International Journal of Innovative Computing, Information and Control
Volume **8**, Number **12**, December **2012**

ICIC International ©2012 ISSN 1349-4198
pp. 8115–8131

HUMAN SKIN COLOR DETECTION: A REVIEW ON NEURAL NETWORK PERSPECTIVE

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Received September 2011; revised March 2012

Abstract. *Skin color is a robust cue in human skin detection. It has been widely used in various human-related image processing applications that skin detection techniques based on skin color information have gained much attention recently. Although several techniques have been proposed, skin color detection still remains as a challenge mainly due to problems such as illumination conditions, camera characteristics, and ethnicity. Among the various techniques used for skin color detection, neural networks have been proven to be one of the most effective tools. In this paper, an up-to-date review of the available neural network-based human skin color detection algorithms is presented.*

Keywords: Skin color detection, Color space, Neural networks

1. Introduction.

Image segmentation is a process of dividing an image into non-overlapping regions consisting of groups of connected homogeneous pixels. Typical parameters that define the homogeneity of a region in a segmentation process are color, depth of layers, gray levels, texture, etc. A good example of image segmentation is skin detection which is achieved by classifying the image pixels into two groups: skin pixels and non-skin pixels using skin color information. The process of utilizing skin color information as a cue in skin detection techniques has gained much attention because skin color provides computationally effective yet, robust information against rotations, scaling and partial occlusions [1]. Skin color detection is primarily an important process in applications such as face detection [2-4], gesture analysis [5], Internet pornographic image filtering [6], surveillance systems [7]. Figure 1 illustrates a general example of exploiting skin color for face detection. In this case, face detection is achieved by extracting the common face features, and utilizing skin color detection as primary steps to minimize the area from which the face features are extracted. As a result, the necessary time for accomplishing face detection can be minimized significantly.

In order to make use of skin color information, many researches have been directed to understanding its characteristics. Research analysis has shown that human skin color has a restricted range of hues and is not deeply saturated, as the appearance of skin is formed by a combination of blood (red) and melanin (brown, yellow) [9]. Therefore, human skin color does not fall randomly in a given color space, but rather clustered within a small area in the color space. Several studies have shown that the major difference in skin color among different people lies largely in their intensity rather than in their chrominance [10]. Thus, if an image is first converted into a color space, which provides a separation of luminance channel and two chrominance components like the normalized (r, g, b) color space, then skin-like regions can easily be detected [11]. Numerous algorithms have been proposed for skin detection during the past few years. However, skin color detection can

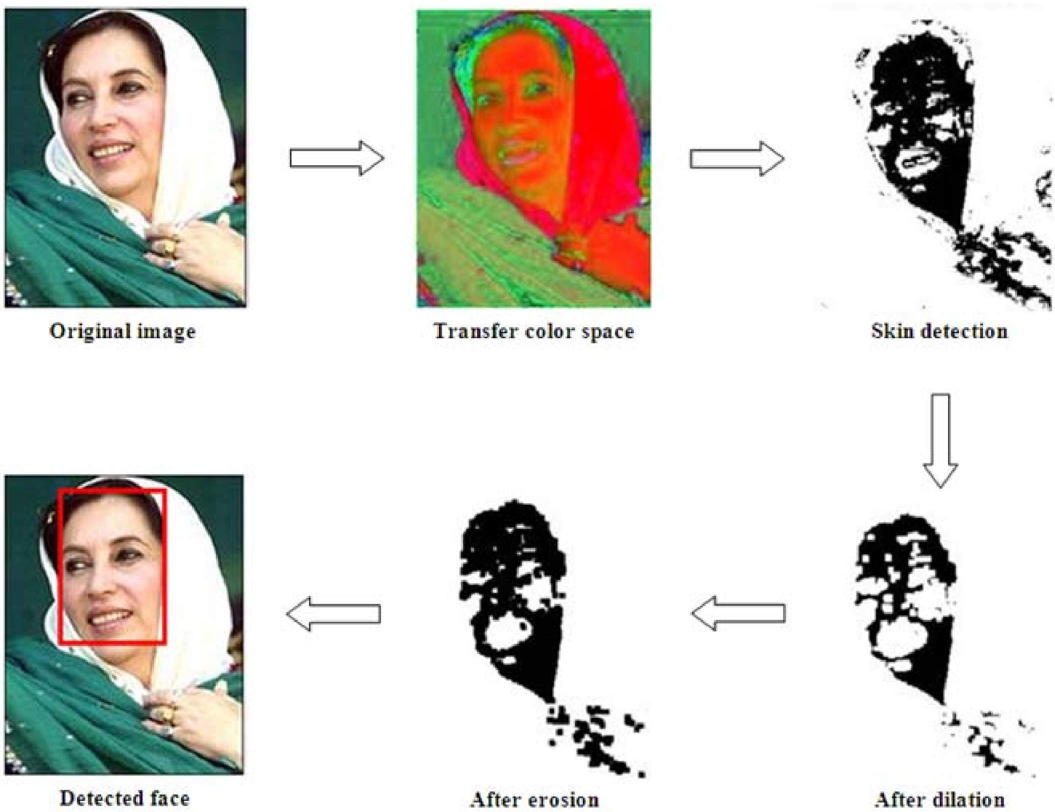

FIGURE 1. Example of face detection process utilizing skin color detection [8]

