VOL. 3, NO.12 Dec, 2012 ISSN 2079-8407
Journal of Emerging Trends in Computing and Information Sciences

http://www.cisjournal.org

Neural Networks Performance for Skin Detection

Saleh Alshehri
Jubail Industrial College, Jubail Industrial City 31961, Saudi Arabia
shehri_a@jic.edu.sa

ABSTRACT

The use of Neural Networks for skin detection has been reported in many research studies. However, direct use of any color space does not produce optimistic results. This is because the feature vectors to be used as training input to the NN is only size three. This research elaborates on the problem of direct use of color space by analyzing a general images database and show that NN performance is limited.

Keywords: *Skin detection, neural networks, RGB color space.*

1. INTRODUCTION

For many applications, skin detection is an important step to be conducted. Examples of such applications can be seen in face detection, facial expression recognition, people identification and others. There have been many methods used for skin detection [1,2,3,4,5]. Neural Network (NN) is a successful one. There have been many research studies done on this method [6,7,8,9]. In spite of their wide use, they lack of either proper use of general images database or have limited performance rate. We show in this research that when RGB components are used, the performance rate of NN may reach low value even with proper NN architecture and enough training samples.

In this research, we have selected 750 images from Compaq database [10]. All skin and non-skin pixels were constructed based on masks images included in the Compaq database. Data analysis was then performed. After that, NN was constructed which produced a successful result on the test samples. In section two, the method of this research study will be explained in detail, followed by a presentation of the research results and then the conclusion.

2. RGB COLOR SPACE AS FEATURE VECTOR

It is well known that NN can perform well when the following are satisfied:

a. Proper feature vector.
b. Adequate training data.
c. Good NN architecture.

To fulfill the last requirement, the only realized approach is expanding and shrinking method [11]. All other methods do not show solid results. There are many image databases which can be used [10,12,13]. However, there are some researchers who choose to build their own data samples [6,14]. By following this approach, it is very difficult to appropriately judge on their results since non-standard image data sets were used. In any case, the general images database is available which satisfies the second requirement. The difficulty arises with the first requirement. Almost all standard color spaces consist of three components which may lead to difficulty in choosing the best color space [15]. This is true with RGB, HSV, and YCbCr...etc. When considering RGB color space, the pixel color components range from 0 to 255. The possibility of intersection between skin and non-skin pixels value is high. So it is obvious that feature vector with 3 features in this application using NN is not adequate. This is discussed in next section.

We have used Compaq images database [10]. It contains about 4600 skin images and 9000 non-skin images. The database contains corresponding masks for each skin image which is used to differentiate between skin/non-skin pixels. All the images were obtained from the World Wide Web. Various ethnicities, skin colors and tones are included in the database. In addition, the images were obtained with different angles, brightness and background conditions. Because the database is vast, we decided to construct a smaller database by reducing the number of images used in our study to 750 images. We attempted to avoid both pornographic images and images noted as very blurry. Based on the given masks, the R, G and B components of the skin and non-skin pixels of all the images were gathered. The result was about 60 x 10^6 pixels. To show the goal of this research, it is enough to use part of these pixels. We tried to show the level of differentiation existing between skin and non-skin pixels.

3. SKIN AND NON-SKIN SEPARATION

The research was carried out using three methods:

a. Plot the scatter data of (R,G), (R,B) and (G,B) pairs of skin and non-skin pixels.
b. Show the behavior of R,G and B components of skin and non-skin pixels using histograms.
c. Construct NN and observe the result.

3.1 Potting Scatter Data

We used 30 x 10^6 pixels in RGB color space. Figure 1 shows the scatter data of (R,G), (R,B) and (G,B) pairs of skin and non-skin pixels. It can be seen that small segments in corresponding figures do not overlapped. These non-overlapped area show the percentage of possible distinguish between skin and non-skin pixels.

