Threshold Based Skin Color Classification

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***Abstract*—In this paper, we presented a new formula for skin classification. The proposed formula can overcome sensitivity to noise. Our approach was based multi-skin color Hue, Saturation, and Value color space and multi-level segmentation. Skin regions were extracted using three skin color classes, namely the Caucasoid, Mongolid and Nigroud. Moreover, in this formula, we adopted Gaussian-based weight k-NN algorithm for skin classification. The experiment result shows that the best result was achieved for Caucasoid class with 84.29 percent f-measure.**

***Index Terms*—Skin Segmentation; Image Noise; K-NN; Multi Skin.**

I. INTRODUCTION

Skin segmentation is an important feature of human faces. Using skin segmentation as a feature for tracking faces has several advantages. Human skin has consistent color, which is distinct from many objects and is highly robust to geometric variations of the face pattern [1]. Color allows fast processing and is invariant to face orientation, scale, stable against occlusions as well as person independent [2]. Skin color has proven to be a useful and robust cue for face detection, localization and tracking [3]. There are mainly two ways to build skin segmentation model: non-parametric skin modeling method (histogram model) and parametric techniques (single Gaussian and mixture of Gaussians models) [4]. The non-parametric methods are fast both in training and in classification as well as independent to shape distribution. The parametric methods can also be fast, and they have a useful ability to interpolate and generalize incomplete training data [5]. However, they can be really slow (like mixture of Gaussians) in both training and work, and their performance depends strongly on the skin distribution shape [6, 7].

The biometric recognition is fast becoming a suitable approach for grouping the human basics on their appearance physically, and by means of a defined identity. Each person in a common society might have similar racial aspects. This can be useful for different areas such as biomedical and archeological scholars, as they are studying ancient and ancestral images of humans in order to conveniently define them in terms of continent of origin [8]. The most popular system is the face recognition developed in areas such as trade centers, international airports, and the stadiums that operate passive recognition tasks, which go unnoticed by anyone being identified [9].

It is assumed accurate and nonintrusive. The facial images of individuals include information such as age, ethnicities, and genders. Gender and age of someone could easily be ascertained. Grouping them according to age will be difficult, and cannot be strategically standardized. If there is a primary knowledge of the suspect's skin color, there will be easier verifications/ Identification and generally involves shorter study times. Usually, it is an experiment developed by means of someone's presentation for facial verification(s)/ identification [10].

Skin segmentation is categorized into two groups: One is the model based approach and another is the Neural Network (NN) based approach (Ng and Pun, 2012). The model based approach tender to build up a standard skin color model, and this model is used to classify all skin pixels existing in image. However, this approach always causes error detection as the skin color diversity is affected by race, hence illuminating variation problem. Therefore, a skin color model could not conclude all of them completely. Another method is the Neural network based approach. This approach attempts to train a neural network by a huge skin pixel set. After the training, it enables to generate a skin probability map(SPM) of image and classify skin pixel from SPM. The NN based method is a robust approach, but the performance is mainly affected by the quality of training set and the NN based approach usually spends high calculation power [11].

II. CLASSIFICATION OF SKIN COLOUR

The aim of skin color pixel classification is to determine if a color pixel is a skin color or non-skin color. Good skin segmentation pixel classification should provide coverage of all different skin types (Caucasoid, Mongoloid, and Negroid) and cater for as many different lighting conditions as possible [12].

Categorizing the individuals according to physical aspects is never easy, and globalization has greatly heterogenized population. Further, by limiting the criteria to some of these traits for instance, the form and colour of hair, skin colour, shape of head, eye, node form and stature, many anthropologists agree with the three relative categories that are distinct in nature, which are the Mongoloid, Caucasoid, and Negroid [13].

The Caucasoid groups who are dominant in North Africa, Europe, and northern India to the Middle East are defined as pure white to dark brown skin, high and thin noses, tall to medium stature, medium lips, and broad or longhead shape. Meanwhile, the Mongoloid skin segmentation existed in China, East Indian, Japan, and neighbouring islands is defined by their straight and long black hairs, among other traits [14].