be a very challenging task as the skin color in an image is sensitive to various factors such as illumination conditions, camera characteristics and ethnicity [1]. The existing algorithms can be classified into four categories: explicit skin cluster classifier, parametric classifiers, nonparametric classifiers, and adaptive/dynamic classifiers [1,12,13], where the first three are static-based. The explicit skin cluster classifiers, which are the simplest and often applied methods, use threshold method to classify skin and non-skin pixels [14-17]. They define the boundaries of the skin cluster in certain color spaces using a set of fixed skin thresholds. Although such techniques are straightforward and can be used without any prior training phase, they may lack flexibility when employed under different imaging conditions. This may result in inaccurate detection of pixels [13].

Parametric classifiers can be based on a single Gaussian model [18,19], a mixture of Gaussian (MoG) models [20,21], multiple Gaussian clusters [22], or an elliptic boundary model [23]. However, the classification speed of these classifiers is generally very slow because they need to process every pixel individually. They are also very slow when integrated in an artificial neural network training phase [24]. Another drawback of these techniques is the inaccuracy of detection because they depend on the approximated parameters instead of the actual distribution of skin colors [13]. Moreover, their performance depends significantly on the color space used [12].

The nonparametric classifiers estimate skin color distribution from a histogram of training images without deriving an explicit model of the skin color [25-28]. This technique estimates a statistical model of the distribution of skin color by training the classifier with a set of training data. There are two advantages of this category which are the quickness in training and usage, and its independence of the shape of skin distribution (which is not true for the above mentioned categories) [12]. However, such statistical models are not accurate enough due to the need for an infinite number of training data. Hence, these models may have low performance and some limitations that make them applicable only in a limited range of imaging conditions [1,13].

In literature, adaptive and dynamic classifiers have been proposed to overcome the generality of skin models which can be found in static classifiers mentioned earlier. Dynamic classifiers are mainly based on neural networks and/or genetic algorithms [11,29-35]. This group of classifiers aims at optimizing the overall performance, i.e., higher skin detection rates with low false positives, using a dynamic model which should be able to update itself to match the changing conditions (camera characteristics, illumination, and background color) [12,31].

The goal of this paper is to present various algorithms that use artificial neural network systems for skin color detection, describe their methods and evaluate their characteristics and performance. The paper is arranged as follows. Section 2 introduces the different color spaces used for skin detection. Section 3 covers the existing neural network-based algorithms. Then discussion and conclusions are presented in Sections 4 and 5, respectively.

2. Color Spaces.

Color is a significant source of information for a wide range of research areas such as segmentation, image analysis classification, and object recognition. However, some of the original colors in an image might not be appropriate for analysis, and the colors must be adjusted. Adjusting the colors can be done by transferring colors from space to another, while preserving the image's original details and natural look at the same time. Skin detection process involves two major steps which are (1) to represent the image using a proper color space, (2) to model the skin and non-skin pixels using inference methodology to obtain information from available skin samples and to extrapolate the results to given samples [1,36]. Selecting proper color space is crucial for skin color detection. In relation to this, how is optimal color space for skin-classification estimated?

Several comparisons between different color spaces used for skin detection can be found in the literature [36-45], but one important question still remains unanswered is, "what is the best color space for skin detection?" Many authors do not provide strict justification of their color space choice [12]. Some of them cannot explain the contradicting results between their experiments or experiments reported by others [44]. Moreover, some authors think that selecting a specific color space is more related to personal taste rather than experimental evidences [36,46]. However, the most common result of the researches obtain on the effect of color space on skin detection is that different modeling methods react very differently on the color space change [1,12]. Nevertheless, this paper will not discuss the topic in further detail as it is beyond its scope, and will only briefly present the common color spaces used.

2.1. RGB.

RGB correspond to three primary colors: red, green and blue. It is one of the most widely used color spaces for processing and storing digital image data. In order to reduce the dependence on lighting, the RGB values are normalized by a simple normalization procedure as follows:

$$\begin{aligned} r &= \frac{R}{R+G+B} \\ g &= \frac{G}{R+G+B} \\ b &= \frac{B}{R+G+B} \end{aligned} \tag{1}$$

The sum of the normalized components of RGB is unity ($r + g + b = 1$), and it means that r and g values are enough to represent this color space as the third component, b, can be calculated directly based on r and g. The RGB and its normalized version are among the popular color spaces used for skin detection and have been commonly used [3,11,29,32,47-49].

2.2. **$\mathbf{YC_bC_r}$.** The YC_bC_r color space is commonly used by European television studios. It is supposed to reduce the redundancy present in RGB color channels and represent the color with statistically independent components [30]. The YC_bC_r represents the color by luminance, Y, and chrominance as the difference between two colors, C_r and C_b using the following set of equations [12]:

$$\begin{aligned} Y &= 0.299R + 0.587G + 0.114B \\ C_b &= B - Y \\ C_r &= R - Y \end{aligned} \tag{2}$$

Compared with the RGB color space, YC_bC_r has an explicit separation of luminance and chrominance components, which makes it very attractive for skin detection [3,19,22,33-35,37,50].

