TechHub Journal Vol. 2, No. 1 pp.63-70 (2022)
ISSN: 2810-2800
www.techhubresearch.com

Effects of the Database on the Performance of the Human Skin Detection Techniques

Hani K. Al-Mohair
Computer and Information Technology
Dammam Community College
King Fahd University of Petroleum & Minerals
Dhahran, 31261, Kingdom of Saudi Arabia.
hanik@kfupm.edu.sa

***Abstract*— In many human-related image processing applications, skin color is used as a cue to detect human skin. An Image database is assumed an important key in increasing the separability between the skin and non-skin classes. This paper examines if the image database brings this benefit by evaluating two famous image databases (Compaq and ECU) used in skin detection. An experiment using Multi-Layer Perceptron Neural Network (MLP), which is a universal classifier, is used to compare the overall performance of the two databases. Surprising results indicate that the image database is a very important element in increasing the classification between the skin and non-skin pixels.**

***Index Terms*—Skin color detection, color space, Neural Networks, Image Database**

I. INTRODUCTION

The process of segmenting images involves dividing them into non-overlapping regions consisting of connected homogeneous pixels. The parameters that define the homogeneity of a region include color, depth of layers, gray levels, and texture [1]. Skin detection is a good example of image segmentation. This is achieved by dividing the pixels in an image into two categories; skin pixels and non-skin pixels based on their color information. Skin color information is being used as a cue in skin detection techniques due to the fact that skin color is computationally efficient and yet robust against rotations, scaling, and partial occlusions. [2]. The determination of skin color is primarily employed in applications such as face detection [3-5], gesture analysis [6], Internet pornographic image filtering [7] and surveillance systems [8-12]. The first large skin database which is the Compaq database is created and used the bayesian classifier with the histogram technique for skin detection [20, 24]. Three different techniques, which are: thresholding the red/green ratio, color space mapping with 1D indicator, and RGB skin probability map are compared on the Compaq database [20]. Creating a new color space and comparing the results with the performance of RGB and LAB color spaces specifically in skin detection application is tested with the Compaq database [23]. One of the largest databases that support many tasks involved in color-based human face detection is ECU face detection database that was constructed at Edith Cowan University [22]. Although most of the researches are involved in the skin color detection, there is no conclusion about the effect of an image database in skin color detection; many authors do not provide strict justification of choosing the database? In this paper, a comparison study using the MLP artificial neural network, which is a dynamic classifier, is used to optimize the overall effect of two famous image databases used in skin color classification. The main goal of this paper is to evaluate two famous image databases to determine the more accurate database used in skin classification using YIQ color space. Multi-Layer Perceptron network system (MLP) is used for skin color classification, moreover to describe and evaluate the effect of image databases tested. The paper is arranged as follows. Section 2 introduces the YIQ color space used in this comparison. Section 3 covers the preparing of datasets used in this work. Section 4 explains the methodology and results. Section 5 discusses the results and Section 6 concludes findings of the work.

II. YIQ Color Space

Despite this fact, some colors in an image may notbe suitable for analysis, and the colors must be adjusted for analysis. Color plays an important role in many scientific research areas such as segmentation, image analysis, classification, and object recognition. YIQ color space is used this paper for comparison purposes .

The YIQ color space is similar to YCbCr and has the advantage of preserving the image's original details and natural appearance [15].The luminance and chrominance are represented by I and Q, respectively, as they belong to the same category of orthogonal color spaces [2]. 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 [14, 16, 17]. The following set of equations is used to transform RGB into YIQ [18]:

$$Y = 0.299R + 0.587G + 0.114B \quad (1)$$
$$I = 0.596R - 0.275G - 0.321B \quad (2)$$
$$Q = 0.212R - 0.523G + 0.311B \quad (3)$$

III. PREPARING THE DATASETS

For the preparation of the dataset, 150 images of skin pixels and 150 images of non-skin pixels were collected. The 150 images that contain the human skin are downloaded from the "Humanae Project" webpage [19]. As shown in Figure 1, for each image in the skin pixels group, 5 blocks of 40x40 pixels were manually selected. Blocks were chosen from the forehead, cheeks, shoulders, or chest. In this manner, any subtle differences in skin color that might exist between different body parts of a single person are taken into account. As a result, 8000 skin pixels were collected from each image (i.e., 40*40*5). Hence, the total number of skin pixels that were collected from 150 images is 1.2 million pixels.

