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Soft Biometrics Authentication:
A Cluster-Based Skin Color Classification System

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ABSTRACT

This manuscript presents the design of a new approach of human skin color authentication. Skin color is one of the most popular soft biometric modalities. Since a soft biometric modality alone cannot reliably authenticate an individual, this new system is designed to combine skin color results with other pure biometric modalities to increase recognition performance. In the classification process, the authors first perform facial skin detection by segmentation using the thresholding method in the HSV color space. Then, the K-means algorithm of the clustering method is used to determine the dominant colors on the skin pixels in the RGB model. Variations according to the R, G, and B components are recorded in a reference model to enable an individual's identity to be predicted on the basis of 30 clusters. Experimental results are promising and give a false acceptance rate (FAR) of 29.47% and a false rejection rate (FRR) of 70.53%.

KEYWORDS

Clustering Method, HSV Color Space, Image Classification, K-Means Algorithm, RGB Image, Skin Detection, Skin Dominant Colors, Skin Segmentation, User Authentication

INTRODUCTION

Adapted multi-biometrics consists of introducing ancillary data into the biometric authentication process to improve recognition performance. These ancillary data can come from the user, the sensor or the acquisition environment. If the ancillary data come from the user, this is called soft biometrics. Djara et al. (2019) have developed a typology of biometric adaptation. Within the wide range of biometric adaptation data, soft biometric data are increasingly being researched. Soft biometrics includes, but are not limited to, height, weight, gender, skin color, hair color, eye color, etc. (Dantcheva, 2011). Skin color is one of the most remarkable means of human differentiation and has been widely used to define human races (Jablonski & Chaplin, 2000). Among these soft biometric modalities, skin color appears to be relevant in terms of discriminatory power. As skin color is a soft biometric modality, it cannot by itself reliably authenticate an individual, but it can be merged with other pure modalities to create a robust multi-modal system. We propose through this manuscript a new approach of authentication by skin color classification.

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RELATED WORKS

Because of its various applications, Skin color detection and classification has been the major concern of many scientists. Detection can be used as a preliminary step in some computer vision applications such as nudity recognition on websites, face detection, skin disease detection, etc. Thus, in the field of skin color detection several works have been carried out through different approaches among which we can cite those of Singh et al. (2003) who used skin color detection for the localization of faces on images. For this purpose, they combined the three color spaces RGB, YCbCr and HSI to obtain a new face detection algorithm based on skin color, the experimental results of which show an accuracy of 95.18%. Later, Abd El-Hafeez (2010) proposed a system to detect skin color regions in images extracted from PDF documents. This system is based on log opponent and HSV color spaces which have been modified to improve detection performance. The results obtained indicate that the log opponent technique provides better skin color detection than the HSV space-based technique. In 2015, Kumar & Malhotra (2015) developed a skin color detection and recognition algorithm using a skin color mapping technique. This algorithm gives a promising result for the threshold value of Cb = [100, 127] and Cr = [130, 175] in the YCbCr color space. An approach based on dynamic detection thresholds has been proposed more recently by Patil et al. (2017). Experimental results obtained using their method give an accuracy of 0.9857. Based on a combination of RGB, HSV and YCbCr color spaces, Kolkur et al. (2017) developed a system for skin color detection. The developed algorithm is capable of processing images under various lighting conditions such as brightness, etc. The technique called RGB-H-CMYK, which uses three color spaces namely RGB, H (HSV hue) and CMYK was developed by Kumar et al. (2019) in 2019 who applied threshold-based rules in their method. Through different combinations such as RC (RGB and CMYK), RH (RGB and H) and RHC (RGB and H and CMYK), the input image in these three hybrid color schemes is explored and then each pixel is qualified as a skin pixel when at least two rules vote in its favor. This skin color detection technique gave an 89% accuracy in the experimental results. In 2020, Li et al. (2020), used an established Gaussian skin color distribution model to obtain candidate regions containing facial skin color in an image. Then they applied a cascade classifier to detect the skin color regions. The results obtained show that this technique can improve the detection of face in an image. The common feature of the works listed in this section is that they focus on skin color detection. However, after the skin color detection step, a second step dedicated to the skin color classification is essential if we want to achieve an authentication system by skin color. One of the challenges of the listed works is therefore the fact that they are limited only to the skin color detection step. As a perspective, it will be necessary to continue these works by adding the stages of classification and authentication by the skin color.