2.3. **YIQ.** The YIQ color space is similar to YC_bC_r color space as they belong to the same category of orthogonal color spaces [1]. The luminance is represented by Y, and the chrominance is represented by I and Q. The I value describes the change from orange to cyan, while Q describes the change from purple to yellow-green. Transforming RGB color space into YIQ color space allows separating the luminance information from hue. This effective separation of information makes the YIQ color space useful for skin color detection [31,47,51]. The following set of equations is used to transform RGB into YIQ [26]:

$$\begin{aligned} Y &= 0.299R + 0.587G + 0.114B \\ I &= 0.596R - 0.275G - 0.321B \\ Q &= 0.212R - 0.523G + 0.311B \end{aligned} \tag{3}$$

3. **Skin Color Detection Using Artificial Neural Networks (ANNs).** Artificial Neural Networks are interconnections of artificial neurons that greatly emulate the biological neurons of the human brain. They are presented on a computer by a labeled acyclic directed graph with a clearly defined set of inputs and outputs. There are many different architectures of ANN in existence. Each one has its own advantages and disadvantages. The aim of an ANN is to be able to learn unknown complex input-output relationships based on training data, and then be able to make predictions for unseen data [52].

The use of ANNs in image processing has a long history of flexibility. ANN are parameterized non-linear models used for empirical regression and classification modeling, which makes them able to discover more general relationships in data than the traditional statistical models [11]. More precisely, the aim of using ANNs in skin color detection is to improve the separability between skin pixels and non-skin pixels [32]. However, to the best of our knowledge, only few skin detection algorithms are based on ANNs. The following sub-sections discuss those algorithms.

3.1. **Back propagation ANN (BP ANN).** Many researches have used BP ANN for skin detection. Among the good ones are described in the following subsections.

3.1.1. *BP ANN with genetic-based optimization.* Chen et al. (2002) proposed a skin detection algorithm using BP ANN, an intelligent system, which has been widely used in artificial intelligence [11]. In their work, they used the normalized RGB color space as a color model in order to reduce the sensitivity to illumination changes while staying very close to the original RGB color space. After converting each pixel into the normalized RGB color space, the image is transformed into a vector of two-dimension (r, g) color feature. This vector becomes the input to a BP ANN, while the output has only one unit indicating that the input pixel belongs to skin (output = 1) or non-skin (output = 0) areas. The neural network used composed of 2 input neurons (for r and g), 4 hidden neurons arranged in 2 layers, and 1 output neuron as shown in Figure 2.

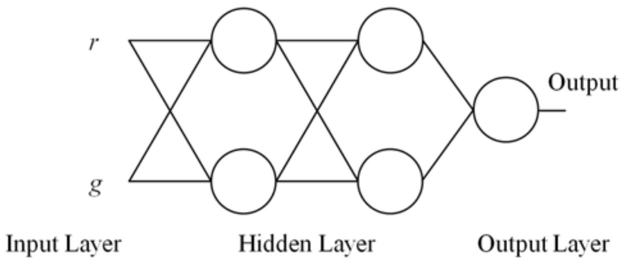

FIGURE 2. Neural network architecture used by Chen et al. (2002)

Each neuron contains the weighted sum of its inputs filtered by a logistic sigmoidal transfer function given by

$$f(x) = \frac{1}{1 + e^{\sigma x}} \tag{4}$$

where σ determines the steepness of the sigmoid curve, x is the sum of the inputs to the neuron, and $f(x)$ is the output.

The larger σ is, the ANN will converge more quickly, but also easy to get unstable and does not converge. That is due to the nature of BP neural network which is very sensitive to initialization conditions. On the other hand, if σ is too small, the convergence of the ANN will be time consuming but an optimal convergence is guaranteed. In order to improve the ANN, Chen et al. have used genetic algorithm (GA) to optimize the selection of σ [11].

After training the optimized BP ANN, the algorithm starts with converting a pixel into normalized RGB color space. If r, g and b satisfy a simple criteria $(r > g)$ or $(r > b)$, then the pixel is fed into the BP ANN for skin and non-skin classification. Otherwise, the process is repeated with the next pixel until all pixels are processed. According to the corresponding output, each pixel is classified into skin-like pixel or non-skin-like pixel.

The researchers applied their proposed algorithm on a set of test images composed of one hundred color images including one face color images from Biometric Identification dataset (BIOID) in [53]. The authors claimed that their algorithm showed better performance compared to some traditional methods especially in difficult conditions. However, they did not show the comparison in terms of detection accuracy, false positive rate, and true positive rate. Some of their results are shown in Figure 3 and Figure 4.