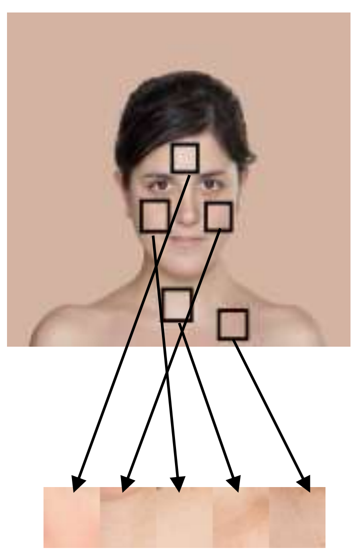

Figure 1: Blocks Extracted for Training from Humanae Dataset

From the non-skin group of 150 images downloaded from the internet, 1.2 million additional non-skin pixels were collected. Which contains no human skin. In section 2, the RGB color space was converted to the YIQ color space, using the equations mentioned there.. Consequently, a dataset was obtained and prepared to be used to train a neural network.

IV. METHODOLOGY AND RESULTS

A. Training the Artificial Neural Network (ANN)

The 2.4 million training data pixels are divided into three subsets; Training 70%, validation 15%, and testing 15%. ANN based on Multi-Layer Perceptron (MLP) is utilized in this study. MLPs are composed of three or more layers of units: an input layer, at least one intermediate hidden layer, and an output layer. A feed-forward connection is typically used, with input units fully connected to units in the hidden layer and hidden units fully connected to units in the output layer. Through the intermediate input-to-hidden and hidden-to-output weights, an input pattern is propagated forward to the output units when a network cycles. Weights are data stored in the neurons that are related to the I/O mapping [13]. The architecture of the MLP that was used is shown in Figure 2.

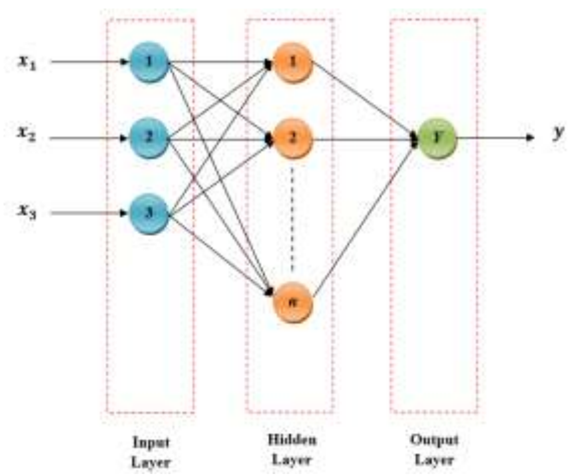

Figure 2: MLP Neural Network Architecture

AC : Accuracy
TP : True positive
TN : True negative
P : Precision

		Truth Data			
		Skin	**non-Skin**	**Classification overall**	**Producer Accuracy (Precision)**
Classifier Data	**skin**	a	b	$a + b$	*Precision* $P = \frac{a}{a+b}$
	non-Skin	c	d	$c + d$	$\frac{d}{c+d}$
	Truth overall	$a + c$	$b + d$	$a + b + c + d$	
	User Accuracy (Recall)	True Positive $TP = \frac{a}{a+c}$	True Negative $TN = \frac{d}{b+d}$		
	Overall Accuracy	$AC = \frac{a+d}{a+b+c+d}$			

Figure 3: Confusion Matrix

In this study, the MLP was constructed with varied numbers of neurons in the hidden layer using the MATLAB Neural Network Toolbox. The training process for each MLP structure was repeated 20 times for each configuration to identify the network's optimal performance (i.e., global minimum error). In terms of minimum mean square error (MSE).

