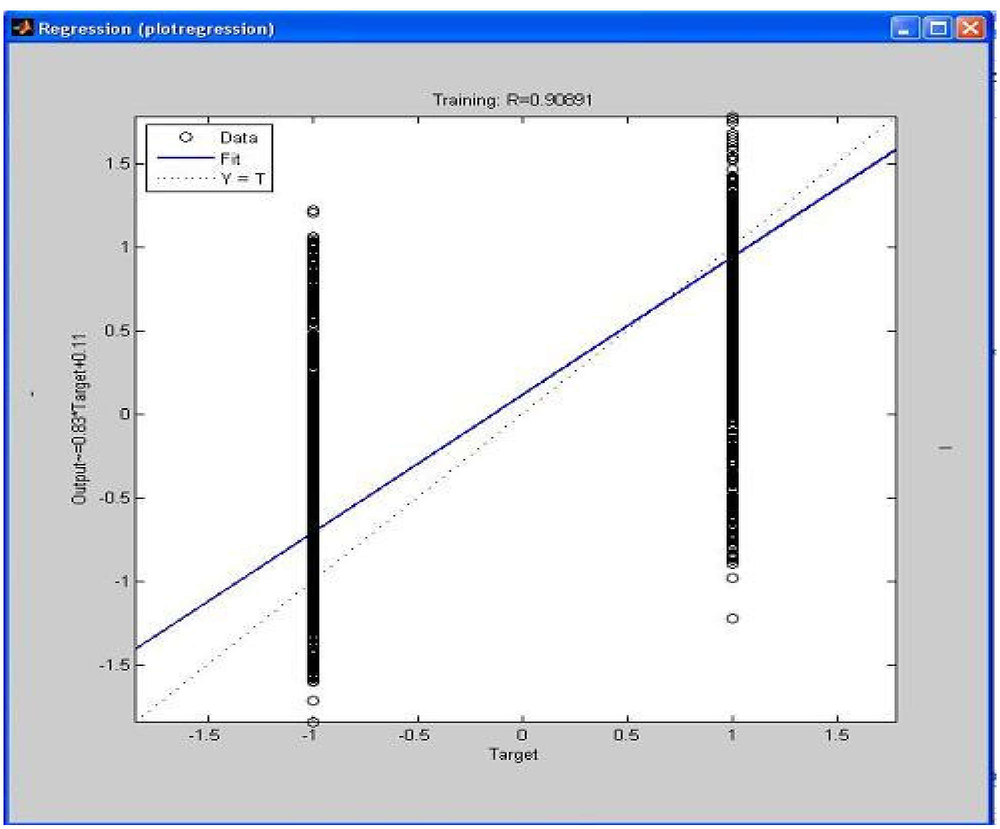

Figure 8. Regression analysis for reducible BPNN.

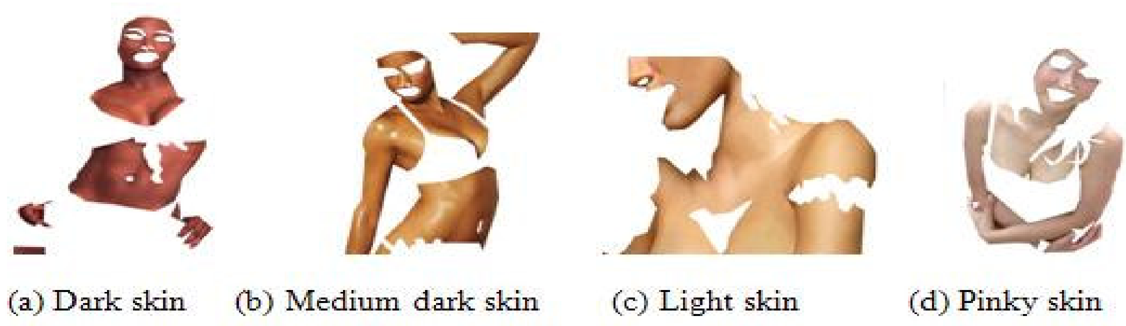

Figure 9. Samples of skin colour in our data set.