3.1.2. *BP ANN for skin color interpolation.* Seow et al. (2003) proposed an ANN-based skin color model for face detection [29] aiming at eliminating limitations pertaining to skin color variations among people. They adopted a three-layered BP ANN to a model of skin color. The primary color components of each plane of color cube (r, g and b) are fed to the ANN system, which was trained using the BP algorithm with skin samples, to

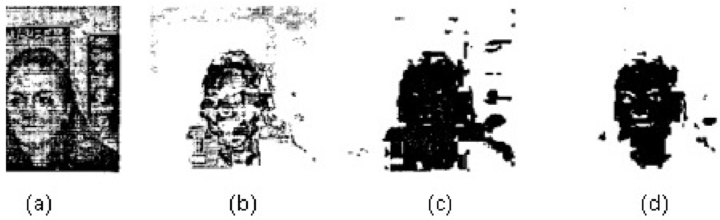

FIGURE 3. Images of (a) original image and classification images using, (b) Gaussian model, (c) BP ANN, and (d) BP ANN with genetic-based optimization

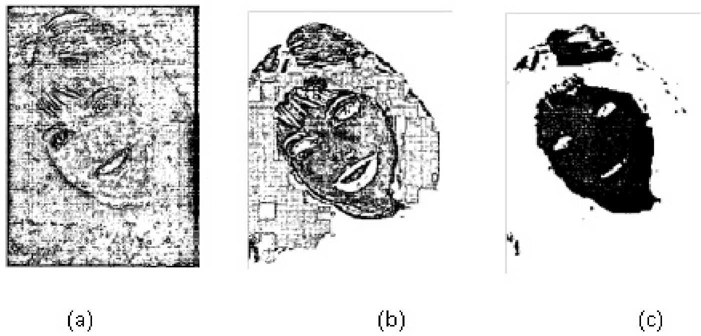

FIGURE 4. Skin detection is performed for (a) original image using, (b) Gauss algorithm, and (c) BP ANN with genetic-based optimization

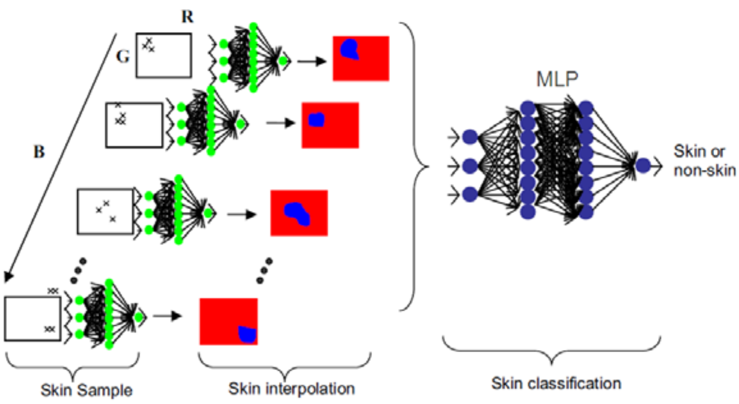

FIGURE 5. Skin detection algorithm stages proposed by Seow et al. (2003)

extract the skin regions from the image. Subsequently, the process of face detection is aided by the extracted skin areas.

The ANN training process involves three stages: skin color collection, skin color interpolation, and skin color classification as shown in Figure 5. Skin color samples from various races around the world were collected from the Internet in the form of 10×10 pixels per sample, and a total of 410 samples were collected. Since the collected samples do not represent the skin color population, the authors interpolated for skin color which is not included in the samples using the skin color of the collected samples. They used a Multi-Layer Perceptron (MLP) ANN trained using a BP algorithm for interpolation.

In order to represent all the possible color combinations, a $256 \times 256 \times 256$ color cube was generated. The MLP learnt to differentiate skin and non-skin samples. The primary color components of each of the 256 slices of the cube were fed to the MLP to extract the skin regions. As the algorithm was proposed originally for face detection, the authors did not illustrate the results of the skin color detection based on the original face detection. Hence, no analysis can be made on the results.

3.1.3. *Adaptive skin color model.* Yang et al. (2010) utilized neural network along with an adaptive skin color model to establish a self-adaptive skin color model [33]. They used luminance information in Y component of the YC_bC_r color space to overcome the influence of illumination and subsequently increase the detection accuracy. They employed BP ANN along with a Gaussian model classifier to design a self-adaptive skin color model as shown in Figure 6.

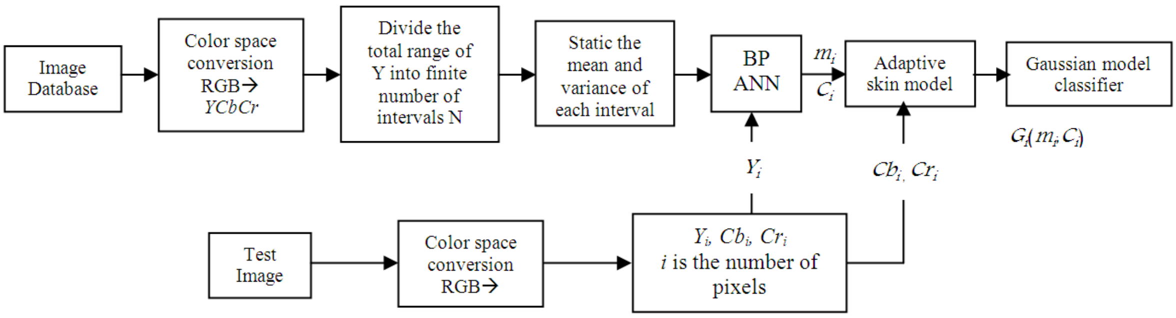

FIGURE 6. The basic architecture of the algorithm proposed by Yang et al. (2010)

In their algorithm, the image is first transferred from RGB color space to YC_bC_r color space. Then, the Y components are ordered in ascending order, and divided into finite number of intervals. After that, the pixels whose luminance values belong to the same intensity interval are collected. The covariance and the mean value of C_b and C_r are calculated with respect to luminance. The mean of each interval Y, the covariance and mean of C_b and C_r were used to train the three layer neural network. The output of the ANN was fed to a Gaussian model classifier.