VOL. 3, NO.12 Dec, 2012 ISSN 2079-8407
Journal of Emerging Trends in Computing and Information Sciences

http://www.cisjournal.org

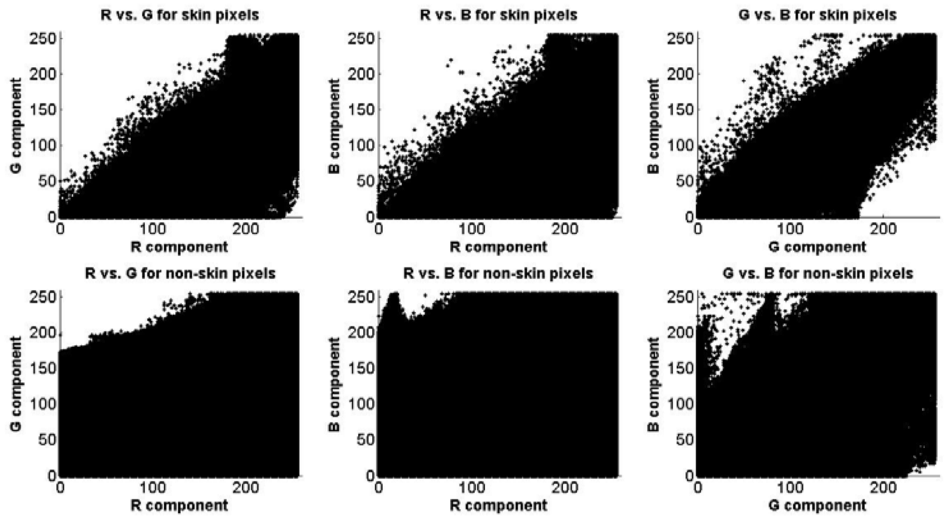

Fig 1: Relationship among RGB components of skin and non-skin pixels.

3.2 R, G and B Components of Skin/Non-Skin Pixels

We found that as the number of pixels being used gets larger, the separation between skin and non-skin decreases.

Figure 2 shows histograms of R, G and B components of skin and non-skin pixels. These values for skin and non-skin span are almost in the same range which makes the separation very difficult.

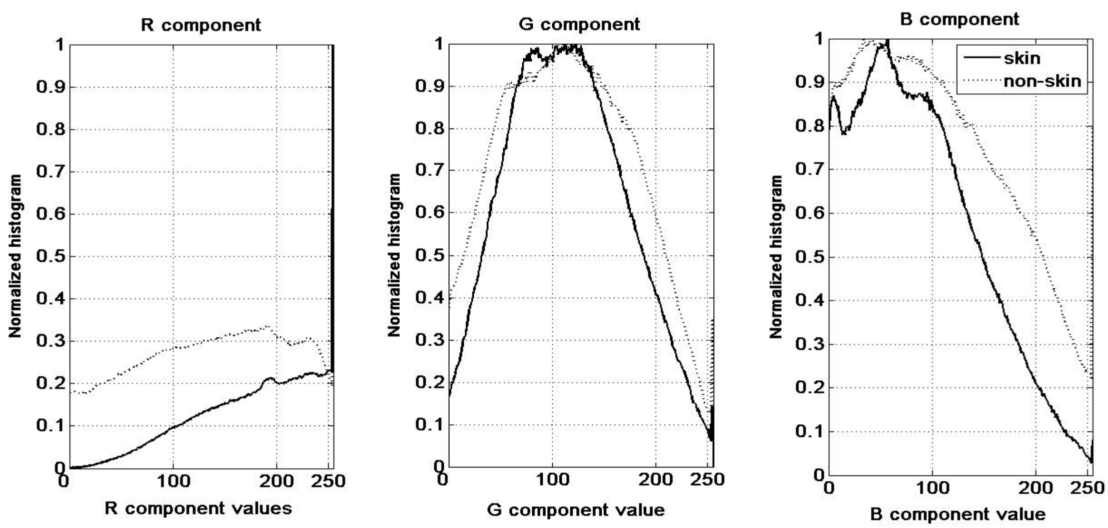

Fig 2: Normalized histogram of RGB components.

