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Skin Classification for Adult Image Recognition Based on Combination of Gaussian and Weight-KNN

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Abstract — **Nowadays, literature has been explored adult image detection automatic which is a replacement for human action in the boring task of moderating online content. One of the mistake scenes with high skin exposure, such as people swimming and get a tan, can be have many wrong alarms. Some condition factors like illumination, occlusion, and poses are more important to image-recognize which any system has to able to recognize. Reasonable amounts of illumination variation between the gallery and probe images need to be taken into account in image recognition algorithms. In the context of image verification, two items are important; illumination variation and skin classification, and these two factors will most likely result in misclassification. There is a lack of research in combining two factors of imaging condition for illuminating and determining skin in image recognition system. The purpose of this paper is to determine and design the proposed scheme to solve illumination variation and integrate with skin classification in image recognition. The proposed method will be analyzed and evaluated based on its performance in terms of accuracy and effectiveness. In this paper, image processing is divided into two phases; preprocessing and image processing. We have used 8,650 images, which are imported from Compaq and Poesia datasets.**

Keywords - illumination;skin classification; imaging condition; conditions factors; datasets

I. Introduction

The quick growth of internet and social media led to a burst of image sharing and distribution globally. Although this phenomenon brought numbers of advantages such as ease of content development and sharing for educational purposes, some concerns were raised as well [1]; and a review on the list of journals publishing on uncontrolled environments shows that light might originate from different image angles [2];

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Chromaticity is an essential factor in image recognition and shows the intensity of the color in a pixel, but it can greatly vary depending on the lighting conditions [1, 3]. Therefore, people of different races can appear to have similar features. The value of the pixels not only varies with light changes; it also varies with the relation or variations between the pixels. As many feature extraction methods relay color/intensity/variability measures between the pixels to obtain relevant data, some researchers prioritize dependency on lighting changes [4, 5]. Different imaging conditions such as different faces, poses, or illuminations are some of these conditions that any practical facial recognition system should be able to recognize [6, 7]. The aim of skin color pixel classification is to determine the type of the color pixel of skin. The skin classification is applied to many biometric applicates such as face, hand, and skin segmentation. Pixel classification should provide coverage of all different skin types such as Caucasoid, Mongoloid, and Negroid [8, 9]. 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 [10, 11].

This paper consists of an introduction and other sections as follows: the related works are described in Section 2, the research methodology detailed in Section 3, the experiment itself explained in Section 4, and the conclusion in Section 5.

II. RELATED WORKS

Many current works have been carried out on the processing of illumination in image recognition [12, 13]. The techniques used for photometric normalization include the techniques used for carrying out the normalization of illumination before the actual processing stage, which is contrary to the methods used for compensating the appearances that have already been induced with illumination at the classification or modeling stage. Illumination normalization techniques are divided into categories of Illumination normalization, Illumination modeling and Illumination invariant feature extraction [14]. The Discrete Cosine Transform or DCT is an invertible linear transformation that can relate data points at a finite sequence based on the sum of cosine functions that oscillate at various frequencies. Several algorithms have been proposed for skin color pixel classification [12, 15]. They include piecewise linear classifiers; the Bayesian classifier with the histogram technique; Gaussian classifiers [16, 17]; and the multilayer perceptron. Skin segmentation is categorized into two groups: One is the model-based approach and another is the Neural Network (NN) based approach. The model-based approach tends to build up a standard skin color model and this model is used to classify all skin pixels existing in an image. However, this approach always causes error detection as the skin color diversity is affected by race, hence the illumination 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 using a huge skin pixel set [18]. Noise in image-taking would result in a noise existing in the image whereby the pixel values are not the exact intensities of the real picture case. Noise makes an image become grainy, rough, mottled or even take on a snowy appearance [19]. On any digital image, the noise magnitude could be in the range of almost a gradual dot until a complete noise appears, which is known as an optical and radio astronomical image [20].