The algorithm was tested using the database in [48] containing 3792 skin color images and 8964 non-skin color images. They compared the experimental results with the results obtained by [54-56]. With a properly selected threshold, the results showed that the classification performance has improved significantly in terms of detection rate (DR), false negative rate (FNR), and false positive rate (FPR) under wide light conditions and complex image background.

3.1.4. *BP Neural network with heuristic rule.* Zaidan et al. (2010) proposed a hybrid module for skin detector using BP ANN and heuristic rule based on YC_bC_r [34]. The goal of the algorithm is to increase the classification reliability of skin detection with different lighting conditions. In their algorithm, the image is transferred from RGB to YC_bC_r color space, and then the YC_bC_r are used to train a three layer neural network as shown in Figure 7.

The image pixels are classified into skin and non-skin pixels depending on the output of the neural network and the heuristic rules, which classify a pixel as skin pixel if the flowing logic operation below is 1:

$$(132 < C_r < 173) \wedge (76 < C_b < 126)$$

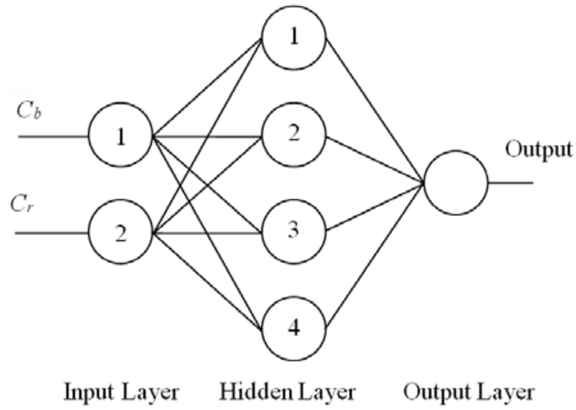

Figure 7. Neural network architecture adopted by Zaidan et al. (2010)

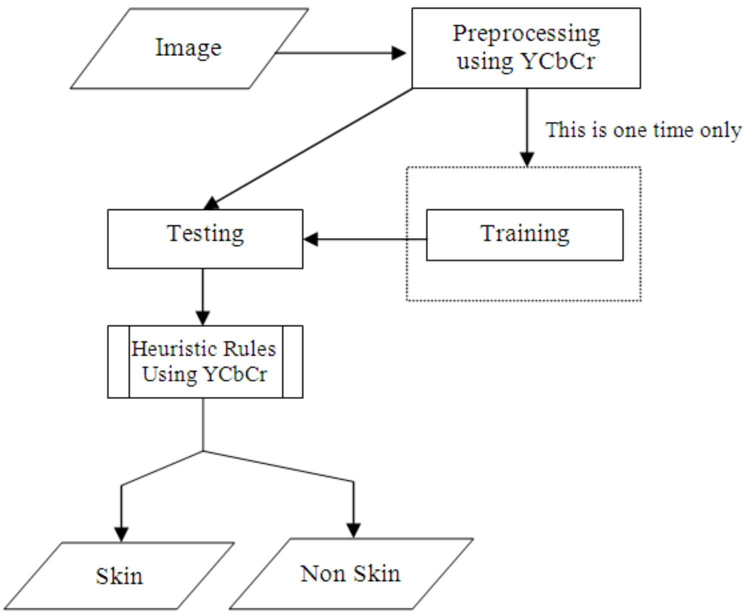

Figure 8. Skin detection using BP NN with heuristic rule

The BP ANN was trained using a dataset of 6000 pixels of various skin tones and 6000 pixels from non-skin pixels, collected from 200 human skin web images. The main structure of the proposed method is as Figure 8.

The researchers compared their experimental results with the results obtained by [57]. With a properly selected threshold, the proposed method achieved a classification accuracy rate of 88.5%. This is higher by 38.5% to the explicit rule method and by 13.5% to BPNN.

3.2. **Image chromatic adaptation.** In order to remove the effect of illumination and to obtain color data that precisely reflects the physical contents of an image, Kakumanu et al. (2004) adopted image chromatic adaptation [30]. They used neural network for detecting adapting human skin color.

Their algorithm consists of two stages: image chromatic adaptation and skin detection. The first stage is to color-correct the image in long, medium and short wavelengths (LMS) cone space for skin color adaptation. The illuminant estimate is predicted by an ANN trained on image data by a BP algorithm. The second stage is to classify the skin pixels and non-skin pixels of the color corrected image using a simple threshold technique in

RGB color space. Image chromatic adaptation transforms an image under an unknown illumination to the corresponding colors under a known canonical illumination. This consists of estimating the illuminant colors and then to correct the image pixel-wise based on estimated illuminant.

The authors used four different algorithms for estimating the illuminant; gray world, white patch, ANN on white patch, ANN on skin patch for comparison. In the neural network on white patch, the expected output estimate of the illuminant is the color of the reference white patch. This model is trained to estimate the color of the white patch in the image. In the second model (neural network on skin patch), the expected output estimate of the illuminant is the color of the facial skin in the image.