As for the classification of skin color, it can be used as metadata in the field of biometrics to verify the identity of individuals. In this field, Yoon et al. (2006) described an automatic skin color classification technique. This technique allows accurate modeling of skin tone non-uniformities, while avoiding contamination by hair, eyes, background and shadows. Four years later, Bhoya & Kakde (2010) presented a pixel-based skin color classification approach to detect skin and non-skin pixels in color images using a symmetric neural network classifier. Their classifier yielded a detection rate of over 90% with an average of 7% false positives. Even in the presence of several ethnic groups on the same image, their classifier is able to classify skin pixels. It is also worth mentioning the work of Bianco et al. (2015) in 2015 who developed a skin color classification method using automatic detection of faces and bodies in an image to adaptively initialize individual ad-hoc skin classifiers. Experiments resulting from their work show that the classifier is less dependent on changes in skin color due to tanning levels, race, gender and lighting conditions. Skin color classification can also be used to detect certain diseases such as skin cancer. In this field, we can mention the work of Qin et al (2020) who used GAN (Generative Adversarial Network) to synthesize images for skin lesion classification. Their GAN efficiently generates good quality skin lesion images allowing for improved classification pattern recognition performance. It should be noted that overall, these works related to skin color classification with a prior detection step, do not address the authentication step. This is a challenge that can be met by complementary works integrating the authentication step.

All these different methods, although having their advantages and disadvantages, have led to promising results in the field of skin color detection and classification. But none of these methods offers an authentication approach based on the results of skin color detection and classification. This observation constitutes the source of motivation behind this work which allowed in a first time to proceed to the detection of the skin color on face images. In a second step, we performed the classification of the skin color resulting from the detection step. Then in a third step we finalized the process of authentication of individuals on the basis of skin color.

MATERIALS AND METHOD OF THE APPROACH DEVELOPED

Database and Materials

Since we are in a context of face detection by skin color, a database containing grey scale images is not appropriate. This constraint contributed to the choice of the Caltech face database (California Institute of Technology, 2019). Collected at the California Institute of Technology, this database contains 450 JPEG images of 896x592 faces. These are captures of 27 unique people under different lighting conditions and backgrounds with varying expressions. After analyzing the data from this database, we can present the summary in Table 1.

Table 1. Database Information

Number of persons	Number of images
16	20 images at least
19	17 images at least
5	5 images exactly
2	1 image exactly
1	7 images exactly

We find that the database is not uniform in terms of the number of images per individual as shown in Table 1. In order to standardize the database for further work, we took the 19 individuals with at least 17 images and reduced them all to exactly 17 images. We used 12 images for model training (learning) and 5 for testing, 70.6% and 29.4% respectively. Thus, we have a total of 323 images of which 228 are used for model training and 95 for model testing. This database normally used for facial recognition will also be used in the skin color classification process. We present in Figure 1 a sample of images from this database showing, for example, the diversity in terms of expression and capture conditions. This is a homogeneous database of 323 images, all of which have been used either for training the model or for testing the model. In terms of skin color categories, it should be noted that the database is made up exclusively of people with white skin, including 17 Westerners and 2 Asians. This makes a total of 289 images of Westerners and 34 images of Asians. For the study of intra-class variations, we used images of 2 black skinned people. These images of the 2 black skinned people come from our own captures and not from the database used in this study.

To conduct the experiments, a laptop computer was used with the technical specifications summarized in Table 2.

Figure 1. Sample image (California Institute of Technology, 2019)

Table 2. Technical specifications of the computer used for the experiments

Features	Values
Processor	Intel Core i5
Processor frequency	2.3 GHz
Ram memory	4 GB

Face Detection

The first step in the skin color authentication process is the detection of the face in an image. Face detection and recognition from an image or video is a popular topic in biometric research (Madhuram et al., 2018). In this manuscript, face detection is performed using the python framework with the OpenCV (Open Source Computer Vision) package. This system contains three modules which are detection, training and recognition. Basically, the detection module detects the face that is on an image and then we select only the detected face area (area of interest) by cropping on this area. Face detection uses classifiers, which are algorithms that detect what a face is or is not on an image. Classifiers have been trained to detect faces using thousands or even millions of images to achieve greater accuracy. OpenCV uses two types of classifiers, LBP (Local Binary Pattern) and Haar Cascades. We use Haar Cascades classifier in the framework of this project. Haar Cascades uses the Adaboost learning algorithm, which selects a small number of important features from a large set to obtain an efficient classification result (Tabora, 2019). Figure 2 shows the characteristics that the Adaboost detection algorithm looks for in an image or video.

