Face Recognition System using Skin Detection with Color Images

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Abstract -In this paper, we present a face recognition system using skin segmentation as feature reduction. Human Skin detection reduces the face region research in the image. In addition, color skin is a robust information face to rotation; scale and illumination variation. Skin regions are extracted using a set of bounding rules based on the skin color distribution obtained from a training set. The proposed RGB-HSV-CbCr skin color model for skin region segmentation was evaluated on a set of three databases. The dataset difers from a controlled and uncontrolled environment. Two classifiers are studied to build our face recognition system; the k nearest neighbor applied for each channel of the segmented image, whereas the second used the Principal component analysis PCA as reduction method followed by knn classifier. Best recognition rate were obtained with Knn classifier.

Keywords -Skin segmentation, RGB YCbCr, Hsv model, PCA, Knn, face recognition.

I. INTRODUCTION

Face is one of the most important biometric identifiers used for human recognition. A lot of research has been developped in this area to propose automated sytems capable of recognizing human faces in controlled and uncontrolled environement.

Due to the increasing need for the surveillance and security related to applications in access control, law enforcement, and information safety due to criminal activities, the research interest in the face recognition using human skin segmentation has grown considerably in the domain ofpattern recognition and image analysis. The first task is to locate the face within the image.

Skin color detection in color images is a very popular technique for face detection; it's one of the most important features in human face recognition. Skin detection plays an important role in a wide range of image processing applications ranging from face detection; face tracking, gesture analysis for sign language, human computer interaction and human robot interaction (HRI).

Human face localization and detection is often the first step in applications such as video surveillance, human computer interface,face recognition and image database management [1].

Face detection from a single image or an image sequences is a difficult task due to variability in pose, size, orientation, color, expression, occlusion and lighting condition. To build a fully automated system that extracts information from images of human faces, it is essential to develop efficient algorithms to detect human faces [2].

A number of approaches for face recognition have been proposed in the literature and widely described by Zhao&al and Chellapa &al. Many researchers have addressed face recognition based on geometrical features and template matching. There are several well known face recognition methods such as Eigenfaces developed by Turk and Pentland in 1991, Fisherfaces by Belhumeur et al in 1997, Laplacian faces by He et al in 2005 [3].

Face detection methods received an important attention and discussed in a lot of work like Yang, M.Het al in 2002, Moghaddam and Pentland in 1997, Schneiderman, and Kanade in 2000, Shih and Liu in 2004[3].

For detecting faces, there are various algorithms including skin color based algorithms. Color is an important feature of human faces. Using skin-color as a feature for tracking a face has several advantages, color processing is much faster than processing other facial features [1].

Human skin detection is an important step for feature extraction used in a lot of techniques such as face detection, face tracking, gesture analysis. Skin detection reduces the face region research in the image. In addition, color skin is a robust information face to rotation, scale and illumination variation. It also provides invariance to geometric transformations.

In addition, Images containing faces and hand poses are essential for vision-based human-robot interaction [2].

Tracking human faces using color as a feature has several problems like the color representation of a face obtained by a camera is influenced by many factors (ambient light, object movement, etc.), different cameras produce significantly different color values even for the same person under the same lighting conditions and skin color differs from person to person [1].

Skin detection is also robust towards changes in orientation and scaling and can tolerate occlusion well. A disadvantage of the color cue is its sensitivity to illumination color changes and, especially in the case of RGB, sensitivity to illumination intensity. One way to increase tolerance toward intensity changes in images is to transform the RGB image into a color space whose intensity and chromaticity are separate and use only chromaticity part for detection [1].

A lot of works has been developed for skin detection using facial images in uniform and complex background. Skin detection still being a powerful tool to describe a face and build a system capable of recognizing an individual in a complex background.

Zhu et al. [1] combined two Gaussian feature spaces where the first one is related to the colour distribution and the second one is related to the skin spatial and shape distribution. The combined feature method performed better compared to single feature and also other generic skin model namely histogram model, single Gaussian model and Gaussian Mixture model. Brand and Mason [2] evaluated the performance of the combined color components or features from the RGB color space and concluded that the combination of (R/G + R/B + G/B) gave better performance than the single color component [4].

Jiang et al. proposed a Skin Probability Map (SPM) based skin detection system that integrated the colour, texture and space information and claimed that their proposed method performed better than the generic SPM method. Gasparini et al. [4] combined different skin classifiers based on different colour features using several combination rules such as the sum rule, the product rule, the majority rule and the author's proposed skin corrected by non-skin (SCNS) rule [4].

Chelsia &al developed a skin classifier using MLP neural network, several chrominance components from the YCbCr color space are used as the skin color features. Several strategies for combining MLP neural networks for skin detection are proposed and their performance on skin detection is evaluated [4].

For this reason, human face detection and recognition has got a great attention from researchers and becomes a challenge problem in face recognition. This paper discuss face detection using skin information in different color spaces as primary step before recognizing an individual in controlled and uncontrolled environment. For this purpose, it's important to build a skin color model that is adaptable to different skin color for different races and different light conditions.

In this work, we present a face recognition system based on skin detection. We search the skin region segmentation of the color images in different spaces: RGB, HSV, YCbCr. For each segmented image and for each channel (First, second and third dimension P1, P2, P3), two classifier are studied to build a face recognition system; the k nearest neighbor knn applied for each channel P1,P2, and P3, whereas the second used the Principal component analysis PCA as reduction method followed by knn classifier. The proposed skin color model for skin region segmentation was evaluated on a set of three databases. The set was choiced in a controlled and uncontrolled environment. A comparative study is done for each database. Recognition rate (RR) is computed for each channel, for each environment and for the total individuals. Fig 1 summary the face recognition system described in our work.