The algorithm used an ANN with two hidden layers. The input layer consists of 1600 neurons, the first hidden layer has 48 neurons, the second hidden layer has 8 neurons and the output layer has 2 neurons. The normalized input RGB space is first transformed into rg color space and then, divided into 40×40 (1600) discrete bins, with each (r, g) histogram bin corresponding to one of the input neurons. The ANN inputs ((r, g) histogram bins) that are a non-zero were marked active and only those active inputs were used during training. The input to the neuron is represented by 1 or 0 indicating that the chromaticity corresponding to the (r, g) histogram bin is either present or not present in the image. The output of the ANN is the expected (r, g) chromaticity of the illuminant in the image. The network was trained using BP algorithm with learning and momentum rates of 10 and 1 respectively. The error function was the Euclidean distance in (r, g) chromaticity space between the ANN's estimate and the provided expected estimate of the image illuminant.

The chromatic adaptation using the four algorithms were tested using an experimental data set consisting of 326 images with various illumination conditions. The performance was expressed in terms the average color value, average color distance, and average pair-wise distance. The results showed that ANN trained on skin patch has better performance over the rest of the methods. The skin detection step is achieved based on the variance value at each pixel of the color adapted image and a simple thresholding technique. Some of the results are shown in Figure 9.

3.3. **Skin color detection using pulse coupled neural network.** Duan et al. (2009) used a synchronous pulse firing mechanism of pulse coupled NN (PCNN) to simulate the skin color detection mechanism of human eyes [31]. The idea behind using PCNN method is its ability to find the relationship between neighboring pixels. This will ease simulating

FIGURE 9. Skin detection using BP NN with heuristic rule

human vision mechanism which can segment similar color into an area block whether the conditions of illumination are.

PCNN differs from an ANN is that it composed of rate-coding neuron, since PCNN neuron can code information toward time axis, and this is the reason behind using PCNN in image segmentation and fusion. Usually, when PCNN is used to segment an image, a single layer two-dimensional network is designed, and the neurons and the pixels are in one-to-one correspondence.

The proposed algorithm starts with converting the input image from RGB color space to YIQ color space, and the I channel image is obtained. After that, the PCNN is used to segment the image. In order to decide the threshold value in PCNN, the histogram of I channel is used to identify the range of I value. The final step is to binary the results of the PCNN multi-value segment. The framework of human skin region detection based on PCNN is as shown in Figure 10.

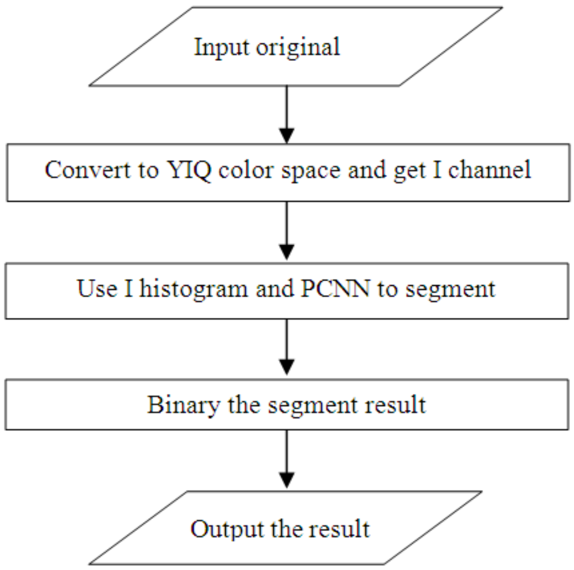

Figure 10. Framework of human skin region detection based on PCNN proposed by Duan et al. (2009)

The authors tested their algorithm on different test images of people from different areas under different illumination conditions. They compared the results with those obtained using algorithms proposed by Tao et al. [58]. The experimental results showed that their algorithm has better performance even with complex illumination conditions. However, the algorithm failed to distinguish brown hair from skin regions. Some of the results are shown in Figure 11.

3.4. **Skin color detection using neural network.** Bhoyar et al. (2010) proposed a novel algorithm based on two output layer neurons: one each for skin and non-skin class [32]. The aim of using a single neuron network classifier is to improve the separability between these two classes. The architecture of the proposed three-layer feed forward neural network used for skin color classification is shown in Figure 12. It has three input neurons, five hidden neurons, and two output neurons. The first neuron in the output layer represents skin class, and the second neuron represents non-skin class.