In Figure 3 we present some examples of face detections performed using the selected face classifier. Figures 3.A and 3.B are from the database described above, while Figures 3.C and 3.D are from our own captures.

Figure 2. Characteristics extracted by Adaboost (Tabora, 2019)

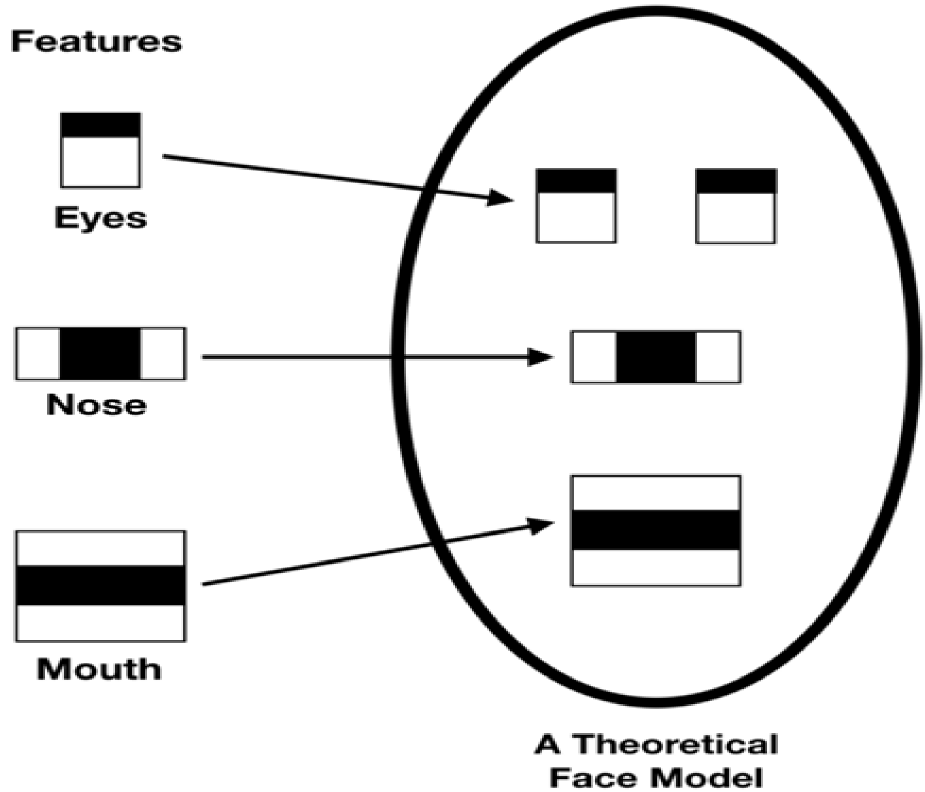


Figure 3. Faces detected and framed

Skin Detection

The rest of the process consists of making a skin detection on the image in order to eliminate all unnecessary parts and keep only the skin pixels. Skin detection is the process of searching for skin pixels and skin color regions on an image or video (Nikolskaia et al., 2018). Several works have been done in the field of detecting human skin on images or videos. In our system, after extraction of the face from an image, we obtain an image containing a large majority of skin pixels as shown in figure 3. Thus, the extraction of the face eliminates a large part of useless pixels. Due to variations in lighting conditions, sensor hardware parameters and the range of skin coloring in humans, a predefined skin color model cannot accurately capture the wide distribution of skin colors on individual images (Zhu et al., 2004). It is therefore necessary to select the appropriate color space.