Different color spaces have been used in skin segmentation. In some cases, color classification is done using only pixel chrominance because it is expected that skin segmentation may become more robust to lighting variations if pixel luminance is discarded [15].

1. RGB: Colors are specified in terms of the three primary colour: red (R), green (G), and blue (B).
2. HSV: Colors are specified in terms of hue (H), saturation and intensity value (V) which are the three attributes perceived about color. The transformation between HSV and RGB is nonlinear. Other similar color spaces are HIS, HLS, and HCI.
3. YCbCr: Colors are specified in terms of luminance (theY channel) and chrominance (Cb and Cr channels). The transformation between YCbCr and RGB is linear. Other similar color spaces include YIQ and YUV.
4. CIE-Lab: Designed to approximate perceptually uniform colour spaces (UCSs), the CIE-Lab color space is related to the RGB color space through a highly nonlinear transformation. Examples of similar color spaces are CIE-Luv and Farnsworth UCS.

Tawny yellow skins, narrow and small skulls instead of flat sides, almond shaped and narrow eyes, low foreheads, and black and long hair are the attributes to define a particular group. Additionally, the most obvious aspects of Negroid in West Indies and Africa are darker skins, curly hair, and black crisps, along with high cheekbones and low foreheads, small and broad chins, broad flat nose, and white strong teeth. They are related to various races, and this fact has been used as a cue to recognize race from the face [13].

III. Classification Algorithm in Skin Color

Several algorithms have been proposed for skin color pixel classification. They include piecewise linear classifiers [16]; the Bayesian classifier with the histogram technique [12]; Gaussian classifiers [12]; and the multilayer perceptron [17].

A. *Piecewise Linear Decision Boundary Classifiers*

In this category of classifiers, skin and non-skin colors are separated using a piecewise linear decision boundary. Piecewise linear functions can be used to approximate non-linear decision boundaries between pattern classes. One hyper plane provides perfect separation when the convex hull of these pattern classes do not intersect [18]. Piecewise linear classifiers have a low memory demand and provide real-time classification. Furthermore, they are very simple to implement and do not contain any parameters which depend on the data set. These low requirements make them very suitable for those applications. However, in general, the determination of piecewise linear boundaries is a complex optimization task [19].

B. *Bayesian Classifier with the Histogram scheme*

The Bayesian decision rule for minimum cost is a well-established scheme in statistical pattern classification [20]. Using this decision rule, a color pixel x is considered as a skin pixel if.

$$p(x|\text{skin})/\text{p(x}|\text{nonskin)} \geq \text{T} \tag{1}$$

where p(X xj skin Þ and pð xj non-skin Þ are the respective class-conditional pdfs of skin and non-skin colors and is a threshold. The theoretical value that minimizes the total classification cost depends on the priori probabilities of skin and nonskin and various classification costs; however, in practice it is often determined empirically. The class-conditional pdfs can be estimated using histogram or parametric density estimation techniques.

C. *Gaussian Classifiers*

A parametric functional form, which is usually chosen to be a unimodal Gaussian or a mixture of Gaussians [21], approximates the class-conditional pdf of skin colors. In the case of the unimodal Gaussian model, the skin class conditional pdf has the form:

$$\begin{aligned} p(\mathrm{x}\,|\,\mathrm{skin}) &= \mathrm{g}(\mathrm{x};\mathrm{m}_s,\mathrm{C}_s) \\ &= (2\pi)^{-d/2}\,|\,C_s\,|^{-1/2}\,\exp\{-\frac{1}{2}(x-m_s)^T C_s^{-1}(\mathrm{x}-\mathrm{m}_s)\} \end{aligned} \tag{2}$$