The proposed method involved training the neural network with Error Back Propagation Training Algorithm (EBPTA) in RGB color space. A threshold θ was used to overcome the overlapping region containing skin and non-skin pixels as follows:

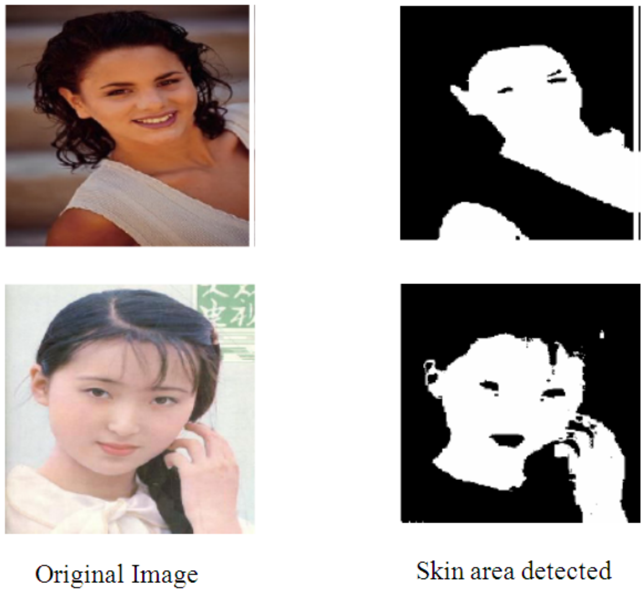

Figure 11. Binary results based on PCNN for original images (left column) and their corresponding skin detection images (right column)

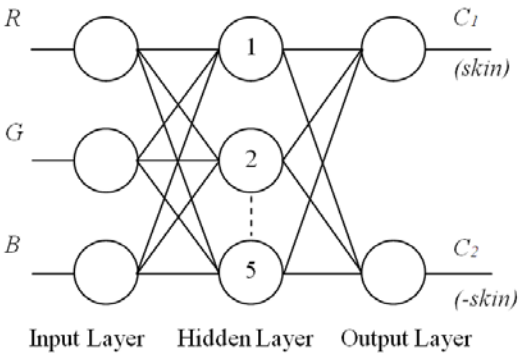

Figure 12. Neural network architecture adopted by Bhoyar et al. (2010)

Lemma 3.1. *If C_1-$C_2 \geq \theta$, Skin Pixels Otherwise, Non-skin pixels where C_1 and C_2 represent skin and non-skin pixel classes respectively.*

The ANN was trained using a data set of 1000 samples each of skin and non-skin pixels. The samples were selected from a collection of 500 web images comprising of different ethnic groups. The experiments showed acceptable results when θ (auto detection) in terms of False Positive Rate (FPR) and Detection Rate (DR). When the value of θ is optimum, the FPR is reduced to 7%. Nevertheless, the relation between the image pixels and such optimum value of θ is missing. Automatic computation of optimum threshold is desired in practical skin detection applications.

3.5. **Combining neural networks for skin detection.** Doukim et al. (2011) proposed several strategies for combining MLP ANNs for skin detection using chrominance components from the YC_bC_r color space [35]. They used the C-HN-O topology neural network, where C indicates the input neuron which is the chrominance component, HN is the number of neurons in the hidden layer and O is the output neuron. In order to determine the number of neurons in the hidden layer, a modified network growing technique was applied.

In the first strategy, Doukim et al. (2011) used a single neuron in the input layer and different numbers of neurons in the hidden layer (91-128). The chrominance components which were used as input are C_b, C_r, C_b/C_r, C_b-C_r, C_r-C_b. In the second strategy, they combined different chromatic components and hence used 2 and 3 neurons in the input layer forming different ANN structures; 2-17-1, 2-114-1, 2-123-1 and 3-51. The chromatic components used in this strategy are (C_b/C_r & C_b-C_r), (C_b-C_r & C_r), (C_b/C_r & C_r) and (C_b-C_r, C_b/C_r & C_r) respectively. In the third strategy, they used separated single neuron input classifiers and combined them using different methods; AND and OR operators, voting rule, and sum of weight rule. In the fourth strategy, also they used separated single neuron input classifiers but combined them using a 3-126-1 neural network.

The database used in this work is the Compaq database [48], which consists of 13,640 images with its corresponding masked images. These images contain skin pixels belonging to persons of different origins, with unconstrained illumination and background conditions. The training sample consists of 420,000 image pixels and the test data consists of 100 images selected at random from the Compaq database. The experimental results indicated that the best performance in terms of correct detection is given by the combination of three classifiers using the "Sum of Weights" rule, which gives 3.98% more correct detection compared to the Bayes' rule classifier in [48].

4. **Discussion.** The aim of using ANN for skin detection is to overcome the drawbacks of static techniques. ANNs have been adopted for enhancing the separability between skin and non-skin pixels benefitting from their flexibility and ability to adapt to the various illumination conditions and background characteristics as in algorithms 3.1.1, 3.1.2, 3.3, 3.4, 3.5. They can be combined with other static methods in order to maximize the performance as in algorithms 3.1.3 and 3.1.4, or can be used to correct the chrominance of the image before applying a simple classification technique as in algorithm 3.2.

The reviewed ANN algorithms claim high performance in terms of detection accuracy, but there is no comparison with the work of others. Some researchers compared their work with some old fashion techniques. Moreover, the researchers used different color spaces and different data sets for evaluation. This makes it very difficult to obtain a fair comparison. A comparison between the algorithms based on their features and the results obtained by the authors is presented in Table 1.

Analysis on existing methods reveals that the algorithms have three common drawbacks:

1. All the algorithms presented in this paper involve a thresholding technique. However, the value of the threshold is determined through extensive experiments, i.e., trial-and-error, and not through an optimization procedure. Only work by Chen et al. [9] used genetic algorithm to optimize the initial values of ANN used during the training step.
2. The color spaces used in the algorithms were selected based on others' work not based on specific experiments done using ANN on specific images.
3. All the algorithms ignored the processing time which is important in real-time detection process.