Our article is presented as follows, section II presents the skin color region segmentation, section III presents the facial datatsets used in our work, section IV discuss results obtained for face recognition developed for the knn classifier and the PCA-knn classifier, conclusion is drawn in section V.

II. SKIN COLOR REGION SEGMENTATION

Information of skin color in a color image is a very popular and useful technique for face detection.

The obvious advantage of this method is simplicity of skin detection rules that leads to construction of a very rapid classifier [1]. In this case, color information is used to discriminate human faces based on color distribution, which is different from background objects.

Much of the research in skin color based face localization and detection is based on RGB, YCbCr and HSI color spaces. The following paragraph decribes the skin color subspace analysis permitting us to propose the best values of the chrominance components for skin detection.

A) Some Review of Skin Color Subspace Analysis

A lot of techniques of segmentation or pixel skin classification have been developed in literature. A skin detector defines a binary decision in the color space representation. For a controlled acquisition condition, we can define a threshold for each color component.

As described in the work of [5]-[6], In RGB space the skin colour region is not well distinguished in all 3 channels. A simple observation of its histogram show that it is uniformly spread across a large spectrum of values.

In HSV space, the H (Hue) channel shows significant discrimination of skin colour regions. In the hue channel, most of the skin color samples are concentrated around values between 0 and 0.1 and between 0.9 and 1.0 (in a normalized scale of 0 to 1) [5].

Some studies have indicated that pixels belonging to skin regions possess similar chrominance (Cb and Cr) values. These values have also been shown to provide good coverage of all human races.Authors [5] demonstrate that the YCbCr space using the Cb-Cr subspace offers the best discrimination between skin and non-skin regions [5].

In [3], the YCbCr color model is used to build the skin color space. It includes all possible skin colors. The skin color space uses only the chromatic color components Cb and Cr for skin color segmentation using the sigma control limits [3].

A lot of techniques of segmentation or pixel skin classification have been developed in literature. A skin detector defines a binary decision in the color space representation. For a controlled acquisition condition, we can define a threshold for each color component.

Human faces are analyzed using the histogram distribution of color values of chrominance to make decision if the pixel is belonging to a skin region.

$$\Gamma i\ , i = 1.....M$$

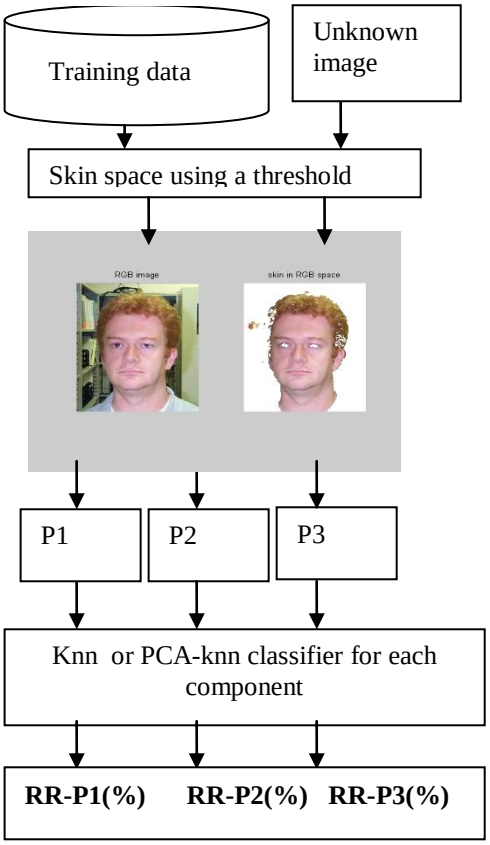


Fig. 1. General diagram of face recognition after skin detection

➢ SKIN DETECTION IN RGB SPACE

In RGB space, we use the skin color rules introduced by Peer et al. [6]. Peer and al define the skin threshold values in RGB space by considering the orientation information and the non uniformity of illumination:

The skin colour at uniform daylight illumination rule is defined as

(R > 95) AND (G > 40) AND (B > 20) AND
(max{R, G, B} − min{R, G, B} > 15) AND rule (1)
(|R−G|> 15) AND (R>G) AND (R>B)

While the skin colour under flashlight or daylight lateral illumination rule is given by :

(R > 220) AND (G > 210) AND (B > 170) AND
(|R − G| ≤ 15) AND (R > B) AND (G > B) rule (2).

To consider both conditions when needed, a logical OR is used to combine both rule (1) and rule (2).

In the work of Vladimir and al [8], the skin is classified in the RGB space using the rules 1 and 2.

➢ SKIN DETECTION IN YCBCR SPACE

It was found that the chrominance component of the skin color fails in a certain range. X is skin color [1], if its projection on the Cb and Cr plane is inside predetermined rectangle

$C_b \in R_{cb}$ *and* $C_r \in R_{cr}$ *ie.*, $C_{r1} \le C_r \le C_{r2}$ and

$C_{b1} \le C_r \le C_{b2}$ *where* $R_{cb} = [C_{b1}, C_{b2}]$ and

$R_{cr} = [C_{r1}, C_{r2}]$,which are found experimentally used to eliminate quickly non-skin face color and also to improve the segmentation of skin color regions [6].

