

PCA BASED CHOICE OF REPRESENTATIVE COLORS FOR SKIN DETECTION

¹K. Chenaoua and ²A. Bouridane

¹Computer Eng. Dept.
KFUPM.

Dhahran 31261 Saudi Arabia
email: kamel@ccse.kfupm.edu.sa

²School of Computer Science
Queens University of Belfast
Belfast BT7 1NN
UK

ABSTRACT

Detection of human skin in colored images has always been performed in known standard color spaces. In this paper a new color space coordinate is proposed based on popular existing color spaces but taking into account the most representative ones. Color components are considered features from which a representative set is derived using the PCA technique. An elliptical model based classifier is used to test the performance of the proposed space transformation.

1. INTRODUCTION

Detection of human skin in color images has been the center of interest of many works in the last decade, a good review of which is given in [1]. Skin segmentation is commonly used in algorithms for face detection, hand gesture analysis [2], and objectionable image filtering [3, 4]. In these applications, the search space for objects of interest, such as faces or hands, can be reduced through the detection of skin regions.

The main attributes used for skin detection are the color space and the classifier [1]. Authors used different existing color spaces, combination of color spaces or sometimes their own proposed color space transformations [5, 6]. Choice of a given color space is driven by its abilities to cluster skin pixels and separate between skin and non skin pixels. Even though comparative studies have been carried out to determine a suitable color space for skin detection [7, 8], it seems that no universal color components basis has been settled down [9].

In this paper we are proposing a new approach for the choice of color components. The Principal component Analysis (PCA) is used as a basis to make a suitable choice for an optimal combination of the different color components where each component is given an appropriate weight. The next section presents an overall view of the proposed approach. The following sections, deal respectively with the different used color spaces, the PCA technique, the elliptical model used for the detection of skin pixels, and finally results and discussions are given at the end of the paper.

2. PROPOSED TECHNIQUE

In this work we are trying to set up a basis for an appropriate choice of color components from existing color spaces and hence propose a new color space transformation. Four combinations of chrominance and luminance components have been used:

On those sets the PCA technique is used to reduce the number of components to a small number of components, based on the respective weights of the corresponding eigenvalues.

An elliptical model based classifier is used for the classification of skin and non-skin pixels. This model seems a more

adequate model, as the distribution of non-skin pixels is not needed. In the gaussian model and the bayesian classifier[1], the distribution of non skin pixels would need a certain number of gaussian components to represent it and depends heavily on the database used [12]. This in fact is a source of false positives.

- Luminance and chrominance components including two proposed color space transformations.
- Chrominance and luminance components reduced to 3 components only.
- Chrominance component set reduced to 3 components only.
- Common Chrominance component set reduced into 3 components only.

3. COLORSPACES

The following color components have been used: RGB, normalized RGB (rgb), YCbCr, YIQ, Lab, HSV, TSL, $(r-g)(r-b)$ and $(Y-Cb)(Y-Cr)$. These color spaces were chosen because they represent different classes of known color spaces [10].

RGB is a common color space that has shown to be among the best ones for skin detection purposes [1]. However, high correlation between channels, significant perceptual non-uniformity, mixing of chrominance and luminance data make RGB not a very favorable choice for color analysis and color based recognition algorithms [1, 11, 12, 16]. Normalized rgb is also being used in skin detection as it preserves the properties of the RGB while reducing the effect of luminance [14, 15]. The remaining color spaces separate chrominance from luminance components [10].

The YCbCr and the YIQ color spaces represent luminance through the Y component and chrominance information through the Cb Cr I and Q components. HSV, TSL and Lab color spaces also separate chrominance from brightness information and are designed to mimic the human visual system[10]. These properties make these color spaces interesting for skin detection as this process is solely based on skin color only [14].

Added to the above components, a linear combination of color components obtained from the normalized RGB and the YCbCr spaces are proposed. These combinations (Eqs. 2, 3) give a good clustering of skin pixels (Fig. 1).

$$r = \frac{R}{R+G+B} \quad g = \frac{G}{R+G+B} \quad b = \frac{B}{R+G+B} \quad (1)$$

Since $r+g+b=1$ the third component is redundant.