Besides the drawbacks, there are some other challenges faced by skin color detection using ANN which constitute obstacles in development of much reliable and robust detection algorithms. The challenges can be summarized as follows:

1. The negative effect of illumination conditions on detection accuracy.
2. The negative effect of near skin color backgrounds.

TABLE 1. A comparison between the reviewed algorithms

Research Aim	Color Space	Network Topology	Training	Number of thresholds	Other techniques involved	Performance
BP ANN with Genetic-Based Optimization [11]	Normalized RGB (only r and g are used)	2 input neurons, 4 neurons in 2 hidden layers, and 1 neuron in the output layer	Back propagation	1 threshold (with genetic algorithm-based optimization)	–	Accurate skin color detection under different illumination conditions based using BIOID dataset
BP ANN for Skin Color Interpolation [29]	RGB	Three-layer network	Back propagation	–	Skin color interpolation for skin color which is not included in the training dataset	Only face detection results were presented
Adaptive Skin Color Model [33]	YC_bC_r	Three-layer network with 50 neurons in the hidden layer	Back propagation	2 thresholds (set through experiment)	Gaussian model classifier	High detection rate (96%) with FPR of (15%) using the Compaq dataset [48]
BP Neural Network with Heuristic Rule [34]	YC_bC_r (only C_b and C_r are used)	2 input neurons, 4 neurons in 2 hidden layers, and 1 neuron in the output layer	Back propagation	3 thresholds	Threshold-based heuristic rules	Achieved an accuracy rate of 88.5% using dataset collected from the Internet
Image chromatic Adaptation [30]	Normalized RGB (only r and g are used)	1600 input neurons, 48 neurons in the first hidden layer, 8 neurons in the second hidden layer and 2 neuron in the output layer	Back propagation	2 thresholds	Simple thresholding technique to detect skin pixels after ANN-based color correction	Better than Gary World and White Patch techniques using dataset collected from the Internet
Skin Color Detection Using Pulse Coupled Neural Network [31]	YIQ (Only I is used)	Single layer two-dimensional network, and the neurons and pixels are in one to one correspondence	Synchronous pulse firing mechanism	1 threshold	Binarization the result of the neural network	Most of skin areas can be detected in spite of high illumination, shadow, or people races
Skin Color Detection Using Neural Network [32]	RGB	3 input neurons, 5 neurons in 1 hidden layer, and 2 neurons in the output layer	Error back propagation (EBPTA)	1 threshold (set through experiment)	Simple thresholding technique to detect skin pixels	High detection rate (up to 99.49%) with FPR of (7%) using dataset collected from the Internet
Combinations of Neural Networks For Skin Detection [35]	YC_bC_r	Several multi-layer MLP with different number of neurons and hidden layers	Back propagation	1, 2 and 3 thresholds	Combining two or more ANN	classifiers Detection rate of 83.8% with FPR of 1.12% using the Compaq dataset

It was mentioned earlier that skin detection is the first step in many applications, and generally is not used aside. Those applications, such as face detection and pornographic blocking, are real-time applications, which means that time is such a critical factor for the overall performance. Compared with an explicit classifier, an ANN-based classifier may need much longer time to achieve the classification task, which makes adopting ANNs in skin color classifiers very challenging. Researchers prefer to work on other static methods which may be less time consuming, and this is the reason behind the lack of ANN-based skin detection algorithm. However, it is believed that a reliable ANN-based skin detection algorithm should fulfill the following requirements:

1. Computation complexity: it should be simple and fast in order to become useful for real time applications.
2. Automation: all necessary thresholds and initial values should be set automatically and dynamically.
3. Adaptability: in order to overcome the illumination conditions, this can be achieved by adopting illumination enhancement pre-detection step.
4. Robustness: in order to overcome near skin color backgrounds, this can be achieved by combining color and texture in the detection process. Another option is to utilize color correction technique prior to skin detection.

Despite the rapidly increasing works done so far in the field of skin detection, ANN-based skin detection approaches are still lacking and in need for more effective as well as fast techniques. Any proposed techniques should satisfy the accuracy and time criteria required by any real-time application. A fair benchmark should be established in order to evaluate the proposed algorithms based on color space, accuracy of detection, and computation time of detection.

5. **Conclusion.** Skin color detection is generally a preprocessing step in many applications such as face detection and gesture tracking, and many algorithms have been proposed for this task. Nevertheless, skin detection is still a challenging task as the proposed techniques could not overcome the problems of illumination and background which produces high FPRs. In order to enhance the detection accuracy, ANNs have been adopted for skin detection. This paper has presented several ANN-based algorithms, which have mostly improved the detection performance. However, a fair benchmark is still required to explore their advantages and disadvantages. Computation time and complexity are very important aspects in any real-time application in which skin detection may be involved, but all reviewed papers have not discussed these aspects. Moreover, the optimum color space for ANN-based skin detection is still unrevealed. More serious trials are expected to come up with more sophisticated ANN-based techniques which fit into real-time application requirements in terms of accuracy and speed of computation as well.

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