where d is the dimension of the feature vector, ms is the mean vector and Cs is the covariance matrix of the skin class. If we assume that the non-skin class is uniformly distributed, the Bayesian rule reduces to the following: a color pixel x is considered as a skin pixel if:

$$(x-m_s)^T C_S^{-1}(x-m_s) \leq T, \tag{3}$$

where T is a threshold and the left hand side is the squared Mahalanobis distance. The resulting decision boundary is an ellipse in 2D space and an ellipsoid in 3D space. In this case, it can easily be shown that x is a skin pixel if :

$$(x-m_s)^T C_S^{-1}(x-m_s) - (\mathrm{x}-m_{ns})^T C_{ns}^{-1}(x-m_{ns}) \leq T, \tag{4}$$

where T is a threshold and m ns and Cns are the mean and the covariance of the non-skin class, respectively.

$$p(X\,|\,\mathrm{skin}) = \sum_{i=1}^{N_s} \omega_{s,ig}(x;m_{s,i},C_{s,i}), \tag{5}$$

$$\mathrm{P}(\mathrm{x}\,|\,\mathrm{nonskin}) = \sum_{i=1}^{N_{ns}} \omega_{s,ig}(x;m_{s,i},C_{s,i}), \tag{6}$$

The parameters of a Gaussian mixture (for example, weights ω, means m, covariance's C) are typically found using the Expectation/ Maximization scheme.

D. *Multilayer Perceptron*

The multilayer perceptron (MLP) is a feed-forward neural network that has been used extensively in classification and regression [12]. Compared to the piecewise linear or the unimodal Gaussian classifiers, the MLP is capable of producing more complex decision boundaries [10].

IV. Image Noise

Noise in image taking would result a noise that exists in the image, whereby the pixel values are not the exact intensities of real picture case. Noise makes an image to become grainy, rough, mottled or even with snowy appearance. On any digital image, the noise magnitude could be in the range between the almost gradual dot and a complete noise, which is known as pticalandradio astronomical images [22].

A. Gaussian Noise

A statistical noise which is also known as Gaussian noise would be uniformly spread over the signal which has become the major part of "read noise" imaging sensor such as in the case of a constant noise level found in dark surrounding of an image [23]. Gaussian distribution is the normal distribution of the Probability Density Function (PDF) of Gaussian noise. It acts as an additional white noise in Additive White Gaussian Noise (AWGN) [24].

B. Salt and Pepper Noise

Salt and pepper noise or the so-called spike noise refers to the fat-tail or impulsive noise distribution. If this noise presents in any image, it would yield dark pixels which are observed as black dots or black pepper particle in the bright region and vice versa for white dots or salt case in the dark region [25]. Median filter, morphological filter or contra harmonic median filter might be a few of the effective methods to get rid of this type of noise [22].

C. Speckle Noise

The speckle noise could cause image quality deterioration on the active radar as well as synthetic aperture radar (SAR) images. The speckle noise is unavoidable as it happens by nature. However, it could be avoided through adaptive and non-adaptive filters. It appears to be a granular noise which is at random, deterministic, and would create interference pattern in the captured image with a medium level of coherent radiation of sub-resolution scatters [26].

V. METHODOLOGY

The skin color classifier introduced in this research was based on Weighted K-NN algorithm introduced in [27]. K-NN algorithm is a non-parametric method employed in many researches for classifications and regressions. K-NN algorithm involves estimating the similarity between the input instance and the K-nearest available instances in the featured space. Each feature has a class label; therefore, the algorithm counts the number of instances belonging to each class. The classification result is the class with the maximum number of assigned instances. It should also be pointed out that all "K" encountered instances have equal votes. The weighted K-NN algorithm employs a similarity method to estimate the value of each instance's vote to improve the classification performance in the following manner,

$$class(x) = argmax \sum_{i=1}^{k} f\big(x, NN_i(x)\big)\delta\big(class(NN_i(x), j)\big) \qquad (7)$$

f(x,y) function estimates the value of each feature vote and δ(i,j)function is the Kronecker Delta function, defined as,