III. RESEARCH METHODOLOGY

This research is the design and implementation of the scheme shown in Figure 1. The design is inclusive of the whole research, must be completed prior to its beginning, and involves preprocessing and image processing steps.

The steps used in this research can be classified into two steps: preprocessing and image processing. Auto contrast is designed to adjust the overall contrast in an image without adjusting its color. After auto contrast balancing is applied to the image, we need to reduce the noise on the input image as noises such as salt and pepper and speckle noises can affect the algorithms' efficiency. Therefore, the Wiener filter is applied to the input image in order to reduce noises. The Wiener filter is used to mean and variance statistical measures for filtering. This method is useful when the image information is poor and the foreground and background are either dark or overexposed.

There are two parts including skin classification and illumination normalization. Most of the facial recognition methods use geometrical features, which are efficient, but there is still room to improve on misclassification. It is a common problem in facial recognition systems due to the similarity of the features between different people, especially when the image lacks quality. In the case when a detected image is far from the camera, or when the size of the subject in the dataset increases, both factors increase the rate of misclassification. We handle these problems by introducing a race classification method. The results of this method are further used to eliminate irrelevant samples form the dataset in order to avoid misclassification of the images.

In the next step, the proposed image processing scheme adopts the Discrete Cosine Transform (DCT-II) normalization algorithm to enhance the image for the feature extraction method. The DCT-II algorithm omits the effect of illumination variation, which is a common problem in current facial recognition algorithms. In order to extract facial features, we have used a Singular Value Decomposition (SVD) feature extraction technique, and these extracted features will then be utilized to train a Hidden Markova Model (HMM) classifier.

The skin classification method proposed in this paper has been very sensitive to illumination intensity. Hence low or high illumination density can affect the result dramatically and due to the fact that the classification performance depends on the proposed method, an extra monitoring step is required to decrease the misclassification rate. In this paper, we have used two datasets, which are the Compaq and Poesia datasets.

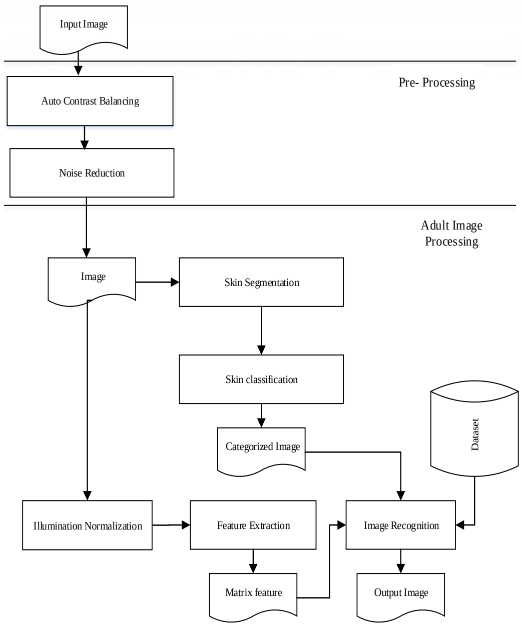

Fig.1 Research Framework

A. Auto Contrast Balancing

The first step of pre-processing is auto contrast balancing. This step tries to balance color channels using the Color Histogram Equalization method. The entire histogram is distributed with a range of pixel intensity values which is balanced by histogram equalization. By modifying the histogram in such a way, it can distribute the intensities over the scale of values available and could possibly extend the histogram with zero as the lowest intensity and the highest intensity as the maximum value.

Histogram equalization is a non-linear process. Channel splitting and equalizing each channel separately is incorrect because equalization involves intensity values of the image, not the color components. So for a simple RGB color image, histogram equalization cannot be applied directly to the channels. It needs to be applied in such a way that the intensity values are equalized without disturbing the color balance of the image. So the first step is to convert the color space of the image from RGB into one of the color spaces that separate intensity values from color components. YCbCr is preferred as it is designed for digital images. Perform histogram equalization on the intensity plane Y. Now convert the resultant YCbCr image back to RGB.

