ROTATION INVARIANT SKIN DETECTION APPROACH BASED ON COMBINATION OF PROBABILISTIC DISTRIBUTION ESTIMATION AND SINGLE SCALE RETINEX

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ABSTRACT: Skin detection is one of the main steps in many image processing systems such as face detection, human identicaton, etc. Since now, many methods are proposed to done it accurately. Most of previous methods have tried to find best match intensity distribution with skin pixels in input image. Experimental Results show that these methods cannot provide accurate results for each kind of human skin colors. In this paper, a two step approach is proposed to solve this problem using color probabilistic distribution estimation technique. The proposed approach consist two steps. In the first step, skin intensity distribution is estimated using some train photos of pure skin. In the second step, the skin areas are detected using Gaussian model and optimal threshold tuning. Single scale retinex technique is used as preprocessing step to increase detection rate. In the result part, the proposed approach is applied on human images and the accuracy rate is computed. The proposed approach can be used for all kinds of skin using train stage which is the main advantages of it. Low sensitivity to impulse noise, low run time complexity, and rotation invariant are another advantages of the proposed approach.
KEYWORDS: Skin detection, Probabilistic Estimation, Threshold tuning, Image Processing, Gaussian Model

1. INTRODUCTION

Image processing is one of the efficient sciences, which play an important role in very applicable and industrial projects. In many of these projects, a skin detection step is needed to get accurate results. Face detection, human identification, hand gesture recognition, web searching, image retrieval, artificial image database filtering are some of these projects. Hence, many methods have been proposed to detect skin yet. Some of them are used RGB color space to solve this problem such as [PBC03, KMB07 and SSA04]. Some of the researchers used other color spaces such as YC_bC_r [HMJ02], HSV [Q+04], CIE LUV [HMJ02], Farnsworth UCS [WY99]. As a common theory in well known skin detection algorithms, most of them tried to find the combination of intensity ranges between color channels which are match by real skin pixels in input images. Texture information of skin area is another type of features which has been proposed to solve skin detection. Wu et al. used wavelet filters for skin analysis and detection [WY99]. Content based image retrieval technique is used in [FST12] and histogram models proposed in [JR02].

There are various kinds of skin colors between real humans. White, black, approximately red or green are some popular skin kinds. An important issue here is detecting all color kinds of skins accurately. Noise resistant, run time complexity, illumination intensity are some other challenges in this problem. Related works are not robust enough to this challenges specially kinds of skin.

We proposed an approach in this paper to solve these issues. The proposed approach consist two main steps and a preprocessing one.

In the first step, some images are provided which include just pure skin pixels in terms of different color types. Next, mean and standard deviation of the input train images are computed to estimate the probability distribution of skin pixels. It is done for each color channels of RGB color space individually. In the test stage, for all of the test pixels, the probabilistic P (Test(i,j)|Skin) is computed using Gaussian model in which one of the RGB channels individually. Finally, using an accurate and separable threshold can detect skin pixels in test images.

Experimental results are provided using two different databases: hand captured and ICPR database. Detection rate, sensitivity and specificity are main measures which are computed to evaluate the performance of the proposed method. The proposed approach provides 89.62% detection rate on ICPR database which is higher than many other approaches in comparison. High detection rate shows the quality of proposed approach. Some other advantages of the proposed approach are as follows:

a) Adaptability to most color kinds of human skin because of using train step

b) Low complexity in computation and run time

c) Low sensitivity to illumination by using tunable threshold

The proposed approach is a general one which can be used for two class classification problems such as defect detection. In the section 6, defect detection is done based on this approach.

1.1 Paper Organization

Next sections of reminder of this paper are as follows: Section two is related to the estimation of skin distribution. Section three is related to the description of using Gaussian model to estimate distribution of skin pixels. Section 4 has a brief description about how tune the Bayesian threshold for optimal point. In section 5, a preprocessing step is described to improve the detection rate based on single scale retinex algorithm. Section six provides a general theory to use proposed skin detection algorithm for surface defect detection, and finally, results and conclusions are included.

2. ESTIMATE OF SKIN DISTRIBUTION

The aim of this paper is to detect skin areas in test images using train step. In the train step, proposed system should learn the skin features. In this respect, some pure skin images should be provided. In the Figure1, a pure skin image which can be used as train step are shown.