Choice of Color Space

The choice of color space is very important in the skin detection process. When the standard RGB color space is used, skin detection can be very complex, difficult under varying lighting and contrast conditions. Therefore, the image must be converted to another color space that is invariant or at least insensitive to changes in lighting, such as HSV (Nikolskaia et al., 2018). The HSV color model is a cylindrical representation of the standard RGB model (Midha et al., 2014). HSV stands for Hue, Saturation and Value. Hue is measured in degrees and ranges from 0 to 360. It forms the base color. Saturation and value (brightness) determine how close white and black are to each other respectively. In the basic model, they range from 0 to 100, but in the OpenCV library used for the face detection step, they range from 0 to 255. To convert the image from the RGB to HSV model, each pixel of the image is subjected to the following transformation (Nikolskaia et al., 2018):

- The maximum and minimum values of R, G, B, C_{max} and C_{min} should be found and their difference M calculated;
- The Hue is calculated by the following formula:

$$H = \begin{cases} 0, & C_{max} = 0 \\ 60 \times \dfrac{G-B}{M}, & C_{max} = R \\ 60 \times \dfrac{B-R}{M} + 120, & C_{max} = G \\ 60 \times \dfrac{R-G}{M} + 240, & C_{max} = B \end{cases}$$

- Saturation is calculated by the following formula:

$$S = \begin{cases} \dfrac{M}{C_{max}}, & C_{max} \neq 0 \\ 0, & C_{max} = 0 \end{cases}$$

- Value is calculated by the following formula:

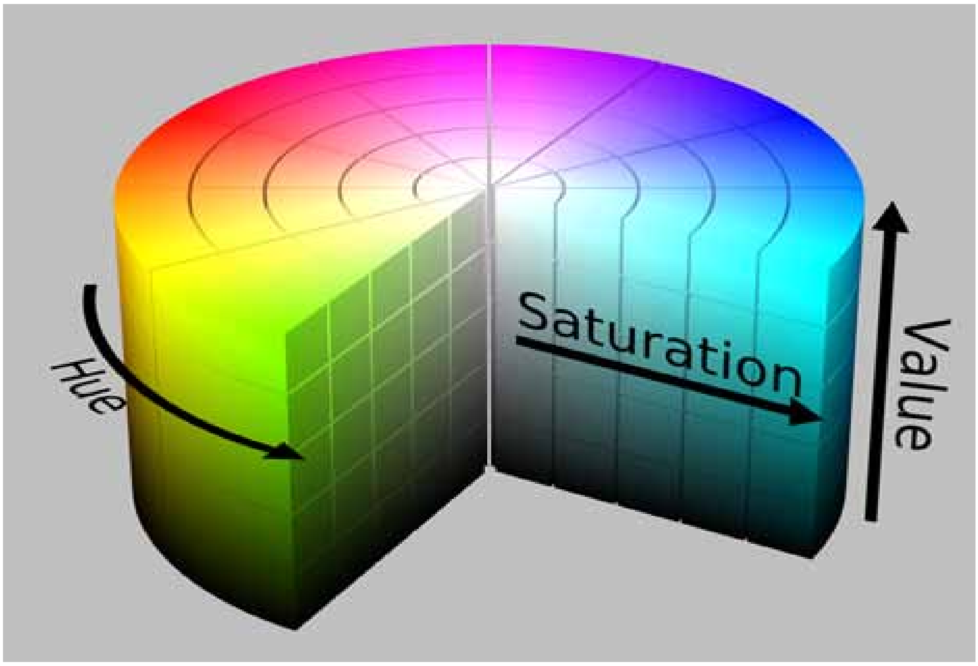
$$\boldsymbol{V} = \boldsymbol{C_{min}}$$

Skin Color Segmentation by Thresholding

Image segmentation is an image processing operation that aims at gathering pixels together according to predefined criteria. The pixels are thus grouped into regions, which constitute a tiling or partition of the image. Segmenting a color image can be extremely expensive. In order to simplify processing, a lot of researches have focused on image binarization. Global thresholding is one method of binarization. Global thresholding techniques attempt to find an appropriate single threshold value (

S) from the global image. Pixels are separated into two classes using the following equation (Fun & Chamchong, 2010):

Figure 4. HSV color model ("HSL and HSV," 2020)



$$I_b\left(x,y\right)=\begin{cases}0, if \ I_f\left(x,y\right)\leq S\\ 1, if \, I_f\left(x,y\right)>S\end{cases}$$

With x and y the pixel coordinates of the image, $I_f\left(x,y\right)$ the pixel of the input image and $I_b\left(x,y\right)$ the pixel of the binary image.