B. Noise Reduction

In the second step, we discussed the method adopted to reduce ambient noise, especially noises created as an effect of Auto Contrast Balancing, which was mentioned in the previous section. We experimented with the Wiener Filter technique to investigate their respective potentials in being applied for facial recognition systems.

The Wiener low pass filter has the best performance for image restoration. Its primitive assumption for all systems is the existence of speckle noise. As a matter of fact, the algorithm is used for removing speckle noises. The Wiener filter uses a pixel-wise adaptive Wiener method based on the statistics estimated from a local neighborhood of each pixel. Eq.(1) estimates the local mean and variance around each pixel.

$$G(u,v)=\frac{H^*(u,v)}{|H(u,v)|^2+\dfrac{P_n(u,v)}{p_s(u,v)}} \qquad (1)$$

Where,

H (u, v) = Degradation function

H*(u, v) = Complex conjugate of degradation function

Pn (u, v) = Power Spectral Density of Noise

Ps (u, v) = Power Spectral Density of un-degraded image.

The term Pn /Ps can be interpreted as the reciprocal of the signal-to-noise ratio.

C. Skin Segmentation

The first step in image processing phase is skin segmentation, which involves detecting image skins and extracting skin pixels. To do so, first, the image frame is converted toYC_b C_r,

YCbCr color space is widely used in image processing. In this format, luminance information is represented by a single component. Y and color information are stored as two color-difference components, Cb and Cr. Component Cb is the difference between the blue component and a reference value, and component Cr is the difference between the red component and a reference value.

$$Y=(0.299\times R)+(0.587\times G)+(0.114\times B) \qquad (2)$$

$$C_b=(B-Y)\times 0.564+135.0 \qquad (3)$$

$$C_r=(R-Y)\times 0.713+128.0 \qquad (4)$$

The converted YC_b C_r image is passed to the next step, which is the extraction of skin pixels. The skin pixels are extracted using following Eq.(5):

$$\left[\begin{array}{l} 85\le C_b\le 135 \\ 135\le C_r\le 180 \end{array}\right] \qquad (5)$$

D. Skin Classification

The next step is skin classification, which is an enhanced combination of the Gaussian-based-KNN algorithm is a non-parametric method employed in many types of research for classifications and regressions. The 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,

$$class(x)=\arg\max \sum_{i=1}^{k} f(x, NN_i(x))\,\delta(class(NN_i(x)), j) \qquad (6)$$

Where:

Class(x): returns the true class of instance x, and a hat on it indicates a prediction class.

K: the number of nearest neighbors used for prediction in k-NN.

NNi(x): the ith nearest neighbor with respect to an unlabeled instance x, i=1,2, …, k;

f (x, y): is a voting weight function that defines how much impact the nearest neighbor y has on x.

δ(class(x), class(y)): means that k-NN assigns an equal weight of one to each of the k nearest neighbors for the majority voting.

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

$$\delta(i,j)=\begin{Bmatrix}1 & i=j\\ 0 & otherwise\end{Bmatrix} \quad (7)$$

Therefore,

$$class(x)=\begin{Bmatrix}\arg\max\sum_{i=1}^{k} f(x,NN_i(x)) & i=j\\ 0 & otherwise\end{Bmatrix} \quad (8)$$

Gaussian kernel functions are chosen for two reasons. First, the Gaussian function is smooth and hence the estimated density function also varies smoothly. Second, if it is assumed that it is a special form of the Gaussian family in which the function is radially symmetrical, the function can be completely specified by a variance parameter only. Eq. (9) shows the Gaussian function.

$$f(x,\mu=y,\Sigma)=\frac{1}{\sqrt{(2\pi)^2|\Sigma|}}\exp(-\frac{1}{2}(x-\mu)^T\Sigma^{-1}(x-\mu)) \quad (9)$$

Where x is the input instance and y is a feature instance, making them RGB vectors (R,G,B). And μ is the mean

A Gaussian based-weighted K-Nearest Neighbor classifier was proposed, which is more sensitive to the minority class. The main idea is to first identify the minority class instances in the training data and then generalize them to the Gaussian function as a concept for the minority class. The approach is based on extending the decision boundary for the minority class. Eq. (10) shows the enhanced Gaussian-based- weight K-NN.