VOL. 3, NO.12 Dec, 2012 ISSN 2079-8407
Journal of Emerging Trends in Computing and Information Sciences

http://www.cisjournal.org

We have identified the unique RGB values for both skin and non-skin images. It is found that there exist many common values. As the samples get larger the percentage of these common values gets larger. Figure 3 shows this relationship. This tells that in any attempt to work using small image database size the result may be optimistic but without generalization. Figure 3 shows that the maximum percentage of the intersection to skin pixels can reach 80%. This means the detection error can reach 80%.

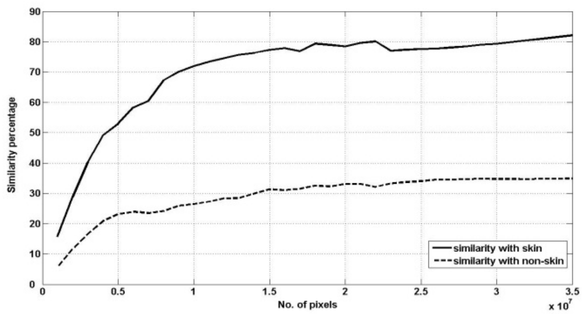

Fig 3: Similarity of skin and non-skin pixels.

3.3 NN Results

Usually as the NN training samples get larger, the performance rate increases. This is true if there is a good pattern. In skin detection case, as we increase the manipulated samples the intersection between skin and non-skin pixels gets larger as shown in figure 3. To show this effect we followed the next procedure:

a. Using RGB color space, prepare 10^6pixels out of the $60x10^6$pixels.
b. Divide it into skin and non-skin groups.
c. Obtain the unique pixels in each group.
d. Find the common pixels between the two groups.
e. Use these groups to train, validate and test a back-propagation NN with 5 hidden nodes and one output. To discover the effect of the common pixels, they can be used in one trial and removed in another.

4. RESULTS

When analyzing 10^6 pixels, it is found that there are 272303 and 739965 unique pixels in skin and non-skin groups respectively. Also, 195820 pixels are common between them. This may lead up to 72% and 26% performance error with skin and non-skin pixels respectively. Figure 4 shows these common pixels and some examples of their RGB values.

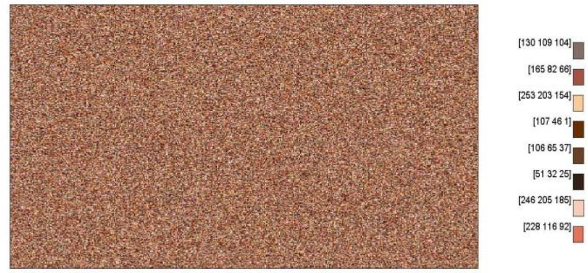

Fig 4: Common pixels between skin and non-skin.

The main point here is to say that if a pixel exists in skin and non-skin domains, it would be impossible to determine which group it belongs to. The performance results were up to 99.9% when the pure skin and non-skin pixels were used to train, validate and test NN. This means that the NN is able to correctly classify all skin and non-skin pixels as long as they are unique. However, this is not the case in reality. So, the reported results in various researches can be achieved based on selected images database. For example, some images in our image samples reached a correct detection rate of 97.5%. However, when applying equations (1)-(4) on the developed database, low performance results achieved as in table 1.

$$SkinDetectionRate(SDR) = \frac{no.of\ correct\ skin\ pixels\ detection}{total\ no.of\ skin\ pixels} \quad (1)$$

$$FalseNegative(FN) = \frac{no.of\ pixels\ identified\ as\ non\_skin}{total\ no.of\ skin\ pixels} \quad (2)$$

$$Non_{SkinDetectionRate\ (NSDR)} = \frac{no.of\ correct\ no\_skin\ pixels\ detection}{total\ no.of\ non\_skin\ pixels} \quad (3)$$

$$FalsePositive(FP) = \frac{no.of\ pixels\ identified\ as\ skin}{total\ no.of\ non\_skin\ pixels} \quad (4)$$

Table 1 : Performance result of the NN.