Chai and Ngan [18] have proposed a face segmentation algorithm using the two components Cb, Cr of the YCbCr model in order to find the color skin. They investigate the domain variation of Cb and Cr using the Caltech database as follows: Dc_b= [77, 127] et Dc_r= [133, 173]. This domain defines correctly the skin pixels [18].

The advantage of these methods is the simplicity of skin detection rules and permits us a fast classification. Whereas, the principal difficulty is how to determine the color space and the decision rules to ensure a good recognition rate.

Another method using training algorithm has been proposed to resolve these problems by Gomes and Morales. The authors adopted the normalized RGB space (where r= R /R+B+G, g = G/ R+B+G and b = B/ R+B+G and the sum of the three components r+g+b= 1).

They applied a constructive algorithm to create a novel domain to the RGB components, a decision rule is made to realize a best recognition rate [21].

➢ SKIN DETECTION IN HSV SPACE

The skin color segmentation in HSV space require a conversion of the original image from the RGB to the HSV space where tge color skin is defined in the following interval for H and S: [18] :

$$\begin{cases} 0 < H < 50° \\ 0.23 < S < 0.68 \end{cases} \quad (1)$$

B) Choice of colorimetric space using facial images

We can use color information as a feature to identify a person's face in an image because human faces have a special color distribution that differs significantly, although not entirely, from those of the background objects.

The choice of a color space adapted for a segmentation application is always complex. A lot of numbers of representation have al advantages and disadvantages in sense of information existing in each component. The choice of our space depends of a lot parameters like: nature of elements to be segmented, pattern having a lot of different color components and the image database (natural/synthetic image, type of illumination, resolution).skin color model can be derived from these values.

- **Experimental test in RGB space**

The sample images are in RGB colors. The RGB color space represents colors with luminance information. Luminance varies from person to person due to different lighting conditions and hence luminance is not a good measure in segmenting the human skin color.

In the RGB space, the luminance can't be separated from the chrominance component. Fig 2 shows the color distribution of a facial RGB image.

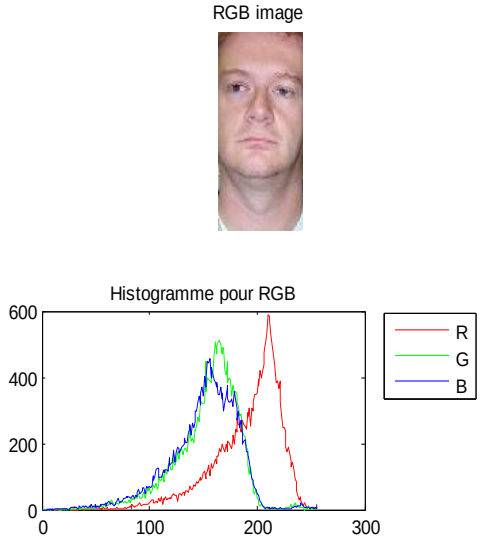


Fig. 2. General diagram of face recognition after skin detection

A little variation in illumination skin intensity affects the color representation for the three components. In addition, the localization of color distribution is variable, particularly for the red component.

Inspite of this limitation, the RGB space is widely used for color segmentation due to its simplicity and satisfactory results obtained with the appropriate choice of the interval described in paragraph II. *A*.

To decide of the optimal threshold, a lot of tests have been carried from the histogram analysis. The values of the three components satisfies the equations described in rule 1.

- **Experimental test in YCbCr space**

The YCbCr color model is used to build the skin color space. It includes all possible skin colors. We are able to extract more facial skin color regions excluding the non-skin regions.

The RGB image is converted into YCbCr model in which luminance is partiall separated [22].

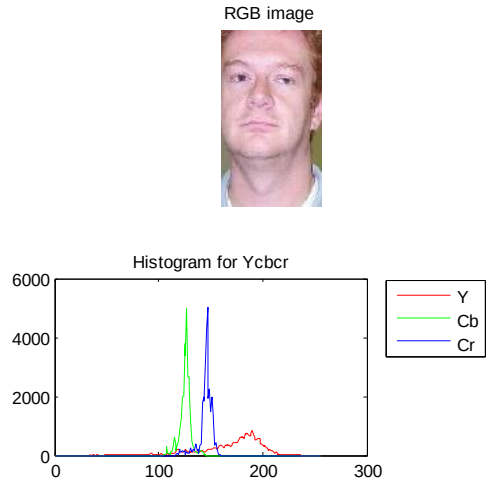


Fig. 3. Color distribution of a facial image in YCbCr space

In the YCbCr color space, chrominance components are represented by Cb and Cr values. The skin color description is based only on the two components of chrominance (Cb;Cr) and will not be affected by the variation of illumination in the Y plan (fig 3). Its propriety of invariance and simplicity of transformation can be used for skin segmentation.

Begin;

Read the facial RGB image;

Convert the image in the appropriate space;

For each space, verify the appurtenance to the interval defined by the equation described;

Test : yes : pixel→1, else pixel→0 ;

Show the segmented image

End.

Figure 4 and 5 show the histogram of a male and female facial image in different color spaces (RGB,YCbCr, Hsv).