(a) (b)

Fig. 1. Cropping Pure Skin Areas
(a). Original Image (b). Pure Skin Area

The intensity distribution of pure skin images can provides discriminate features. In this section, an algorithm is proposed to estimate the intensities distribution of color face images. The main theory of the proposed approach is based on estimating skin distribution. Gaussian model can be used to estimate an statistical distribution just like skin pixels. Hence, first of all some train images which contains just pure skin pixels, should be provided.
In [AML08], Akhloufi et al. are proved that study RGB channels individually can provide discriminative features. Akhloufi et al. [AML08], are computed statistical features such as mean, entropy, energy, standard deviation, etc from Red, Green and blue histograms individually to classification the textures.

In order to model a Gaussian distribution for skin pixels, *mean* and *standard deviation* should be used. The well known previous researches show that intensity range of skin pixels in color channels is too different. So, a Gaussian model should be estimated for each color channel of input pure skin image separately. It is shown in equations (1) and (2), for Red channel.

$$\mathrm{Mean(R)} = {}^{1}\!/_{\mathrm{n} \times \mathrm{m}} \sum_{\substack{0 \le i \le m \\ 0<j<n}} \mathrm{P(i,j,RED)} \qquad (1)$$

$$\mathrm{STD(R)} = \sqrt{{}^{1}\!/_{\mathrm{n} \times \mathrm{m}} \sum_{\substack{0 \le i \le m \\ 0<j<n}} (\mathrm{P(i,j,RED)} - \mathrm{mean(R)})^2} \qquad (2)$$

Where, P(i, j, RED) means the intensity of pixel in i_{th} row and j_{th} column of input image in red channel. Also, *m* and *n* are the size of train image. By using a similar way, the Mean and STD in green and blue channels can be computed. Now, three different Gaussian models are built on each color channels. These can be used as a good identification for pure skin in human facial train images. In order to built Gaussian models, just mean and standard deviation are used. In order to compute the mean and standard deviations, whole image is considered rather than local features. So, the proposed approach is not sensitive to rotation.

3. GAUSSIAN MODEL FOR SKIN CLASSIFICATION

Skin detection can be considered as a visual two class classification problem. So, in this step the aim is to detect skin pixels in test images using train information.
We know that, each pixel in test image can be "skin" or "not". We used a gaussian model to estimate skin distribution in previous section. Here, the probability skin being of pixel coordinates (i,j) (*P(Test(i,j)|Skin)*) should be computed.
In order to estimate *P(Test(i,j)|Skin)*, by assuming independency assumption between RGB channels, we have equation (3).

$$\mathrm{P\ (Test(i,j)|\ Skin)} = \mathrm{P\ (R_{Test}(i,j)|Skin)} \times \mathrm{P(G_{Test}(i,j)|Skin)} \times \mathrm{P\ (B_{Test}(i,j)|Skin)} \qquad (3)$$

Where, P $(\mathrm{Test}_t(i,j)|$ Skin) shows the probability that pixel (i,j) in test images be skin. Now, Gaussian model can be used to compute the probability estimation between RGB channels and Skin distribution. Equation (4) shows these algorithms. Where Gaussian function is the Gaussian distribution and R, G and B are test pixels intensities in each channel.

$$P(Test(i,j) \mid skin) = Gaussian(R_{Test}(i,j), Mean_{R(Train)}, STD_{R(Train)}) \times Gaussian(G_{Test}(i,j), Mean_{G(Train)}, STD_{G(Train)}) \times Gaussian(B_{Test}(i,j), Mean_{B(Train)}, STD_{B(Train)}) \quad (4)$$

Where, P(Test(i,j)|Skin) shows the probability that pixel (i,j) be skin.
$R_{Test}(i,j)$, $G_{Test}(i,j)$ and $B_{Test}(i,j)$ are intensity value of pixel coordinate (i,j) in red, green and blue color channels.
$Mean_{R(Train)}$, $Mean_{G(Train)}$, and $Mean_{G(Train)}$ are mean intensities of red, green and blue channels that are computed for pure skin images in train step.
$STD_{R(Train)}$, $STD_{G(Train)}$, and $STD_{G(Train)}$ are standard deviation of color channels that are computed for pure skin images in train step.
Also, Gaussian(X, Mean, STD) shows the Gaussian distribution for input x that can be computed using equation (5). The STD is the square root of an unbiased estimator of the variance of the population from which X is drawn, as long as X consists of independent, identically distributed samples.

$$Gaussian(x, mean, STD) = \exp\left\{-0.5 \times \left.(x - mean)^2\right/_{STD}\right\} \quad (5)$$

Finally, a threshold should be computed for probability to classify skin pixels from non-skin pixels. Pixels which have probability (equation (4)) more than threshold are skin and the pixels with probability value less than threshold are not skin. Threshold optimizing algorithm is described in next section.