Indicators	Results
SDR	99 %
FN	1 %
NSDR	41 %
FP	59 %

From figure 3 it can be deduced that the performance accuracy of NN using RGB color space can be as low as 18% and 65% for skin and non-skin classification respectively. The source of error is the common RGB pixels exist in both skin and non-skin regions. NN can be used successfully when used in controlled environment. For example, it performs well for intrusion detection application where the background on the taken images is almost fixed. But for general application with variety of background pixels such as World Wide Web, the performance may degrade substantially. It is then required to search for more than just using RGB pixels values for NN training. For example, the texture of skin or the relation with neighbor pixels can be used.

5. CONCLUSIONS

It has been shown that the use of NN on RGB pixels values may not necessary lead to good performance. There is high number of RGB pixels which exit in both skin and non-skin regions. This fact may lead to a low NN performance rate. It is the images database and the type of application that can affect the results. Adding more information besides the pure RGB pixels values may lead to better performance. This will be our future work.

REFERENCES

[1] Vezhnevets V., Sazonov V. and Andreeva A. (2003) “A Survey on Pixel-Based Color Detection Techniques”, Proceedings of the GraphicCon, 85-92.

[2] Peer P., Kovac J. and Solina F. (2003) “Human skin color clustering for face detection”, EUROCON – International Conference on Computer as a Tool.

[3] Ma Z. and Leijon A. (2010) “Human Skin Color Detection in RGB Space with Baysian Estimation of Beta Mixture Models”, 18the European Signal Processing Conference, Aalborg, Denmark, August 23-27.

[4] Kakumanu P., Makrogiamis S. and Bourdalis N. (2007) “A survey of skin-color modeling and detection methods”, Pattern Recognition, vol. 40, pp. 1106–1122.

[5] Zheng Q., Zeng W., Wen G. and Wang W. (2004) “Shape-based Adult Image Detection”, Proceedings of the Third International Conference on Image and Graphics.

[6] BhoyarK. K. and Kakde O. G. (2010) “Skin Color Detection Model Using Neural Networks and its Performance Evaluation”, Journal of Computer Science, Vol. 6, pp. 963-968.

[7] Doukim, Darpham J., CheckimaA. and Omatu S. (2010)“Combining Neural Networks For skin Detection”, Signal & Image Processing: An International Journal, vol.1 no.2, pp. 1-11.

[8] Zolfaghari H., Nekonam A. and Haddania J. (2011) “ Color-Bae Skin Detection Using Hybrid Neural Network & Genetic Algorith for Real Times,” (IJCSIS) International Journal of computer Science and Information Security, vol. 9, No. 10, pp. 67-71.

[9] Al-Mohair, H., Mohamad-Saleh J. and Suandi S. (2012), “Human skin Color Detection: A Review on Neural Network Perspective”, International Journal of Innovative Computing, Information and Control, vol. 8, no. 12, pp. 8115-8131.

[10] Jones M. J. and Rehg J. M. (2002)“Statistical color models with application to skin detection”, International Journal of Computer Vision,vol.46, pp. 81–96.

[11] C. M. Bishop (1997), Neural Networks for Pattern Recognition: Oxford University Press.

[12] http://www.cs.cmu.edu/~cil/v-images.html

[13] http://lbmedia.ece.ucsb.edu/resources/dataset/

[14] Taqa A. and Jalab H. (2010), “Increasing Reliability of Skin Detectors”, Scientific Research and Essays, vol. 5, no. 17, pp. 2480-2490.

[15] Albiol A., Torres L. and Delp E. (2001) “Optimum Color Spaces for Skin Detection”, Proceedings of the International Conference on Image Processing 1, pp. 122-124.