The outcomes of the training phase are shown in Table 1 for the various color spaces used.

TABLE 1: BEST VALIDATION PERFORMANCE (MSE)

Color Sapce	Number of neurons (in hidden layer)	Best validation performance (MSE)
RGB	8	0.099
norRGB	15	0.118
YCbCr	15	0.098
YDbDr	15	0.099
YIQ	15	0.099
YUV	12	0.100
LAB	15	0.100
HSV	20	0.157

B. Testing the NN

On two different databases, all trained neural networks are tested. The first database is the Compaq image database, which has 100 images with a total resolution of 11,340,800 pixels.) with its corresponding masked images (ground truth). The ECU image database is the second database, which contains 800 images (212,472,234 pixels) chosen at random [22, 25]. The two databases' images feature skin pixels are from people of various ethnicities, with unrestricted lighting and background conditions.

The trained MLPs were evaluated on two datasets, Compaq and ECU, and different thresholds were tested to optimize the outcomes. As illustrated in Figure 3, the confusion matrix was utilized to display the network's actual and expected classifications. The performance of such an MLP is commonly evaluated using the data in the matrix [21]. Figure 3 displays the components of a confusion matrix, whereas Figures 4 and 5 show the YIQ color space confusion matrix utilizing Compaq and ECU datasets, respectively.

YIQ Color Space		**Truth Data**			
		Skin	**non-Skin**	**Classification overall**	**Producer Accuracy (Precision)**
Classifier Data	**skin**	24,114,739	8,608,890	32,723,629	73.69%
	non-Skin	7,998,576	171,750,029	179,748,605	95.55%
	Truth overall	32,113,315	180,358,919	212,472,234	
	User Accuracy (Recall)	75.09%	95.23%		

Overall Accuracy	92.18 %

Figure 4: Confusion matrix for Skin Color Detection using YIQ with Compaq Database

YIQ Color Space		**Truth Data**			
		Skin	**non-Skin**	**Classification overall**	**Producer Accuracy (Precision)**
Classifier Data	**skin**	1,438,614	806,233	2,244,847	64.09%
	non-Skin	416,519	8,679,434	9,095,953	95.42%
	Truth overall	1,855,133	9,485,667	11,340,800	
	User Accuracy (Recall)	77.55%	91.50%		

Overall Accuracy	89.22 %

Figure 5 : Confusion matrix for skin color detection using YIQ with ECU Database

The overall performance of the trained ANN is measured by the overall accuracy (*AC*), which is the proportion of the total number of predictions that were correct.

TechHub Journal Vol. 2, No. 1 pp.63-70 (2022)
ISSN: 2810-2800
www.techhubresearch.com

For comparison purposes, we have used the accuracy (*AC)* to evaluate the performance of the MLP as shown in Tables 2.

TABLE 2: AVERAGE ACCURACY MEASURED BY *AC* WITH COMPAQ AND ECU DATABASES

Color Space	*Database*	*Th* (threshold)	*TP* (%)	*FP* (%)	*Precision* (%)	*AC* (%)
YIQ	Compaq	0.1	77.55	8.50	64.09	89.22
YIQ	ECU	0.12	75.09	4.77	73.69	92.18

From tables 2 it is clear that the ECU database gives the highest accuracy, while Compaq database gives lower accuracy. Two examples of skin detection using the trained MLP are shown in Figures 6 and 7.