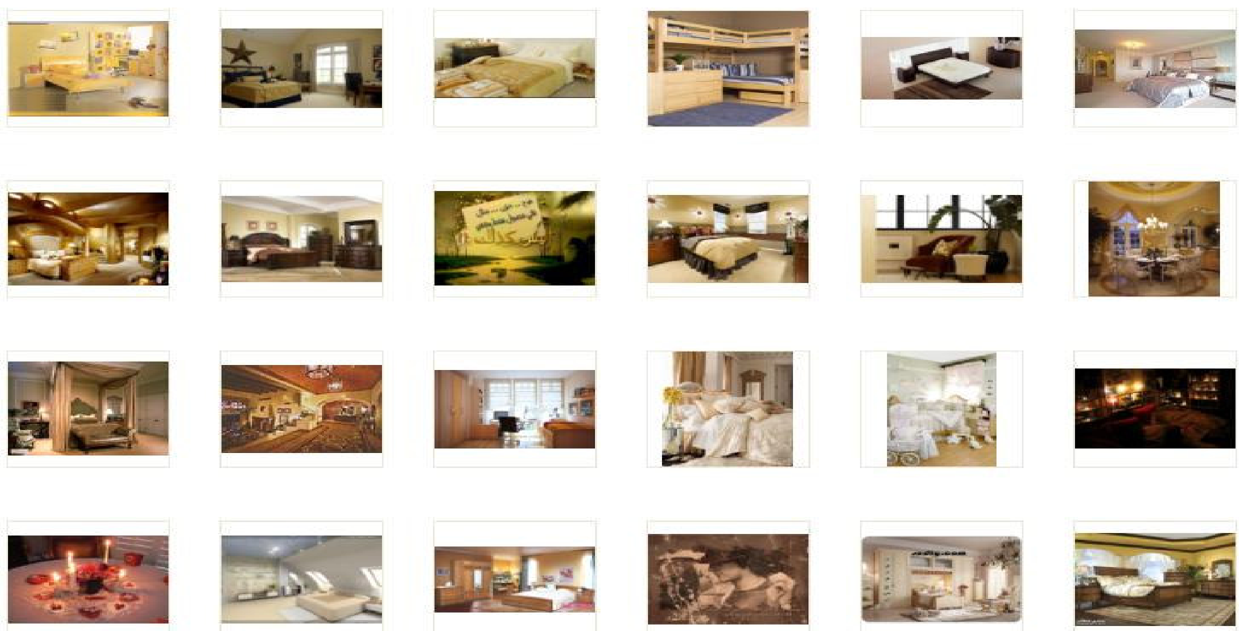

Figure 10. Samples of non skin colour in our data set for gray colour.