4. THRESHOLD OPTIMIZATING

Using a threshold, after computing probability of all test pixels, can finalize the skin detection algorithm. In this respect, calculating an accurate and severable threshold is necessary.
In order to find optimize threshold, it's easy to compute the probability of each train pixels P (Train(i,j) |Skin) using equation(6), and finally choose the lowest computed probability as optimal threshold for skin detection.

Threshold = Minimum {P (Train(i,j) | Skin) **|** For Each Train pixels**}**

Where,
P (Train(i,j) | Skin) $= Gaussian(R_{Train}(i,j), Mean_{R(Train)}, STD_{R(Train)}) \times Gaussian(G_{Train}(i,j), Mean_{G(Train)}, STD_{G(Train)}) \times Gaussian(B_{Train}(i,j), Mean_{B(Train)}, STD_{B(Train)})$ (6)

P (Train(i,j) | Skin) shows the probability that pixel(i,j) be skin in train image.

It will be provide the ability to classify every colors of skin in common and homogeneous images. In Figure 2, skin detection is done based on some various thresholds and then they are compared by tuned optimal threshold.

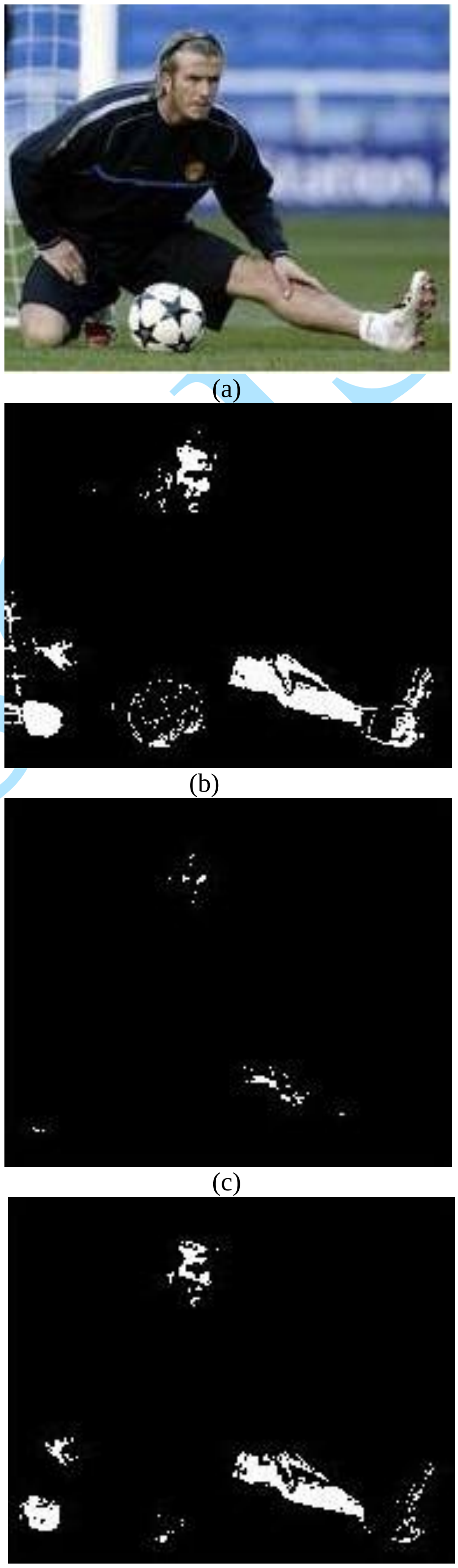


Fig. 2. (a) Original image (b) Threshold less than optimal (c) Threshold more than optimal (d) Optimal Threshold