Original image | Ground truth | Skin image YIQ *Th = 0.06* *AC = 98.45%*

Figure 6: Skin detection using YIQ color spaces for an image from Compaq dataset

Original image | Ground truth | Skin image YIQ *Th = 0.06* *AC = 98.45%*

Figure 7: Skin detection using YIQ color spaces for an image from ECU dataset

V. DISCUSSION

Artificial Neural Networks (ANNs) have been used to improve the separability of skin and non-skin pixels, owing to their flexibility and capacity to adapt to different lighting situations and background characteristics.. Many color spaces can be used for representing color images. In this paper YIQ color space has been used for comparison, and different numbers of neurons in the hidden layer have been exploited. During the training process, all the color spaces, except HSV, have almost the same performance in terms of MSE as shown in Table 1. When compared, the trained MLPs used for evaluation, we found that the average accuracy using Compaq dataset is 86.83% to 89.22%, which is lower than the accuracy performed using ECU database as the average accuracy ranges from 91.17% to 92.18% as shown in Figure 8.

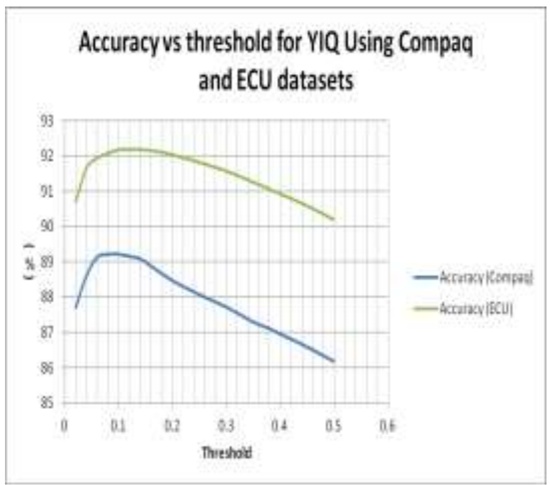

Figure 8: average accuracy using Compaq and ECU database

VI. CONCLUSION

In many computer vision systems, skin detection is a crucial step. The type of image database is assumed to improve the separability of skin and non-skin pixels. In this paper, we compared between two famous image databases (Compaq and ECU) using the MLP neural network, the experimental results showed that the ECU database gives the highest separability between skin and non-skin pixels measured by accuracy *AC* in comparison with Compaq database.

REFERENCES

[1] C. C. Liu and P. C. Chung, Objects extraction algorithm of color image using adaptive forecasting filters created automatically, *International Journal of Innovative Computing, Information and Control*, vol.7, no.10, pp.5771-5787, 2011.

[2] P. Kakumanu, , S. Makrogiannis, and N. Bourbakis, A survey of skin-color modeling and detection methods, *Pattern Recognition*, vol.40, no.3, pp.1106-1122, 2007.

[3] C. Zhipeng, H. Junda and Z. Wenbin, Face detection system based on skin color model, *2nd International Conference on Networking and Digital Society (ICNDS)*, vol.2, pp.664-667, 2010.

[4] J. M. Chaves-Gonzalez, M. A. Vega-Rodriguez, J. A. Gomez-Pulido and J. M. Sanchez-Perez , Detecting skin in face recognition systems: A colour spaces study, *Digital Signal Processing*, vol.20, no.3, pp.806-823, 2010.