network is one of the famous appearance-based methods for skin detection system Therefore, in this paper the study used neural network as part of the proposed segmentation method. Based on the first testing the researcher realized that the skin-like colour increases 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 and non skin colour issues in this method, two basic things must be done. Firstly, the researcher have collected more than 200 images having variety of skin colour and used these images for training phase of skin part to train the system to different types of skin pixels in order to avoid overlapping as much as possible. An example of our skin data set is shown in Figure 9. Secondly, in the models of the images displayed in the Figure 10, the study uses different tones of gray colours images in the training phase of non skin part. The study focuses on using the gray colour because this colour works similarly with the skin colour and use for training a large number of images that contain the colour gray but they are non skin. Also when using the colour gray as part of the training, the study able to get more efficient module with high reliability for skin detector. The study presented the results using the YCbCr colour space to eliminate the affect of illumination changes by using Y component. Classification using only pixel chrominance Cb and Cr (pure colour), skin segmentation it became more robust to lighting variations when pixel luminance is discarded. Also in this part of the result and discussion the study presented the results of backprobgation neural network alone, where the researcher found that backprobgation neural network alone is not enough to give the results of high reliability. The researcher notes that the backprobgation neural network detects the skin pixel and also detects the non skin pixels. Hence the study concludes that the backprobgation neural network alone in this proposed system will produce a lot of the skin-like colour. In other words, the skin detector is not reliable. The aim of new heuristic rules in this system is to remedy this problem from the results which is back from backprobgation neural network. The study proposed heuristic rules to pass the output of the backprobgation neural network to the heuristic rules. These heuristic rules have been developed to remove the non skin pixel which is the result from neural system as the skin. The hybrid module for skin detector using backprobgation neural network and explicit rules are considered as adequate and efficient to detect the skin pixels with high accuracy and reliability. Our proposed system has achieved high detection rates of 88.5% classification as can be seen in Figure 11c. Also there are some limitations that we faced in this technique the author used pixel as based for training this thing made in the determinants of the number of pixels trainable as a gap where we have known for more number of pixels trained gives better results. Therefore, we had to wait a long time to train a number of pixels to make the system detect the image well, where this training took two consecutive days. Other limitation we faced deity that data which is collected from internet, which used in this system was not available, we mean that, there is no images content just the skin pixels with white background in the internet which are used for training process, where we collected of these images from the internet that contain skin with the any background and we segmented them manually using Photoshop, this action spend more time, It took us about a month and a half we were able to segment the skin only from the 200 images deity skin part of the training.

Results comparison

The study presents results that were compared with (Chin, 2008), study on defined rules of skin region and backprobgation neural network (BPNN) used in (Zakaria et al., 2009). This will be followed by accuracy rates comparison.

Comparison on skin classification rate between backprobgation neural network, explicitly defined skin region and the proposed method

Here, the result of human skin classification of the proposed method is compared with the simulation result based on the method stated by (Chin, 2008; Peer et al., 2009; Zakaria et al., 2009). Figure12 shows the comparison of ROC curves of the three different methods; backprobgation neural network (BPPNN), explicitly rule method and hybrid / combination method of BBPNN and explicit rule. It is observed that the performance of the study proposed (hybrid neural-explicitly rule) classification method is better than that of (Peer et al., 2009) explicit rule stand alone but worse than that of (Zakaria et al., 2009). Backprobgation neural network (BPPNN). It is shown that the value of the area under ROC curve for explicitly rule method is 0.943, while the value of the area under ROC curve for BPNN method is 0.764. The area difference between the proposed method and the BPNN method is 0.0435 while the difference of area between our proposed method and the explicitly rule method is 0.135.

Accuracy rates comparison between the study's proposed method, explicitly defined skin region and backprobgation neural network on human skin images

Based on the proposed hybrid method, the accuracy of our proposed method is the best when compared to the other two methods. The proposed method achieved an accuracy rate of 88.5%, that is, higher by 38.5% to the explicitly rule method and by 13.5% to BPNN (Figure 13).

Discussion and future work

This paper discussed the problem of skin-like but didn't tried to detected more than one person in the same image and detect the skin even if development of reflective glass or reflective water in front of any post-show glass skin or water skin, it is detected as considered for appeared as skin. These points are considered problems for all skin detectors available and has proposed a new hybrid module to overcome the weaknesses of the BPPN and the explicitly rule methods. Nevertheless, the study found that some pixels still have problem and the researcher cannot solved the problem completely as indicated in figure 11C. The reason is when using the neural system for the first stage of proposed system, the output image from the neural system contains many pixels that are not skin but is detecting as skin as indicated in fig 11 B and the images of that were extracted from neural system enters as an input to heretical rules to filter the image of pixels, the output from these rules in some pixels as skin we considered as non skin. The study concluded that this proposed hybrid method is still not fully reliable. Future study must find a new way to resolve this problem. Future study must adopt other feature in addition to the colour feature which was used in the neural system to give better results than what is available now. The study also