In our system a range of values represents the skin color and constitute a first class. The other values outside this range are the second class. According to formula 4, the pixels within this range (first class) are then kept and the others are eliminated. Thus, the segmentation of the skin is carried out using thresholding in the HSV color space using a predefined skin color range. Figure 5 shows some results obtained with this method. On the first line, we have the images of detected faces (area of interest) and below each input image, we have the image obtained after segmentation.

Extraction of Dominant Colors from The Skin

On the same skin, variations in color can be observed from one area of the skin to another. After detection of the facial skin, we then move on to the detection of the dominant colors on the skin. To achieve this, we use the K-means algorithm of the clustering method.

Figure 5. Skin threshold segmentation

Clustering

Clustering is one of data analysis methods. It aims at dividing a set of data into different homogeneous “packets”, in the sense that the data of each subset share common characteristics, which most often correspond to proximity criteria (computational similarity) that are defined by introducing measures and classes of distance between objects. Thus, clustering means the creation of groups of objects based on their characteristics in such a way that the objects belonging to the same groups are similar and those belonging to different groups are dissimilar (Velmurugan & Santhanam, 2010).

The K-Means Algorithm

This is the most widely used partition clustering algorithm (Aggarwa & Reddy, 2014). The k-means algorithm starts by choosing representative points as initial centroids. Each point is then assigned to the closest centroid based on a particular proximity measurement chosen. Once clusters are formed, the centroids for each cluster (group or class) are updated. The algorithm then repeats these two steps iteratively until the centroids do not change and no further convergence criteria are met. Given n data points $x_1 \ldots, x_n$ in R^p and a k-partition $C = \left(C_1, \ldots, C_k\right)$ of the set $O = \{1, \ldots, n\}$ of underlying ’objects’ with non-empty classes $C_i \subset O$, the criterion of variance or inertia is given by (Bock, 2008):

$$g_n\left(C\right) := \sum_{i=1}^{k} \sum_{i \in c_i} \| x_l - \bar{x}_{c_i} \|^2 \rightarrow \begin{matrix} min \\ C \end{matrix}$$

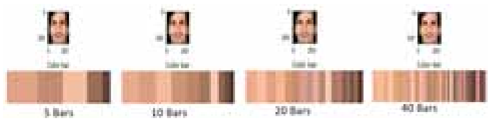
Where $\bar{x}_{c_i}$ denotes the centroid of the data points x_l “belonging” to the class C_i (i.e. with $\in C_i$). We look for a k-partition from O with the minimum value of the criterion $g_n\left(C\right)$. We’re talking about minimizing intra-class distance.

Figure 6 illustrates the process of group formation during the k-means algorithm.

Figure 6. Graph of the k-means algorithm flowchart

We use this clustering method to determine groups of skin pixels with similar colors. In order to have a good separation of the groups, the number of clusters should be well chosen. As a matter of fact, when the number of clusters is low, some normally different groups are forced to come together to form a new group and this does not allow a good separation of the groups. On figure 7, we have used for the same individual, different clusters and generated the color bars. We can see that the colors obtained vary and are better separated when the number of clusters increases.

Figure 7. Color variation according to the number of clusters



However, the increase in the clusters number also increases the program execution time. Table 3 shows that the execution time is approximately doubled when the number of clusters is doubled.

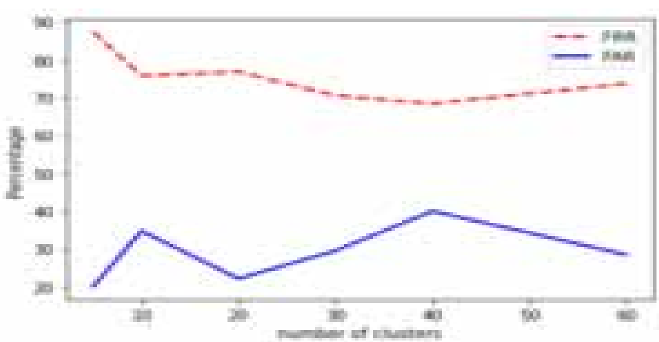
Table 3. Algorithm execution time as a function of the number of clusters

Number of clusters	Execution time in seconds
5	1.410046
10	3.229928
20	7.212621
40	14.290107

Choosing the Optimal Number of Clusters

For further experimentation, the number of clusters to be used for each image should be chosen. We have opted for the graphical determination of this number. The characteristic values of the false rejection rate (FRR) and false acceptance rate (FAR) were respectively measured for 10, 20, 30, 40, 50 and 60 clusters. The graphical representation of the curves of these two rates is shown in Figure 8.