[5] Z. Zakaria, N. A. Isa and S. A. Suandi, Combining Skin Colour and Neural Network for Multiface Detection in Static Images, *Symposium on Information & Communication Technology (SPICT09)*, Kuala Lumpur, pp.147-154, 2009.
[6] J. Han, G. Awad and A. Sutherland, Automatic skin segmentation and tracking in sign language recognition, *Computer Vision, IET*, vol.3, no.1, pp.24-35, 2009.
[7] J. S. Lee, Y. M. Kuo and P. C. Chung, Detecting Nakedness in Color Images. *Intelligent Multimedia Analysis for Security Applications*, Springer Berlin , Heidelberg SCI 282, pp. 225-236, 2010.
[8] Z. Zhang, H. Gunes, and M. Piccardi, Head detection for video surveillance based on categorical hair and skin colour models, *16th IEEE International Conference on Image Processing (ICIP)*, pp.1137-1140, 2009.
[9] Yen H. C, Kai T. H. and Shanq J. R, Statistical skin color detection method without color transformation for real-time surveillance systems, *Journal Engineering Applications of Artificial Intelligence*, Volume 25 Issue 7, pp. 1331-1337October, 2012.
[10] Nils Janssen and Neil Robertson, on the detection of low-resolution skin regions in surveillance images, *The Eighth International Workshop on Visual Surveillance* - VS2008, 2008.
[11] Y. M. Mustafah, T. Shan a , A. W. Azman, A. Bigdeli and C. Lovell, Real-Time Face Detection and Tracking for High Resolution Smart Camera System, *Digital Image Computing Techniques and Applications*, 2007.
[12] Megha Sharma,Seema Verma, A S Mandal, Block Based Skin Color Detection for Automated Video Surveillance System, *International Journal of Scientific & Engineering Research*, Volume 3, Issue 11, November-2012
[13] D. Chai, S. L. Phung, and A. Bouzerdoum, A Bayesian skin/non-skin color classifier using non-parametric density estimation, *International Symposium on Circuits and Systems*, ISCAS, vol.2, pp.464-467, 2003.
[14] L. Duan, Z. Lin, J. Miao and Y. Qiao, A Method of Human Skin Region Detection Based on PCNN, *Advances in Neural Networks* , pp.486-493, 2009.
[15] C. C. Liu, A Global Color Transfer Scheme Between Images Based On Multiple Regression Analysis, *International Journal of Innovative Computing, Information and Control*, vol.8, no.1A, pp.167-186, 2012.
[16] J. Brand and J. S. Mason, A comparative assessment of three approaches to pixel-level human skin-detection, *15th International Conference on Pattern Recognition Proceedings*, pp.1056-1059, 2000.
[17] Y. Dai and Y. Nakano, Face-texture model based on SGLD and its application in face detection in a color scene, *Pattern Recognition*, vol.29, no.6, pp.1007-1017, 1996.
[18] S. Yun Q. and Sun, Huifang Image and Video Compression for Multimedia Engineering, CRC Press, 2000
[19] (http://humanae.tumblr.com/
[20] S.L. Phung, A. Bouzerdoum, D. Chai, Skin segmentation using color pixel classification: analysis and comparison, IEEE Trans. Pattern Anal. Mach. Intell. 27 (1) (2005)
[21] http://www2.cs.uregina.ca/~dbd/cs831/notes/confusion_matrix/confusion_matrix.html
[22] S. Lam Phung, A. Bouzerdoum, and D. Chai, "SKIN SEGMENTATION USING COLOR AND EDGE INFORMATION". Proc. Int. Symposium on Signal Processing and its Applications, 1-4 July 2003, Paris, France.
[23] K.Nazaria, S.Mazaherib, and B. S. Bighamc, Creating A New Color Space utilizing PSO and FCM to Perform Skin Detection by using Neural Network and ANFIS, Computer Vision and Pattern Recognition, 2021.
[24] H. A. H.Al Naffakh, R. Ghazali, N. K. El Abbadi, A. N. Razzaq, review of human skin detection applications based on image processing, Bulletin of Electrical Engineering and Informatics, Vol. 10, No. 1, February 2021, pp. 129~137.
[25] H. Zuo, H. Fan, E. Blasch, and H. Ling, Combining Convolutional and Recurrent Neural Networks for Human Skin Detection, signal processing letters , 2017.

Hani K. Al-Mohair obtained his B.Sc from University of Technology, Baghdad Iraq, M.Sc from UPM, Selangor Malaysia in 2000 and 2005 respectively. Obtained his Ph.D from USM, Malaysia in 2018. Currently he is a lecturer at KFUPM CIT department teaching computer and Information Technology courses. His research interests includes Image processing, ANN and computer Vision.