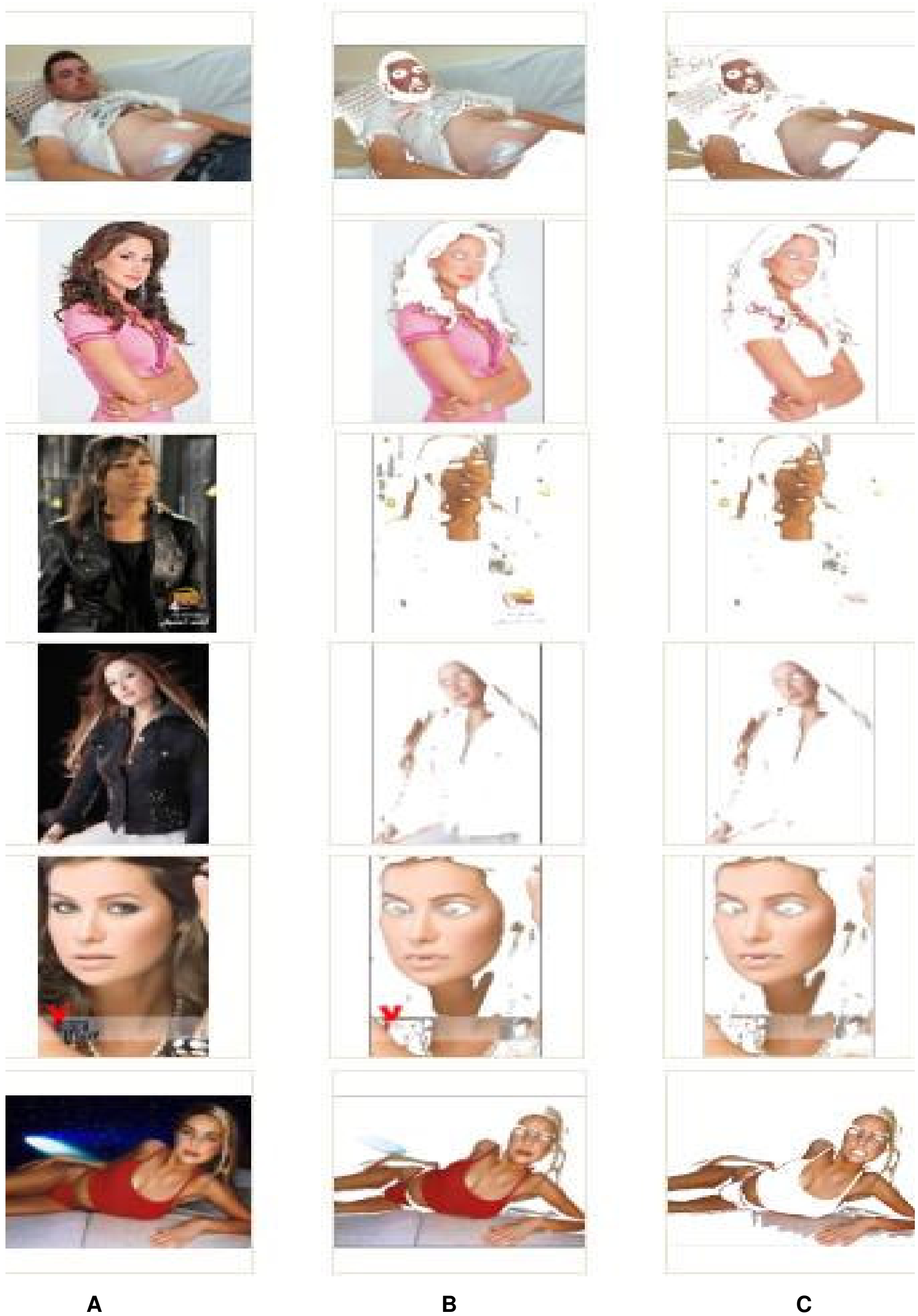

Figure 11. Results from the proposed system (A) Original image, (B) Results from neural system (C) Samples of skin colours with high detection rate (88.5% or more).

found that the use of YCbCr colour space of explicit rules and backprobgation neural network succeeded in reducing the lighting effect but some pixels are still affected by different lighting factors as indicated in Figure 11C.