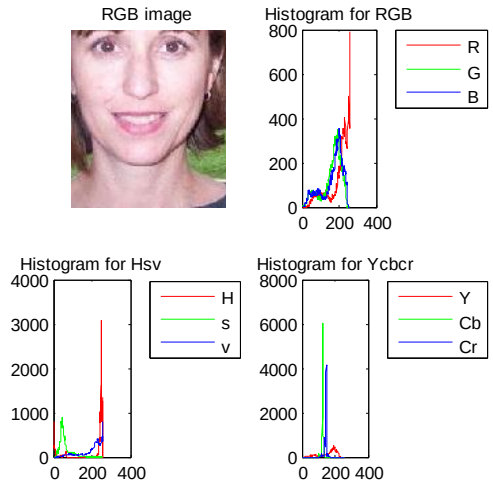


Fig 4. The histogram of a female facial image in different color spaces (RGB,YCbCr, Hsv).

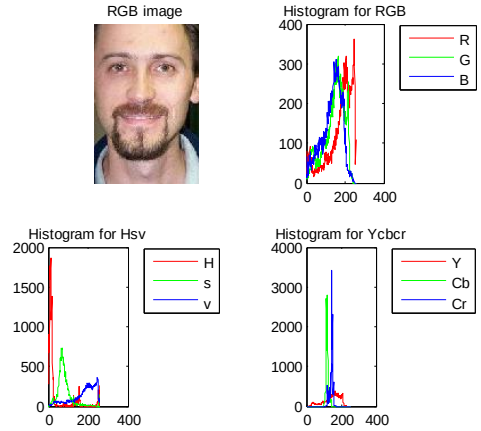


Fig 5. The histogram of a male facial image in different color spaces (RGB,YCbCr, Hsv).

The proposed RGB, YCbCr and HSV skin color model for skin region segmentation was evaluated on a face detection system using three data set containing a total of 600 unique faces. Three databases in controlled and uncontrolled environment are used in our work.

III. FACIAL DATASETS

A) Computer vision database (controlled environment CE1)

This database contains facial images of 153 individuals, with 20 images for each individual. This

data set contains images of people of various racial origins, mainly of first year undergraduate students, so the majority of individuals are between 18-20 years old. Each image for one person differs from each other in lighting, facial expression. The images are 256 color level with size of 200*180. Some individuals are wearing glasses and beards. The total number of images is 7900. Samples of the database are shown in fig 8.

Fig. 6. Some examples of training images (CE1).

B) LCPTS Facial database (controlled environment CE2)

This database contains 200 facial images for ten (10) Algerian speaking male and female subjects. A database of facial features is assigned for one of each known individuals. The recordings were made on camera canon video with 25 frames of size 576*720pixels per second at the speech communication and signal processing Laboratory (LCPTS) in Algiers. The database includes 5600 face images from ten (10) different subjects. Some examples are shown in fig 7.

Fig. 7. Some examples of LCPTS training images (CE2).

C) CALTECH database (uncontrolled environment UCE)

This database contains 396 facial images for 24 subjects with different view, pose and facial expression and background. Fig. 8 shows some examples. Resolution were reduced at 255*311 to normalize all images for classification task.

Fig. 8. Some examples from CALTECH database (UCE)

IV. SIMULATION RESULTS

A) SKIN facial results

The first step consists to build the proposed RGB-CbCr skin model using a set of skin-cropped training images. The RGB and the YCbCr color spaces are used to construct the proposed method.

Bounding planes or rules for each skin color subspace are constructed from their respective skin color distributions (fig 4 and 5).

We use then each component (P1, P2, P3) of the detected faces to build the face recognition system. The training and test images are treated under different image conditions such as illumination variation, pose and orientation.

In order to build the skin colour model, a set of training images were used to analyze the properties and distribution of skin colour in various colour subspaces. The skin regions in all training images were manually cropped for the purpose of examining their color distribution.

In our work, for each pixel luminance value, we evaluate our RGB skin segmentation using the values described by the condition of rule (1).

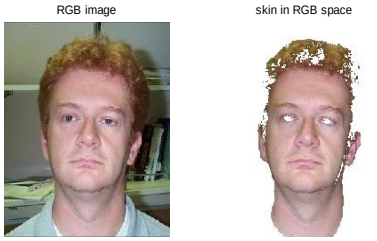
For each pixel luminance f (I,j):

R(i,j)>95 & G(i,j)>40 & B(i,j)>20 & max(max(R(i,j),G(i,j)),B(i,j))-min(min(R(i,j),G(i,j)),B(i,j))>15 & abs(R(i,j)-G(i,j))>15 & R(i,j)>G(i,j) & R(i,j)>B(i,j)

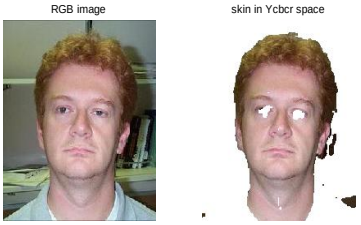
In the YCbCr color space, chrominance components are represented by Cb and Cr values. Thus, skin color model can be derived from these values. The following values of Cb and Cr were tested to build the YCbCr skin segmentation:

cr > 133 && cr < 173 && cb > 77 && cb < 127)

Good results were obtained for skin detection in YCbCr and RGB space and for the three databases; we retain the two spaces for face characterization to build our face recognition system. Fig 9 shows the results obtained.