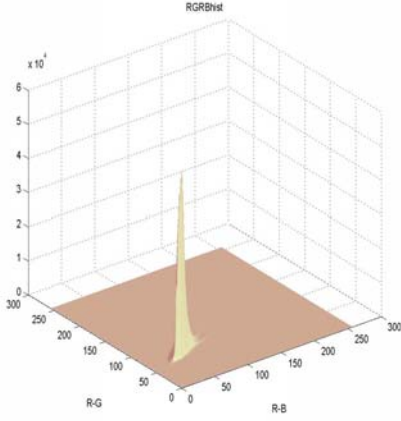


Figure 1: Skin Distribution in the $(r-g)$ vs. $(r-b)$ space

$$rg = r - g \quad rb = r - b \quad (2)$$

$$YCb = Y - Cb \quad YCr = Y - Cr \quad (3)$$

4. COLOR COMPONENTS REDUCTION

The data used in this work is taken from the ECU face detection database constructed at Edith Cowan University. The database consists of over 3,000 color images that have been manually segmented for skin regions and face regions [11]. Each image is converted from the RGB color space, to different color spaces. The color components are considered as features. The dimensionality of this set is transformed to a reduced set of linearly transformed features, that is representative of the original feature set. A feature vector would then be made up of the following 24 features (Eq. 4).

$$X = \begin{bmatrix} R & G & B & rn & gn & bn & Y_{cbcr} & Cb & \dots \\ Cr & Y & I & Q & H & S & V & L & \dots \\ a & b & T & S_{is} & rg & rb & YCB & YCR & \dots \end{bmatrix} \quad (4)$$

The above vector contains all occurrences of skin pixels in the 24 different components. The number N of data pixels is over 13 million pixels, giving a raw data vector of $24 \times N$ components. The covariance of X is computed by (Eq. 6),

$$\bar{X} = E(X) \quad (5)$$

$$C = E\{(X - \bar{X})(X - \bar{X})^T\} \quad (6)$$

where \bar{X} is the vector mean.

X is linearly transformed to a lower dimensional vector Y of dimension k where $k < n$ (Eq. 7).

$$Y = A^T(X - \bar{X}) \quad (7)$$

where

$$A^T \cdot A = I_k \quad (8)$$

and I_k is a $k \times k$ identity matrix.

In PCA, the transformation matrix A is an $n \times k$ matrix whose columns are the k orthogonal eigenvectors corresponding to the

largest k eigenvalues of the covariance matrix C .

The covariance matrix can be diagonalized by:

$$\Sigma = A \cdot \Lambda \cdot A^T \quad (9)$$

where Λ is the diagonal matrix whose diagonal elements are the eigenvalues of C : $\lambda_1 > \lambda_2 > \dots > \lambda_n$. A_k is the matrix made up of the first k columns of A . The new vector $Y = A^T \cdot X$ will be a $k \times N$ elements, where all the row elements are uncorrelated.

5. ELLIPTIC BOUNDARY MODEL

Due to asymmetry of the skin cluster with respect to its centroid, usage of the symmetric Gaussian model would lead to high false positives rates. Based on this observation, and the shape of skin distribution (Fig. 3), an elliptical boundary model was proposed as an alternative [13] to the Gaussian model. The model was found to be as fast and simple in training and evaluation as the single Gaussian model and faster compared to both single and mixture of Gaussians models (GMM) [12].

If X is the pixel color value, the elliptical boundary model is defined as:

$$\Phi(X) = (X - \Psi)^T \Lambda^{-1} (X - \Psi) \quad (10)$$

5.1 Model Training

Model training is performed in two steps:

- First, up to 5% of the training color samples with low frequency are eliminated to remove noise and negligible data.
- Then, model parameters (Ψ and Λ) are estimated by:

$$\Psi = \frac{1}{n} \cdot \sum_{i=1}^n X_i \quad (11)$$

$$\Lambda = \frac{1}{N} \cdot \sum_{i=1}^n f_i \cdot (X_i - \mu)(X_i - \mu)^T \quad (12)$$

where

$$N = \sum_{i=1}^n f_i \quad \mu = \frac{1}{n} \cdot \sum_{i=1}^n f_i \cdot X_i \quad (13)$$

and n is the total number of distinctive training color vectors X_i of the training skin pixel set and f_i the number of skin samples of color vector X_i .

5.2 Classification

A pixel with color X is classified as skin if $\Phi(X) < \Theta$, where Θ is a threshold value. The equality $\Phi(X) = \Theta$ defines an elliptical boundary between skin and non-skin chrominance. The centroid of the elliptical model is given by Ψ and the principal axes by Λ . The threshold value Θ trades off between true positives (TP) and false alarms (FA) or false positives. When the threshold value increases, true positive rate increases and so does the false positive rate.