Conclusion

The study applied the hybrid method incorporating the explicit rules and Backprobgation Neural Network Based on YCbCr colour space. The study concluded that the

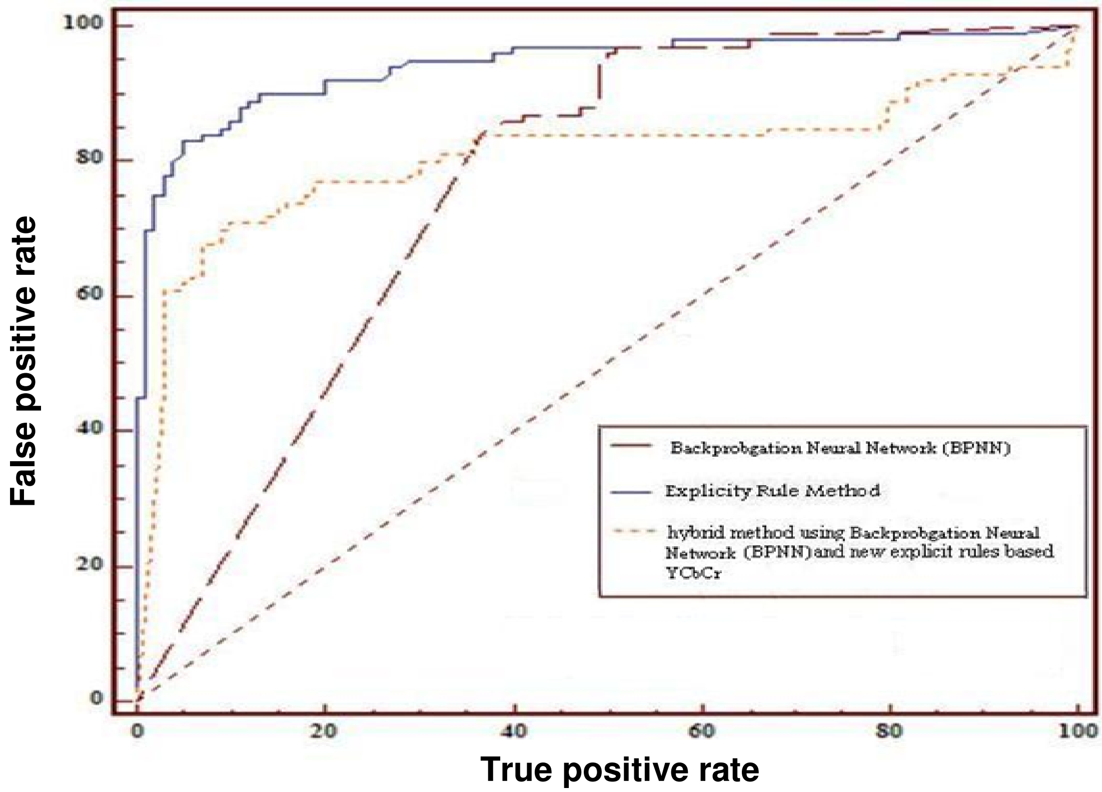

Figure 12. ROC comparison of human skin images classification methods.