-a-



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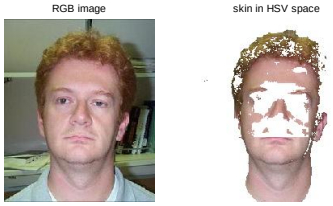

-c-

Fig. 9. Results of skin detetction : a-in RGB space; b- in YCbCr space; c- in Hsv space

Skin segmentation permits to get satisfactory results in the first controlled environment CE1 and the uncontrolled environment UCE in RGB space, whereas for the second controlled environment CE2 , we've got a lot of false detection. We've tested another threshold values for Cr and Cb component in YCbCr space. The following interval permits good skin detection:

$$140 \le C_r \le 165$$
$$140 \le C_b \le 195$$

The following figure shows segmentation results using the appropriate values of Cb and Cr in YCbCr space for the second controlled environment:

Fig. 10. Example of skin detection in YCbCrusing different threshold (2nd dataset CE2).

After a lot of tests, we've retained the RGB and the YCbCr spaces to build our face recognition, the choice of the color components in each space improves significantly the human skin detection. We have used the cropped facial images to decide the relevant values used for our purpose. We have implemented skin color detection according to rules 1 and 2 described earlier, we've demonstrated that the RGB system using the specified values (R,G and B) and The YCbCr with the specified values [Cr, Cb] provide good coverage of human races. In addition, results obtained in controlled environment are better than those in uncontrolled environment due to variations in lot parameters like illumination and background variation, etc.

B) Face Recognition System

After realizing the skin segmentation using the appropriate value of threshold to the components R, G, B, Cb and Cr for the corresponding color space, the characteristic facial vector corresponding to each channel will be used as a novel template vector. This reduction will be followed by another spatial reduction known as the principal component analysis PCA. After, the k nearest neighbor will used to decide the recognized person.

C) Nearest Neighbor Classifier

The skin segmentation is done for every individual and for all the facial images used, three databases are used for comparison between images taken under controlled and uncontrolled environment. Ten classes were used with twenty images for each individual and each facial database.

Training and a test matrix were constructed for the whole database of each environment; the k nearest neighbor classifier is used to find the proximity measure between template vectors (P1, P2, P3) of each training and test image.

However, we will find the face class k that minimizes the euclidian distance:

$$\varepsilon_k = \sqrt{\left\|\Omega_i - \Omega_K\right\|^2} \quad (2)$$

where Ω_K is a vector describing the kth face class. Ωi the training vector.

A face is classified as belonging to a certain class when the minimum ε_k is below some certain threshold. Results of face recognition system are shown in fig 11,12,13,14.

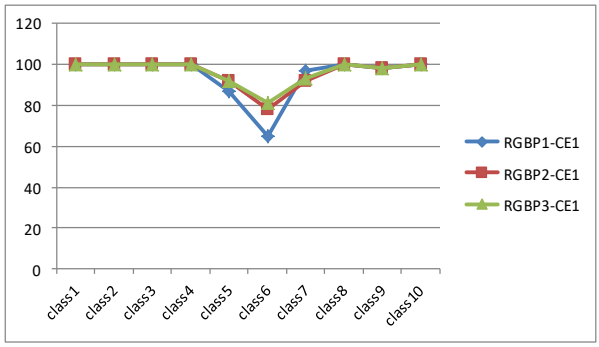

Fig. 11. RGB Recognition rate for k nearest neighbor classifier (1st controlled environment).

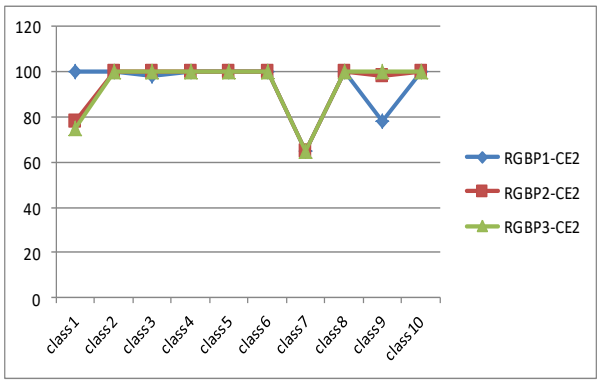

Fig. 12. RGB Recognition rate for k nearest neighbor classifier (2nd controlled environment).

We conclude that our skin detection model is appropriate for person parameterization; skin information is then a good feature descriptor.

Fig 10 and 11 show the efficiency obtained using RGB space in the 1st and 2nd controlled environement. Whereas Figs. 13 and 14 show recognition rate obtained in YCbCr space.

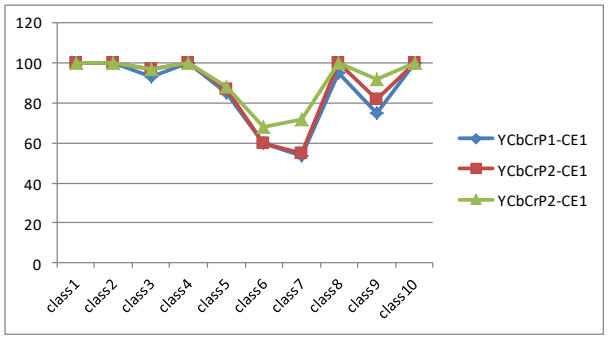

Fig.13. YCbCr Recognition rate for k nearest neighbor classifier (1st controlled environment)

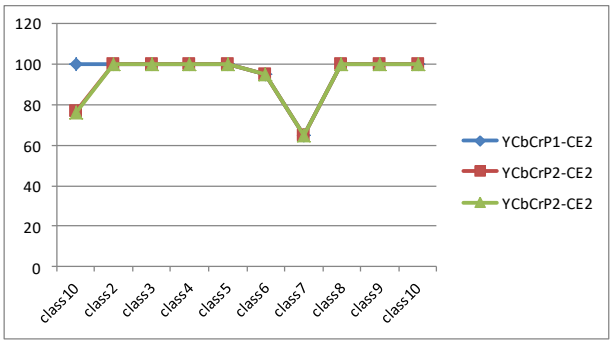

Fig. 14. YCbCr Recognition rate for k nearest neighbor classifier (2nd controlled environment).