$$\delta(i,j) = \{(1, i = j@0, otherwise)\} \qquad (8)$$

f(x,y)is defined in this research in the following manner,

$$f(x, \mu = y, \Sigma) = 1/\sqrt{((2\pi)^3\ |\Sigma|\ )}\ \exp(-1/2\ (x - \mu)^{\wedge}T\ \Sigma^{\wedge}(-1)\ (x - \mu)) \qquad (9)$$

where x is the input instance and y is a feature instance, making them RGB vectors (R, G, B). The Gaussian-based weighted K-NN formula is improved, as follows:

$$Class(x) = \arg\max \sum_{i=1}^{k} \frac{1}{\sqrt{(2\pi)^3 \left|\sum\right|}} \exp(-\frac{1}{2}(x-\mu)^T \sum^{-1}(x-\mu)\sigma(class(NN_i(x), j). \qquad (10)$$

The system uses the dataset, including referenced face images that help determine the different skin classes, which is used to classify facial images. Feature vectors will be extracted from the images. The training data instances' skin classes are determined using the introduced classifier, where K is set to 10. During the training phase, the input data instances' class is determined, while the illumination normalization is also applied on the data instances. To apply the skin classification algorithm, the skin segmentation algorithm is applied to the image to extract face pixels, and then, the average of face pixels is calculated using simple mean function for each channel. The resulting color vector is passed to the classifier to determine the class label. Distances between the extracted feature vectors of image and feature vectors of the dataset will be calculated. Those values will be checked against Equation (10) to determine the label of each class.

VI. RESULT AND EXPERIENCE

Skin classification is another element that influences the F-measure rate. In the proposed scheme, three skin colors were included: Coucasoid, Mongolid, and Nigroud. These separate classifiers were separately trained for skin classes. Each input face image was passed to the classifier with the same skin class that was to be recognized. Table1 shows the F-measure rate for each skin class.

Table 1
F-measure rate for each skin class

Skin class	F-measure rate
Coucasoid	0.8429
Mongolid	0.838
Nigroud	0.8261

Caucasoid classifier shows the best results among the other skin classification. The results are illustrated in Figure 1.

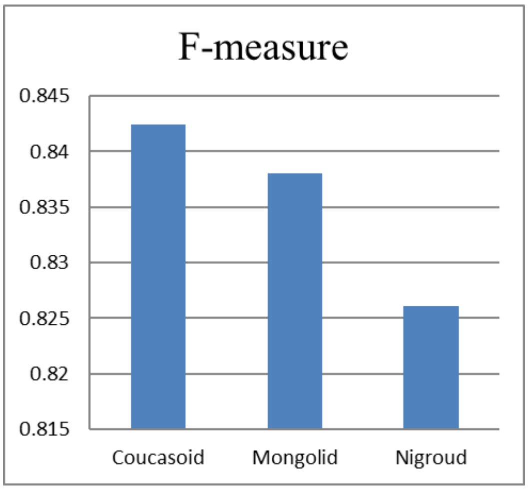

Figure 1: result of skin classification

Analysis of F-measure with different skin classifier

Differences in F-measure rate of skin classes were achieved due to different appropriation of the Equation (4) formula in skin classification for different skin colors. Cb and Cr values for Caucasoid image showed the best match in the formula because of our proposed formula can extract more accurate on different condition about image. Nigroud images revealed the least fit in the formula, thus the least accuracy was achieved for Nigroud images. The range of skin colors for Caucasoid images the best fit in the range which is mentioned in equation (1). However, Cb and Cr values for Nigroud images were distributed beyond the stated range. Therefore, classification for Nigroud images showed less F-measure.

VII. CONCLUSION

In this paper, we proposed a new formula for skin classification using a Gaussian-based weight K_NN algorithm. The excrement results show that the best result was achieved for Coucasooid while the lowest F-measure was achieved for Nigoud skin colour.

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