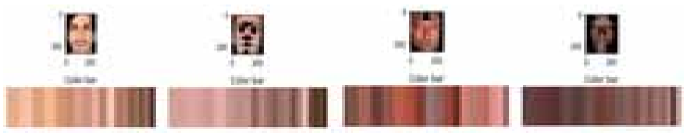
Figure 8. Evolution of error rates as a function of the number of clusters



In figure 8, we can see a proximity of the two curves at the level where the number of clusters is equal to 40. However, since the FAR rate is high at the level of 40 clusters, we choosed to use 30 clusters. Indeed, there is little variation in the FRR rate between the level of 30 clusters and the level of 40 clusters. On the other hand, the FAR rate is much lower at the 30 cluster level than at the 40 cluster level. This is what justifies our choice for the 30 clusters. Taking into account the execution time constraints in Table 3 and the analysis in Figure 8, we then used 30 clusters for the following implementation.

Then, the clusters are classified in ascending order of dominance on the skin. This way we get the dominant skin colors. We have illustrated some results for four individuals in Figure 9.

Figure 9. Extraction of dominant colors from the skin



Identity Prediction

In order to be able to predict an individual's identity, we first form a model that records useful information about each person's identity in a database. For an individual, skin color varies from one region of the face to another, although this color is influenced by lighting conditions as shown in Figure 10. Thus, for the same person, the R, G and B components of the dominant color on the skin may vary from one image to another. Therefore, it is not possible to record a fixed color value for a person. The variation in color implies a variation in the three components R, G and B. We then use the variation in the R, G and B components to predict an individual's identity. To create the model, we use the 12 images available per individual in the database and proceed as follows for each individual:

- For each image, the first 2 dominant colors are taken from each of the three components of the RGB color space. These values are stored in three different tables for the 12 images. Thus, each of the three tables contains 24 values per component, at the rate of 2 dominant colors multiplied by the 12 images.
- Then, the k-means algorithm is applied to each of the three tables in order to output two classes of values per table. The first class represents the low values and the second represents the high values. The centroid of each class is then selected. This allows to have per class a representative value characterizing the class. Thus, each of the tables gives two values which correspond to the useful information on each of the components of the RGB color space. These two values will make it possible to have a confidence interval following each of the components R, G and B.
- The two values obtained per component are recorded in the database for the individual. We then have a total of 6 values recorded in the model per individual.

Table 4 shows the values stored in the model for the 19 users contained in the database. In Table 4, on each row corresponding to an individual, the first two values represent the confidence interval for the R component, the next two values represent the confidence interval for the G component, and the last two values represent the confidence interval for the B component. Once the model has been created, the phase of predicting the identity of the individuals comes next. During identity prediction, the dominant color on the input face image is determined and it is checked whether at least two of the values of the R, G and B components obtained belong to the confidence intervals recorded in the model following each of these components.

Table 4. Data recorded in the model

[197, 218, 161, 195, 153, 180]
[219, 115, 84 , 162, 169, 68]
[162, 233, 195, 127, 197, 135]
[222, 69 , 127, 183, 178, 78]
[231, 35 , 200, 138, 186, 33]
[240, 220, 202, 173, 171, 202]
[221, 152, 209, 149, 188, 125]
[220, 70 , 180, 78 , 57 , 180]
[216, 85 , 179, 163, 175, 159]
[212, 237, 230, 206, 199, 178]
[241, 117, 205, 101, 213, 129]
[220, 74 , 142, 38 , 157, 87]
[230, 186, 178, 148, 169, 194]
[214, 235, 145, 182, 167, 197]
[241, 10 , 181, 12 , 7 , 202]
[222, 172, 134, 177, 187, 149]
[250, 242, 190, 218, 223, 203]
[231, 86 , 64 , 212, 72 , 212]
[216, 14 , 175, 4 , 180, 6]

Identity Prediction Algorithm Flowchart

Variables:

Let i be the set of individuals with $i = \left(1, 2, \ldots, \ n\right)$

Let x_{ij} be the set of images of individuals with $j = \left(1, 2, \ldots, \ m\right)$ and x_i the image of an individual

Let R_{ij}, G_{ij} and B_{ij} be the values of the dominant colors respectively according to the components R, G and B of the RGB color space

Let IR_{i0} and IR_{i1} be the bounds of the confidence interval for individual i following the R component of the RGB color space

Let IG_{i0} and IG_{i1} be the bounds of the confidence interval for individual i following the G component of the RGB color space

Let IB_{i0} and IB_{i1} be the bounds of the confidence interval for individual i following the B component of the RGB color space

Let R_i, G_i and B_i be the values of the dominant color for an image under authentication

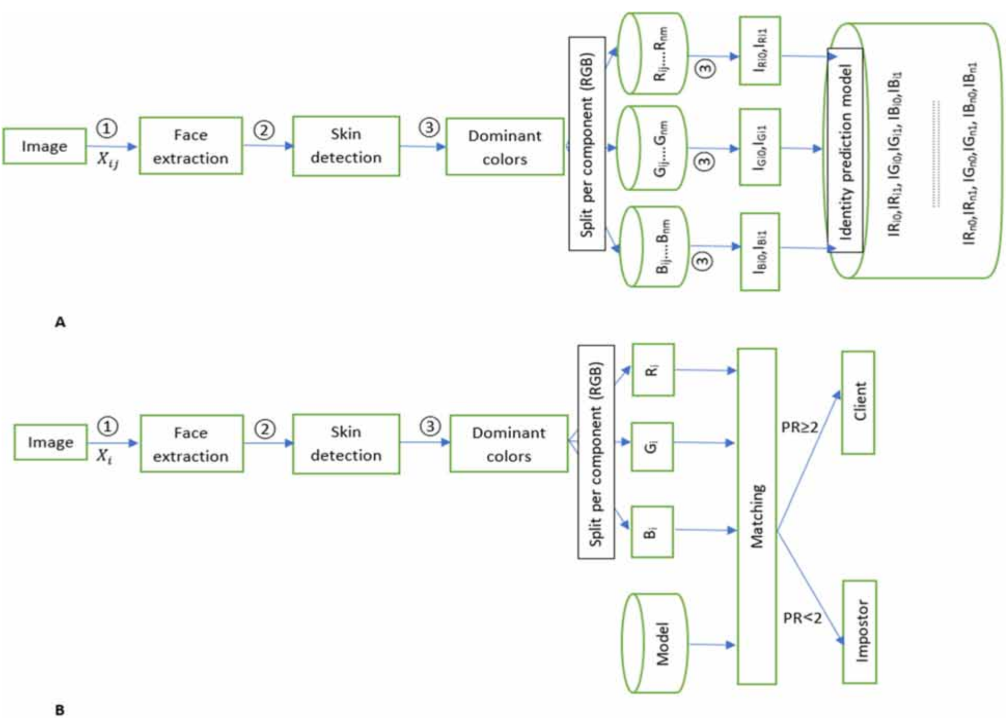
Let Y_R, Y_G and Y_B be the values characterizing the positions of R_i, G_i and B_i respectively with respect to the confidence intervals

With $Y_R = \begin{cases} 1, R_i \in \left[IR_{i0}, IR_{i1}\right] \\ 0,\ if\, not \end{cases}$; $Y_G = \begin{cases} 1, G_i \in \left[IG_{i0}, IG_{i1}\right] \\ 0,\ if\, not \end{cases}$ and $Y_B = \begin{cases} 1, B_i \in \left[IB_{i0}, IB_{i1}\right] \\ 0, if\, not \end{cases}$

Let PR be the probability ratio for the authentication of an individual with $PR = Y_R + Y_G + Y_B$
Symbols:

①: Haar Cascade operator
②:Segmentation by thresholding
③: K-means algorithm

Figure 10. Identity prediction model construction (A) and authentication process (B)



Effect of Intra-Class Variations

Intra-class color variations can be caused by factors such as the effect of age, tanning, depigmentation, lighting conditions, make-up, etc. Figure 11 illustrates these variations for three individuals. For each individual, two different images are used to extract the 30 dominant colors and their importance.

The resulting color bars show the difference between the two images even though they come from the same individual.