Good recognition rate were obtained varying from 86% to 96% in CE1 and from 93% to 96% in CE2. We note that the images analyzed in the second controlled environment were taken by camera canon with resolution of 720*576 pixels in bmp format without compression, It can explain the correctness of the skin model in this database.

The Knn which is a simplest classifier permits us to have better efficiency, results presented in table 1 shows the detail of recognition rate obtained in each plane (P1,P2,P3) , whereas fig 11 to Fig14 show the variation of RR for each class. It's clear that the worst recognition rate was obtained for class 7 for the RGB and YCbCr parameterization of skin information.

TABLE 1. KNN RECOGNITION RATE

knn		**CE1**	**CE2**
	P 1	94.66 %	94.16 %
RGB	P 2	95.99 %	94.16 %
	P 3	**96.49 %**	94%
	P 1	86.16 %	**96%**
YCbCr	P 2	87.99 %	93.66 %
	P 3	91.66 %	93.33 %

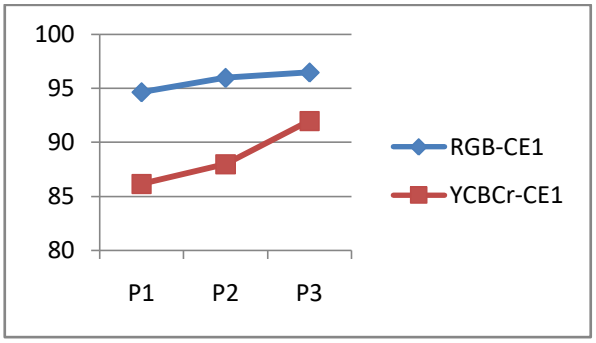

Fig. 15. RR for Knn classifier (1nd controlled environment).

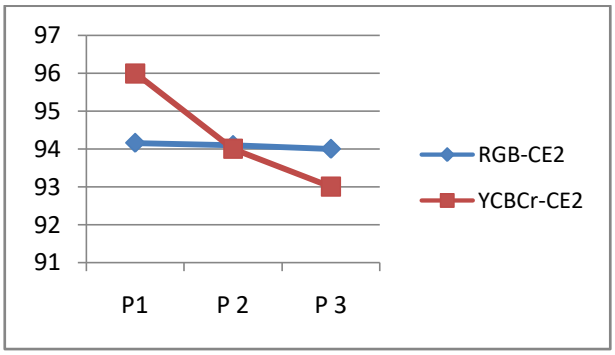

Fig. 16. RR for Knn classifier (2nd controlled environment).

The following paragraph try to demonstrate the efficiency of color space reduction by principal component analysis PCA applied for each plan P1, P2 and P3.

D) PCA-Knn Face Recognition system

Principal Component Analysis (PCA) is a dimensionality reduction which is used for compression and recognition problems. It is also known as eigenspace projection and closely related to popular signal processing technique known as the karhunen loeve transformation KLT [9]-[10]-[12]-[13]-[14].

The PCA basis vectors are defined as eigenvectors of the total scatter matrix ST of M images:

$$S_T = \sum_{i=1}^{M} (xi - \Psi)(xi - \Psi)^T \quad (3)$$

Ψ : The mean of all images (the average face).

x_i :the ith image with its columns concatenated in a vector.

Training phase: initialization of the system

Let the training set of M face images be $\Gamma_1 ; \Gamma_2 ; \Gamma_3 ..... \Gamma_M$, each vector Γ_i represents an image of size $N = n \times m$. The average face of the training is defined by:

$$\Psi = \frac{1}{M} \sum_{n=1}^{M} \Gamma_n \quad (4)$$

Each face differs from the average face by the vector

$$\Phi_i = \Gamma_i - \Psi \quad (5)$$

where i = 1 to M.

We rearrange then these vectors in a matrix $\phi = [\phi_i ..... \phi_M]$ of dimension $N \times M$.

The second step is to find a set of the M orthogonal vectors ui; which best describes the distribution of the input data in a least squares sense [10] .We find the covariance matrix C:

$$C = \frac{1}{M} . \sum_{n=1}^{M} \Phi^T{}_n . \Phi_n \quad (6)$$

The eigenvalues λ_i and the eigenvectors ui are obtained from covariance matrix. C is real and symmetric.λ is a diagonal matrix with eigenvalues on its main diagonal.

$$\lambda_i = \frac{1}{M} . \sum_{n=1}^{M} \mathrm{var}(u_i . \Gamma_n^T) \quad (7)$$

In PCA, we keep only the best k eigen vectors (with the highest k eigenvalues) (Turk&pentland, 1991[10,12].