6. ALGORITHM DESCRIPTION

An image is first transformed to the different 24 color components, which are considered as features. These are reduced to only 3 planes using the PCA approach. To determine whether a pixel belongs to skin or non skin regions, a metric is used. This metric imposed by the elliptic model and given by (Eq. 10) is the Mahalanobis distance. This distance is computed from each pixel to the centroid of the skin distribution, assumed to be an ellipsoid. Once this distance is computed for all pixels, a skin distance map is obtained. The skin map is low pass filtered to remove noise that could lead to misclassified pixels. Then a threshold, determined empirically through experiments, is applied to the skin

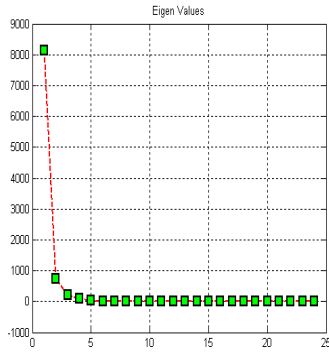


Figure 2: Eigenvalues

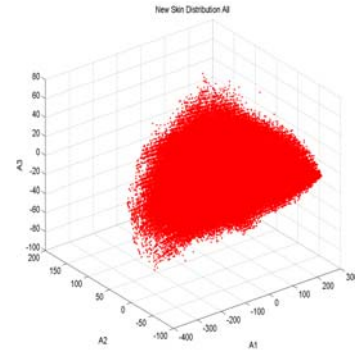


Figure 3: Skin Cluster in the New Space

distance map (Table 1). Thresholding produces a skin mask, from which holes and small patches are removed using morphological filtering. Finally a convex Hull that surrounds the skin area is found.

To measure of the accuracy of the proposed approach, ROC curves are computed without the use of the convex hull. This allows us to better compare the approach to other works and assess the ability of the proposed transformation to separate skin pixels. The convex Hull step is a preparation for a future work on face localization and detection.

Components	Threshold Value
All	3.3
Chrominance	2.8
Common Chrominance	2.7

Table 1: Threshold Values

7. RESULTS

Two performance measures are used to evaluate the performance of the new transformation and that of the classifier used: the ROC curve and the area under the ROC curve (AUC). Based on the distribution of the eigenvalues (Fig. 2), it can be noticed that the first three values represent about 98% of the total sum of eigenvalues. Therefore the corresponding eigenvectors are enough for the design of the new transformation.

7.1 All Components

When all the 24 components are used and the set is reduced to 3 components only, the ROC (Fig. 7) gives an AUC equal to 0.904. Reduction to 4 components is of no benefit as the AUC in this case is 0.892. Some of the eigenvector components are less than 1% and therefore do not contribute much to the newly formed components. By eliminating those vector components, contribution due to some color and luminance components such as H S I and Q components is reduced.

7.2 Chrominance Components

Skin detection is based on color information only, hence it has been suggested to use only the chrominance components including the $(r-g)(r-b)$ and $(Y-Cb)(Y-Cr)$ components. Skin data is very well clustered through the new transformation (Fig. 3). The ROC curve obtained in that case is very similar to that obtained when all components are considered (Fig. 7), with an AUC equal to 0.890 slightly lower than the previous case (0.904).

7.3 Common Chrominance Components

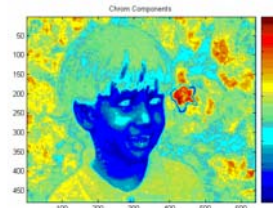
In this case, the $(r-g)(r-b)$ and $(Y-Cb)(Y-Cr)$ are not used as these were proposed for mere testing. This choice seems to give better results than if all chrominance components are considered (Fig.7), with an AUC equal to 0.897.

7.4 Reduced Common Chrominance Components

This case is similar to the previous one, except that reduction is done at 2 components only instead of 3. Performance has degraded giving an AUC of 0.875.



(a) Original Image



(b) Score Image



(c) Skin Image

Figure 4: Original (a) Score (b) and Skin (c) Images Using All Components.

Components	AUC
Chrominance and Luminance reduced to 3	0.904
Chrominance and Luminance reduced to 4	0.892
Common Chrominance	0.897
Chrominance	0.887
Chrominance Reduced to 2	0.875
Reference Paper	0.852

Table 2: Area Under Curve

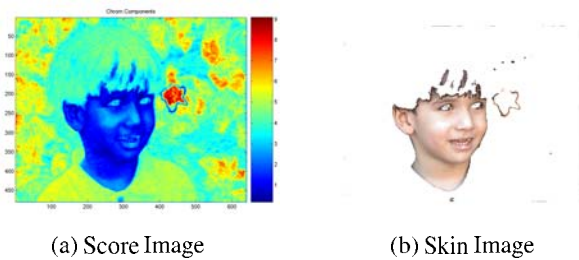


Figure 5: Score (a) and Skin (b) Images using Chrominance Components

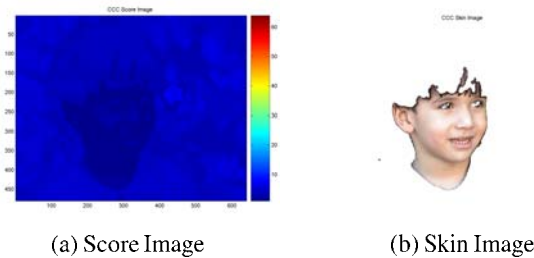


Figure 6: Score (a) and Skin (b) Images using Common Chrominance Components

8. CONCLUSION

In this paper a new trend in the choice of color components for the purpose of designing a classifier for human skin detection is proposed. The proposed approach gives better results when compared to the GMM proposed in [12] as seen in (Table 2).