KNN= class(x)

$$class(x)=\arg\max\sum_{i=1}^{k} f(x,NN_i(x))\delta(class(NN_i(x),j))$$

Gaussian $=f(x,\mu=y,\Sigma)$

$$f(x,\mu=y,\Sigma)=\frac{1}{\sqrt{(2\pi)^2|\Sigma|}}\exp(-\frac{1}{2}(x-\mu)^T\Sigma^{-1}(x-\mu))$$

Gaussian based KNN= K-NN + Gaussian

Class(x) ' = KNN+Gaussian

$$=class(x+f(x,\mu=y,\Sigma)\delta(class(NN_i(x),j)$$
$$=$$

$$class(x)'=\arg\max\sum_{i=1}^{k}\frac{1}{\sqrt{(2\pi)^2|\Sigma|}}\exp(-\frac{1}{2}(x-\mu)^T\Sigma^{-1}(x-\mu))\delta(class(NN_i(x),j) \quad (10)$$

Thresholding is used for skin data detection in the YCbCr color system, therefore we need to change the image to this system and then delete all pixels which are out of a predefined range of data. The color vector is passed to the K-NN classifier when the mean of the extracted pixels is calculated from the vector (R, G, B). In this paper, weight-*K*-NN has been selected because weight *K*-NN has been considered to be a very well-organized classifier for minor datasets since it does not need to be trained and reliable. The *K*-NN classifier calculates the Euclidean distance of the color vector and all samples inside the database, where *K* is set to 50. Then it sorts the distances ascendingly. Further, it chose the *K* nearest distances. The Gaussian-based scoring system calculates a Gaussian value based on the sample distance from the vector, and the scheme calculates all the scores for each class label separately. The class label with the highest score is chosen to be the sample's label. The outcome of this step is a categorized image that represents one of the skin groups: Caucasoid, Negroid or Mongoloid.

E. illumination Normalization

Illumination variation in image recognition systems may cause decrement of performance. To solve this problem, we employed the (DCT-II) algorithm as an illumination normalization method. Illumination Normalization techniques perform some transitions on the targeted image to create a standard form without any illumination variation effects and discarding low-frequency DCT coefficients in the logarithm domain is equivalent to compensating for illumination variations.

F. Feature Extraction

The next step in image processing is feature extraction. Singular value decomposition (SVD) is adopted to extract features that are used to recognize a wide variety of images. A singular value feature is more effective in image recognition because a singular value feature is not sensitive to gray variation that occurs during the recognition process and can overcome the impact of some other factors such as illumination variation, noise, pose and other factors. There are three major perspectives facing SVD features, which are: first, SVD can be assumed to be a method of transforming correlated variables into a set of uncorrelated ones, exposing the various relationships among the original data items more efficiently; second, SVD is a method used to identify and order the data dimensions along which data points exhibit the most variation; and third, once we have identified where the variation is highest, it is possible to determine the best approximation of the original data points using fewer dimensions. Hence, SVD can be seen as a method for reducing data.

SVD feature extraction deals with singular matrices, which may be very close to being singular. They are regarded as an extension of Eigen decomposition that suits non-square matrices. Any matrix may be decomposed into a set of characteristic eigenvector pairs called component factors, while their associated eigenvalues are called singular values. The SVD equation for an (m × n) singular matrix A is A=UΣV^T, where U is an (m × m) orthogonal matrix, V is an (n × n) orthogonal matrix, and Σ is an (m × n) diagonal matrix, containing the singular values of A arranged in a decreasing order of magnitude. A vector in an orthogonal matrix can be expressed as a linear combination of the other vectors. The vectors in this space are thus also mutually independent, and a solution for x can now be calculated. The equation for Singular Value Decomposition (SVD) needs to be further explained by showing the significance of the eigenvectors and the singular values.