A typical threshold is 0,9 (90 % of total energy). If we define Ei as the energy of the ith eigenvector, it is the ratio of the sum of all the eigenvalues up to and including i over the sum of all the eigenvalues: ([10]-[11]-[12]-[16][15]-[14]

$$E_i = \frac{\sum_{j=1}^{k} \lambda_j}{\sum_{i=1}^{M} \lambda_i} \quad (8)$$

Where M is the total number of eigenvectors or eigenvalues.We can then reconstruct faces in the new space with the best eigenvectors (respectively eigenvalues) that verify the equation:

$$[(\Gamma_i - \psi)]_{rc} = \sum_{k=1}^{L} [\Gamma_i - \psi]_{re} . u_{ik} \quad (9)$$

$[(\Gamma_i - \psi)]_{rc}$ means the reconstructed (projected) images.

$[(\Gamma_i - \psi)]_{re}$ means the real projection of initial images.

Fig 17 shows the variation of eigenvalues calculated from the covariance matrix. We use only six eigenvalues to reconstruct our images obtained from skin segmentation step. In such way, 92% of original information or energy was retained in those six eigenvectors.

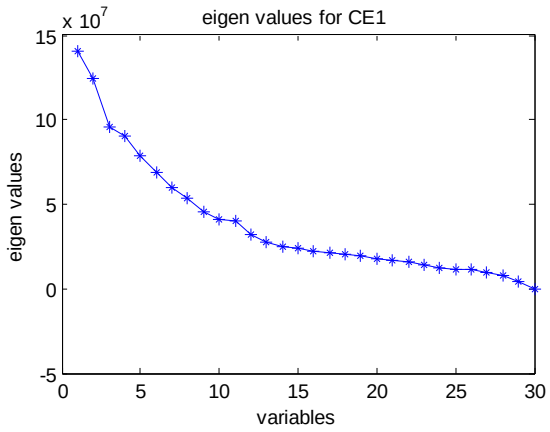

Fig. 17. Variation of eignenvalues from the 30 training images (1st controlled environment).

For each class or person we compute the matrix of prototypes by calculating the mean image in eigen face space, the corresponding matrix is called Ωk [15].

$$\Omega_K = \left[\Gamma_{moy1} \quad .....\Gamma_{moyK}\right] \tag{10}$$

The training images are projected onto the eigenspace by calculating the dot product of the image with each eigenvectors as described in equation 7.

Recognition phase :

After creating the eigenspace, we can proceed to recognition using eigenfaces. Given a new image of an individual (Γx), the pixels are concatenated as the same way as the training image after skin detection in RGB and YCbCrspace , where the mean image ψ is subtracted $\varepsilon_k^2 = \|\Omega_i - \Omega_K\|^2$ and the result is projected onto the face space:

$$\Gamma_{x\,projected} = \sum_{k=1}^{L}(\Gamma_x - \psi)u_{ik} = \Omega_i \tag{11}$$

This is the projection of an unknown face into the eigen face space. Ωi is then used to establish the predefined face class that best describes the new face. However, we will find the face class k that minimizes the Euclidian distance:

$$\varepsilon_k = \sqrt{\|\Omega_i - \Omega_K\|^2} \tag{12}$$

where Ω_K is a vector describing the kth face class. A face is classified as belonging to a certain class when the minimum εk is below some certain threshold [14][15]-[17].

Results of PCA-Knn classifier using skin detection in controlled and uncontrolled environment are presented in fig 18, 19, 20, 21.

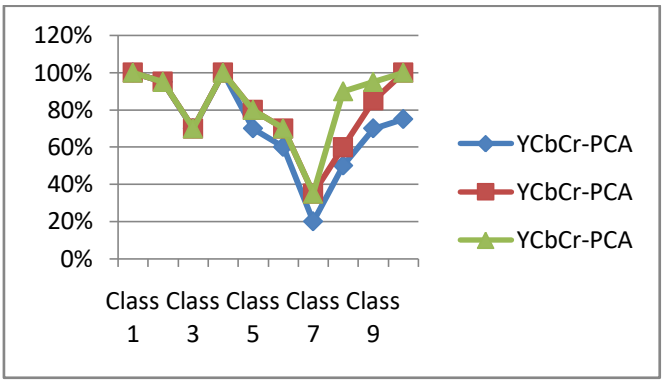

Fig. 18. PCA- Knn recognition rate in controlled environment (YCbCrCE1).

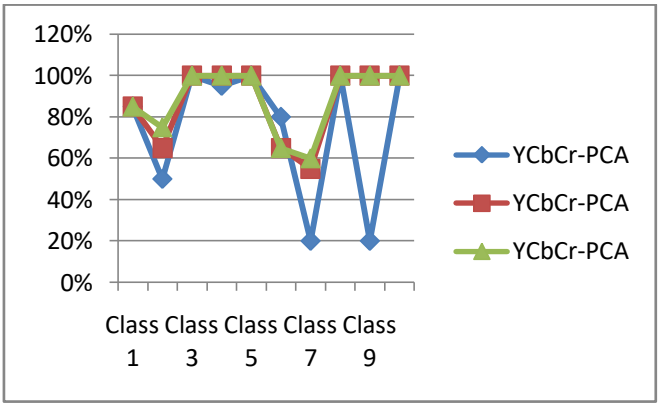

Fig. 19. PCA- Knn recognition rate in controlled environment (YCbCrCE2).