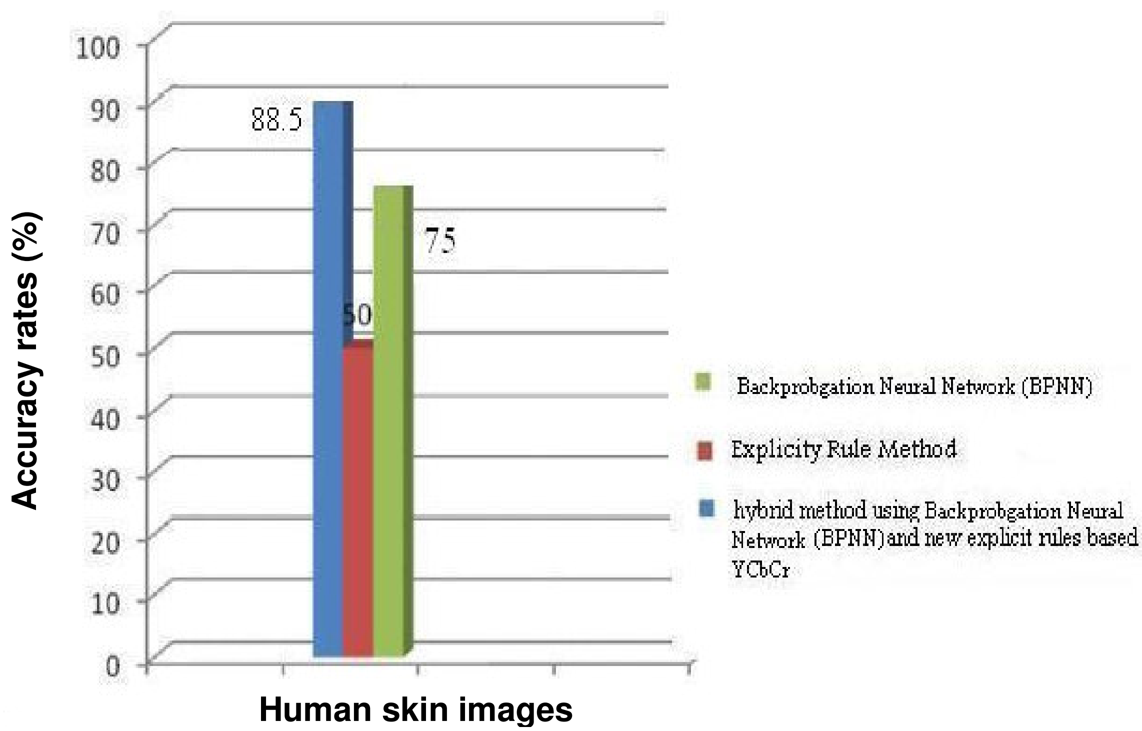

Figure 13. Comparison of accuracy rates between our proposed method, explicitly defined skin region and backprobgation neural network (BPNN).

results as satisfactory. First, the modification for the classical use of backprobgation neural network in skin detection is tested only on the skin candidate pixel for skin, thus the search space is reduced. Moreover, the researchers have used the explicit rule as a filter to the image after applying the neural method to obtain better performances. Secondly, a skin colour hybrid module is created in the level of YCbCr colour space. The method used chrolninance blue and chrolninance red (Cb and Cr) colour space instead of YCbCr in order to eliminate the affect of illumination changes by eliminating Y component. Classification using only pixel chrominance Cb and Cr (pure colour) skin segmentation became more robust to lighting variations when pixel luminance is discarded and to narrow the search and speed up the calculation for detecting the skin regions, hence reducing the colour space. Thirdly, the researcher discovered 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 used in this study is not reliable. To overcome this wide range skin colour issue, the researchers have collected more than 200 images with variety of skin colour. After updating the data set with wider range of skin colour, the researchers found that the results are more reliable. The results suggest that collecting variety of skin colour at the early stage is a more powerful cue for detecting people in unconstrained imagery. Our solution achieve 88.5% effective classification rate. This technique will be improved by considering different illumination levels at the preprocessing stage. The study also suggests future studies to consider different features such as texture segment technique. By using texture segment technique, the human object can be extracted from the images and filter other unwanted noise and the homogeneity region of skin found within the images. The skin and non skin boundary can easily be defined. With the combination between colour and segment technique for new hybrid module the study shows that a better classification performance can be achieved. Also when using multi colour space as suggested and choosing the suitable colour space can overcome the lighting problem that usually affects the effective rate of skin detector classification.

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