G. Image Recognition

This is the last step in image processing. An experiment has been done using the HMM technique to investigate their respective potentials in being applied to image recognition systems.

Regarding using a Hidden Markov Model as a recognition engine, it is a statistical Markov model, where the system being modeled is assumed to be a Markov process with unobserved (hidden) states. An HMM can be presented as the simplest dynamic Bayesian network.

IV. EXPERIMENTS

This paper has used 8,650 images from two datasets, which are the Compaq and Poesia datasets. These images include adult images and normal images. 70 percent of these images are used for training and the rest are used for testing as we are focused on the problem of illumination in this paper. In statistical analysis, the F-measure is a measure of a test's accuracy expressed as a percentage. It took into account both Recall "R" and Precision "P" of the evaluation results to compute the score. Precision and Recall are the basic measures used in evaluating search strategies. Recall is the ratio of the number of relevant records retrieved to the total number of relevant records in the database. Precision is the ratio of the number of relevant records retrieved to the total number of irrelevant and relevant records being retrieved. It is expressed in the form of percentages where a higher percentage indicates higher accuracy. (Eq. (11) and (12)) approached precision and recall,

$$P = TP/(TP+FP) \qquad (11)$$

$$R = TP/(TP+FP) \qquad (12)$$

A True Positive (TP) occurs when an instance is correctly predicted to be in class i; it is counted as a True Positive, while TN occurs when an instance is correctly predicted not to be in class i; it is counted as a True Negative.

TP	:	True Positive
FP	:	False Positive
FN	:	False Negative
TN	:	True Negative

A FP occurs when an instance is wrongly predicted not to be in class i, where it is regarded as a False Positive, and finally, a FN occurs when an instance is wrongly assigned to class i, where it is regarded as a False Negative. By using these measures, the F-measure score can be calculated by Eq. (13).

$$\text{F-measure} = \sum_{i=1}^{N} \frac{2n_i}{N} \frac{\text{precision}_i.\text{recall}_i}{\text{precision}_i+\text{recall}_i} \qquad (13)$$

Where i is the class index,n_iis number of signals encoded by class i, and N is the total number of received signals.

A. Skin Cclassification Evalution

Skin classification is another element that influences the F-measure rate. In the proposed method, there are three skins; Caucasoid, Mongoloid, and Negroid. These separate classifiers are separately trained for skin classes. Each input image is passed to the classifier with the same skin class that is to be recognized. Table 1 shows the F-measure rate for each skin class.

Table 1: F-measure rate for each skin class

Skin Class	F-measure rate
Caucasoid	0.903
Mongoloid	0.893
Negroid	0.886

Differences in the F-measure rate of race classes are achieved due to different appropriations of the Eq. (10) formula in race classification for different s. Cb and Cr values for Caucasoid images shows the best match in the formula because of our proposed formula can extract more accurate features on different conditions about these images. Negroid images reveal to fit in the formula least and thus the least accuracy is achieved for Negroid images. The range of s for Caucasoid images is the best fit in the range which is mentioned in reduce the noise in the input image Eq. (5). However, Cb and Cr values for Negroid images are distributed beyond the stated range. Therefore, classification for Negroid images shows a lower F-measure.

B. Analysis of F-measures with Different Illumination Algorithms

An illumination algorithm includes illumination normalization to prevent illumination variations. The following normalization algorithms are tested in order to determine the method with the highest performance for these algorithms, where Discrete Cosine Transform (DCT-II), Single Scale Retinex (SSR), and Differences of Gaussian (DOG). In Table 2, the F-measure rates are measured and running time using all the illumination variation algorithms. DCT-II and SSR exhibited superior performance compared to DOG. The SSR and DCT-II have the minimum computation time compared to other methods, but because the DCT-II algorithm exhibited superior performance, we employed DCT-II for illumination normalization.