Figure 11. Different individuals' intra-class variation

Experimental Results

To evaluate the performance of the skin color classification system, we opted for the characteristic FAR and FRR error rates announced in section 3.4.2. Five (5) images per individual were used for testing the system by referring to the authentication procedure described in the section on identity prediction. We measure two parameters related to the error rates of biometric authentication systems (El-Abed, 2011):

- False acceptance rate (FAR): The proportion of impostor transactions accepted in error. For this rate we use 5 images of different people that we compare with the model of an individual. The operation is repeated for the 19 individuals present in the database. We obtained a rate of 29.47% for this parameter. For the computation of the false acceptance rate, we have 95 test images, 5 images for each of the 19 individuals in the database. For this rate, we compare the reference model of each individual to 5 different images of other individuals in the database. The results obtained give us a rate of 29.47% of individuals abnormally accepted by the system. Of all the users who will present themselves to the authentication system designed, 29.47% will be accepted by error. In practice, this means that the system makes few errors (in 29.47% of cases) in accepting impostors.

- False Rejection Rate (FRR): Proportion of legitimate users' transactions that are erroneously rejected. These transactions are rejected, by the matching algorithm, due to mismatching as well as those rejected due to acquisition failure. For this rate we use 5 images of the same person and compare them to the person model. The operation is repeated also for the 19 individuals present in the database. We obtained a rate of 70.53% for this second parameter. For the computation of the false rejection rate, we have 95 test images at a rate of 5 images for each of the 19 individuals present in the database. For this rate, we compare each image of the individuals to their reference model available in the database. The results obtained give a rate of 70.53% of abnormally rejected individuals. A user who presents himself to the designed authentication system will be erroneously rejected at a rate of 70.53%. This means that in 70.54% of the cases, a legitimate user will be rejected by the system. Nevertheless, the FAR and FRR rates are to be put into perspective because the skin color authentication system will in practice be combined with another authentication system using a pure biometric modality such as face or fingerprint. In terms of interpretation, we will take into account the error rates of the system resulting from the combination between soft biometrics and pure biometrics.

Discussion of Results

Skin detection was done by segmentation. The global thresholding method was used. It has the advantage of being quick to implement. There are several segmentation methods for the detection of human skin that give interesting results. Among others, we can cite the fusion method proposed by Tan et al. (2014) for skin detection. This method could provide better results. Furthermore, in our system we use the components of the RGB color space to authenticate an individual. We could have better results by using a combination of RGB, YCbCr and HSI color spaces as proposed by Singh et al. (2003). On another level, it is worth noting the significant effect of the factors causing intra-class variations. These variations are inherent to the Human being; this justifies the implementation of a weighting system as proposed by Jain et al. (2004) in 2004.

CONCLUSION AND FUTURE WORK

In this work we have developed a new system for authenticating people by skin color. This system is based on the clustering method, precisely the k-means algorithm. According to the obtained-results, we notice that the false rejection rate is very high (70.53%). This means that the system rejects a lot of people who should normally be recognized and authenticated. On the other hand, the false acceptance rate is relatively low (29.47%). These results are characteristic of high-level security authentication systems. However, it should be kept in mind that the system is not designed to be used in a single mode authentication approach. It is designed to be combined with pure biometric modalities (such as face, fingerprint, etc.) in a multibiometric approach. In perspective, we plan to implement a soft biometric authentication system based on skin color using a combination of RGB, YCbCr and HSI color spaces. Thus, it would be possible to make a comparative study between the use of a single colorimetric space on the one hand and the combination of several colorimetric spaces on the other hand. Another field of investigation will be the design of a system capable of circumventing the limitations related to the influence of external factors such as lighting conditions in order to improve skin detection. Once the skin color authentication system is in place, the next step in this work will be the implementation of the face and contactless fingerprint before combining the three modalities using the adapted sequential fusion algorithm proposed by Sobabe et al. (2019) in 2019. It will thus be possible to assess the level of contribution of skin color in improving the performance of the face and contactless fingerprint authentication system. The database used in this study contains a total of 323 images from people with white skin color only. We plan to extend this study by using a larger database containing faces with all skin colors of the human species. This will allow further refinement of the quality of the results obtained and their implementation in real life. Such a database could not be found at the beginning of the present study. It is therefore a challenge for the research community in soft biometric authentication.

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