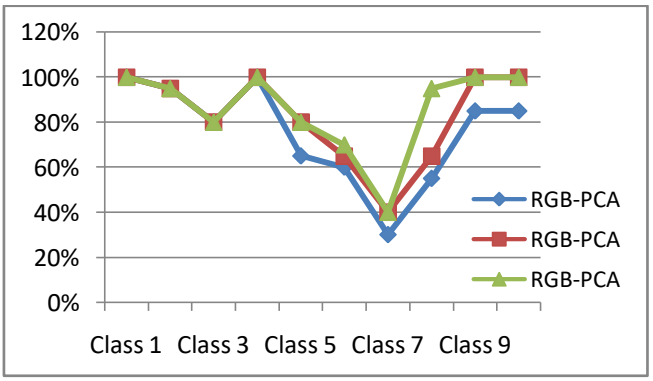

Fig. 20. PCA- Knn recognition rate in controlled environment (RGB-CE1)

Fig.21. PCA- Knn recognition rate in controlled environment (RGB-CE2)

We summary the total results obtained in table 2.

TABLE 2. PCA-KNN RECOGNITION RATE

PCA-Knn		CE1	CE2
	P 1	75.5 %	63.5 %
RGB	P 2	82.5 %	75.5 %
	P 3	86%	76%
	P 1	71%	75%
YCbCr	P 2	79.5 %	87%
	P 3	83.5 %	88.5 %

The following figures resume the results obtained.

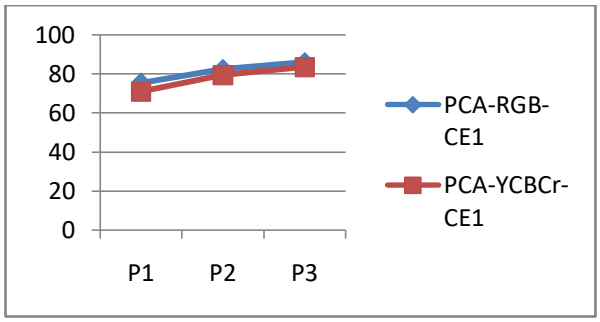

Fig. 22. RR for PCA- Knn classifier (1nd controlled environment).

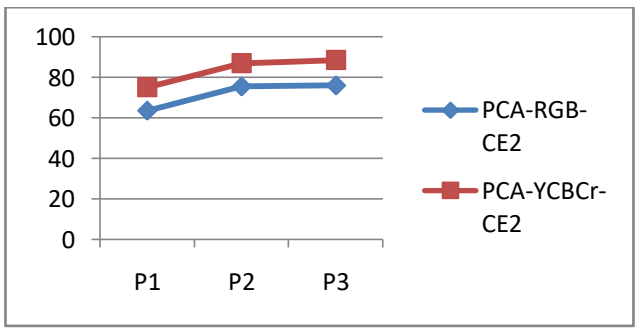

Fig. 23. RR for PCA- Knn classifier (2nd controlled environment)

The skin detection step is very important for the development of face recognition system. From the analysis of the results obtained with k-nearest neighbor and Principal component combined with knn, we noticed:

For the first controlled environment (CE1), good classification rate were obtained in RGB space compared with YCbCr space.

For the second controlled environment (CE2), skin detection is better in YCbCr space than RGB space, good recognition rate were obtained in YCbCr space, about 96%. We conclude that Knn classifier using Euclidean distance is efficient for human face recognition with skin segmentation.

We conclude that classification rate depends of the skin detection efficiency. This step depends also of a lot parameters like illumination variation, noise, background and the conditions of acquisition,etc.

Therefore, dimensionality reduction or image parameterization is a very important step which improves the performance of the facial recognition system based on skin detection.

Compared to literature, we can draw some conclusions:

Xuan et al[20] investigate in their work the use of eigen face and skin detection to build face recognition in video, the work is a combination of eigenface and adaptive skin color model. After skin region detection corresponding to frontal human face, eigenface technique is applied; video recognition achieves about 82% for CMUMobo database, 92% for PaxPlanck database and 100% for the XM2VTSDB database.

Padma Polash &al[19]present a robust approach for face recognition from video sequences where face detection uses modified skin color modeling to detect human skin regions. The obtained images are then projected onto a feature space defined by multilinear principal component MLPCA to produce a biometric feature template. Their system is tested two databases, they find best results using MLPCA and Euclidean distance about 97% for MIDTIMIT and 95% for AT&T databse.

For our work, we‘ve presented automatic face recognition for color images taken under different light conditions. We’ve demonstrated that skin color model improves the face detection performance, we’ve also demonstrate that Knn classifier applied on the segmented result images improve the system performance for face recognition compared to the combined PCA-Knn classifier. PCA is not always

optimal for face recognition especially when the dimension of database is important.

V. CONCLUSION

In this work, we have realized two face recognition system based on skin detection, the first used the k-nearest neighbor classifier applied for each component of the skin component, whereas the second used the Principal component as reduction method followed by knn classifier. We opted for the skin region segmentation of the color images in different spaces: RGB, HSV, YCbCr. After,we applied the two classifier described for the segmented images. After a lot of test, we decide to retain the RGB and YCbCr spaces for feature extraction based on results obtained from the spatial distribution of each colorThree data base were tested, two in a controlled environment with approximatively the same illumination conditions and background, the third database in an uncontrolled environment that present a lot of variation in illumination , pose and background.

The best results for skin detection were obtained in RGB and YCbCr spaces. We retained those for classification phase.The knn classifier applied on the segmented images permits us to get satisfied recognition rate from 91 to96 % for al the classes studied on the whole database.

PCA method permits us a reduction of the system but doesn't guarantee a good recognition rate compared to the simple knn classifier applied for the segmented images. Other non linear classifiers must be investigated in future work.

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