Table 2: F-measure rate and running time for each skin class

Illumination algorithm	F-measure With 70% training rate	Running time per each sample
DCT-II	0.903	0.032
SSR	0.87	0.031
DOG	0.82	0.051

The DCT-II illumination algorithm demonstrated the best results with an F-measure of 0.903 compared to the other tested illuminations algorithms. The results are illustrated in Table 2, Because illumination variations mostly lie on low-band frequencies, applying DCT to discard the appropriate number of DCT-II coefficients will result in the minimization of variations under different lightening conditions. This is akin to setting DCT-II coefficients to zero. SSR makes the details in the images more prominent. DoG enhances the contrast via histogram equalization. Although this method is very effective, its ability to handle extreme or uneven illumination variations is rather limited.

C. Analysis of Wiener Filter

In order to determine the best combination of noise reduction filters and illumination algorithms, all possible combinations were tested using 20 similar experiments. Table 3 shows the results of F-measures for the combinations of Wiener noise reduction filter with DCT-II, SSR and DoG algorithms. The best accuracy was obtained from the combination of Wiener noise reduction filter and DCT-II illumination algorithm because it shows the highest medium value and the range between the minimum and maximum for the results among the achieved values of experiments is low. On the other hand, the combination of Wiener noise reduction filter and (DOG) illumination algorithm resulted in the highest values for maximums in the experiments, but the range between the minimum and maximum values of experiments is quite large, making the combination unsuitable. Table, 3 shows the F-measures of the maximum, minimum and medium of 20 test experiments for combinations of Wiener filter and illumination normalization.

Table3: F-measure of maximum, minimum and medium of Wiener with different illumination normalizations

Algorithm	Minimum	Maximum	Medium
Wiener /DCT-II	90.300	91.070	90.68
Wiener /SSR	89.989	90.790	90.38
Wiener /DoG	85.876	92.143	89.09

The combination of Wiener noise reduction filter and DOG illumination algorithm shows the maximum and minimum value of 92.143 and 85.876 among other tested combinations of algorithms illustrated in Fig. 2.

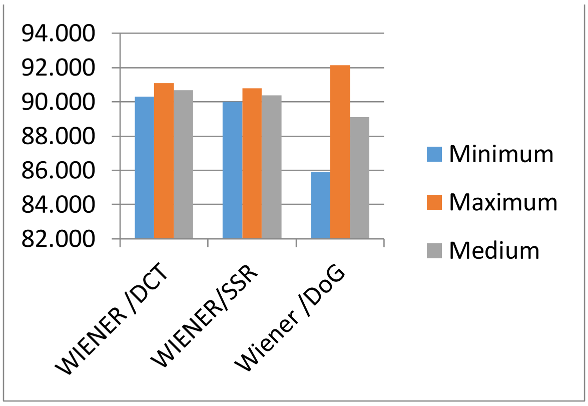

Fig. 2: Combination of wiener noise reduction filters with illuminations normalization

V. Conclusion

This paper presents an adult images recognition method by utilizing the combination of Gaussian and weight-KNN. The proposed method has been analyzed and evaluated on the basis of performance in terms of accuracy and effectiveness. In this paper, image processing is divided into two phases. The first is the preprocessing phase. There are two preprocessing phases comprising of auto contrast balance and noise reduction. The second phase is image processing, which contains five steps; illumination normalization, feature extraction, skin segmentation, skin classification, and image recognition. We have used 8650 images selected randomly from the Compaq and Poesia datasets. The paper proved that illumination variation and integration with skin classification in an image recognition method will improve the accuracy of the F-measure by 90.3 percent.

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