However, some enhancements could be added to improve the performance of the proposed technique. Choice of another type of classifier and combination of more color spaces are options that need to be further investigated. This could help in the choice of color spaces that are more adequate for human skin detection applications by considering the eigenvalues corresponding to each eigenvector and the weights of each eigenvector component that corresponds to the different color components.

The elliptical model based classifier choice is driven by the fact that skin data clusters well in the new space. However, it is

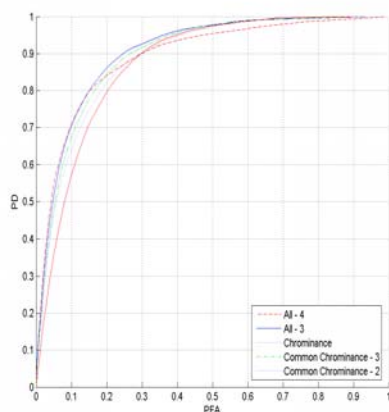


Figure 7: ROC Curves

planned to enhance the technique through careful consideration of skin clusters. These in fact could be considered as multiple elliptical models, due to the different ethnic groups of people used in the database. Therefore, a mixture of elliptical model, in a way similar to the GMM, is planned.

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REFERENCES

- [1] Vezhnevets V. Sazonov V. Andreeva A. "A Survey on Pixel-Based Skin Color Detection Techniques". In *Graphicon-2003*, Moscow, Russia, Sep. 2003.
- [2] Ming Hsuan Yang and Narendra Ahuja "Face Detection and Gesture Recognition for Human-Computer Interaction". *Kluwer Academic Publishers*, 2001.
- [3] Arentez, W., Olstad, B. "Classifying Offensive Sites Based on Image Content". In *Vision and Image Understanding*, Science Direct Journals, vol 94, no. 1-3, pp. 295-310, 2002.
- [4] Bosson, A., Cawley, G., Chan, Y., Harvey, R., "Non-retrieval: blocking pornographic images", In *CIVR*, pp. 50-60, 2002.
- [5] Gomez, G. "On Selecting Colour Components for Skin Detection" In *Proc. of the ICPR*, vol. 2, pp. 961-964, 2000
- [6] Gomez, G. Sanchez M. and Sucar L.E. "On Selecting an Appropriate Color Space for Skin Detection" In *Proceedings of the Second Mexican International Conference on Artificial Intelligence*, Vol. 2313, pp. 69-78, 2000
- [7] Zarit, B. D., Super, B. J., and Quek, F. K. H. . "Comparison of Five Color Models in Skin Pixel Classification" In *Intl Workshop on Recognition, Analysis and Tracking of Faces and Gestures in Real-Time Systems*, pp. 58-63, 1999
- [8] Terrillon, J.-C., Shirazi, M. N., Fukamachi, H., and Akamatsu, S. "Comparative Performance of Different Skin Chrominance Models and Chrominance Spaces for the Automatic Detection of Human Faces in Color Images" In *Proc. of the International Conference on Face and Gesture Recognition*, pp. 54-61, 2000.
- [9] Shin, M. C., Chang, K. I., and Tsap, L. V. "Does Color space Transformation Make any Difference on Skin Detection?", In *IEEE Workshop on Applications of Computer Vision*, 2002.
- [10] N. Plataniotis A.N. Venetsanopoulos. *Color Image Processing and Applications*. Springer Verlag, 2000.
- [11] D. Phung S. L. Bouzerdoum A. Chai. "Skin Segmentation Using Color and Edge Information". In *ISPA*, pp. 525-528, Paris, France, 2003.
- [12] Jones M. J. Rehg J. M. "Statistical Color Models with Application to Skin Detection" In *Proc. of the CVPR 99*, volume 1, pp. 274-280, 1999.
- [13] Jae Y. Lee and Suk I. Yoo "An Elliptical Boundary Model for Skin Color Detection". In *Proc. of the 2002 International Conference on Imaging Science, Systems, and Technology* 2002.
- [14] Skarbek, W., and Koschan, A. 1994. "Colour Image Segmentation: a Survey". Tech. rep., Institute for Technical Informatics, Technical University of Berlin, October 1994.
- [15] Brown, D., Craw, I., and Lewthwaite, J. "A SOM Based Approach to Skin Detection with Application in Real Time Systems" In *Proc. of the British Machine Vision Conference* 2001.
- [16] Brand, J., and Mason, J. "A Comparative Assessment of Three Approaches to Pixel Level Human Skin Detection". In *Proc. of the International Conference on Pattern Recognition* Vol. 1, PP. 1056-1059.