5. IMAGE NORMALIZATION BASED ON SSR

Land and McCann [LM71], proposed an idea that each image is the product of two elements, illumination L(x, y) and reflectance R(x, y).

$$I(x, y) = L(x, y) . R(x, y) \quad (7)$$

Reflectance contains information about the main objects in image. Illumination contains geometric properties of the scene. Reflectance information is more important than illumination in image processing applications. So, the reflectance of the objects should be very similar to the original manner. Illumination varies slowly in different locations of the image but reflectance may be changes rapidly than illumination in the same locations. There is a basic assumption here that reflectance information may be far from original manner due to illumination effects. So, illumination should be drastically reduced due to the high-pass filtering, while the reflectance after this filtering should still be very close to the original reflectance. The reflectance can be also found by dividing the image by the low pass version if the original image, which is representing illumination components.
Land et al [LM71] proposed a technique called retinex, as combination of the cortex and retina. The most interesting point for illumination normalization is the assumption that perception depends on the relative or surrounding illumination. It means that reflectance R(x, y) equals the quotient of image I(x, y) and the illumination L(x, y) calculated by the neighborhood of I(x, y). It improves the visibility of dark object while maintaining the visual different of the light area.
In 1997, Jobson et al, [JRW97] proposed an algorithm to estimate illumination of a local neighborhood. The proposed algorithm by [JRW97] is called signal scale retinex (SSR).
In SSR, first a Gaussian kernel is defined to estimate the local illumination of interested neighborhood. Next, the logarithmic transformation is used to compress the dynamic range of interested local neighborhood. Finally, reflectance image can be computed using the following equation.

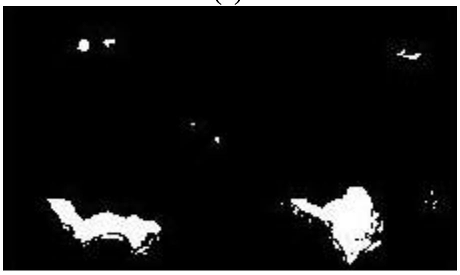
$$\mathbf{SSR(x, y)} = \log I(x, y) - \log [F(x, y) * I(x, y)] \quad (8)$$

F(x, y) shows the surrounding Gaussian function. Also, (*) denotes the convolution operation.
Single scale retinex algorithm has a high power for image normalization especially enhancement of objects in dark areas. SSR has been used as a preprocess step in different cases such as face recognition [Les10], image enhancement [C+08] and stoned porosity detection [TF14]. SSR can be used in our skin detection case as a preprocess step for normalization of the human facial images.
Results shows that using a preprocess image normalization stage based on SSR can improve the skin detection rate of proposed approach. In most of the inspection systems, the light source location, shine orientation, camera set are not the same. So, the captured images may be different in contrast, brightness and illumination. Regarding to this problems, a preprocessing step like image normalization is necessary. So far, many various techniques have been proposed for normalizing images, Such as gamma intensity correction [GW02], Block based histogram equalization [XL05], Homomorphic filtering, Adaptive histogram equalization [PA87]. According to the following reasons, SSR technique is used in this paper.
I) In the train step, Gaussian model is applied on the whole image. Also, Single Scale Retinx normalizes the illumination in the whole image regardless many other normalization techniques. Hence, the basic features which are extracted from the pure skin images have are more accurate.
II) According to the section (2), the Gaussian distribution estimation describes global contrast of an image.SSR normalizes the entire contrast. So, the performance of the estimation operator may be increased.

6. PROPOSED APPROACH FOR SURFACE DEFECT DETECTION

Visual surface defect detection is an active topic research for image processing scientists. The main issue of surface defect detection is same with skin detection. Different surface types can effect on performance of the detection system just like different skin color types. The proposed approach can be used for defect detection, because of using a train step. Of course, that is not design especially for defect detection problems. But some of the results are showed that it can be efficient in some cases such as stone porosity detection.
If train images, provides of absolutely non-defect images. It is easy to estimate distribution of the absolutely non-defect pixels. After this, according to section 3, using gaussian model in each channel and estimation the probability of test pixels can detect the defects. Figure 3 has been shows some of the results by applying proposed approach on stones.

(a)



(b)

Fig. 3. (a) Original image of stone with porosity (b) Defect Detection after applying skin detection approach

7. RESULT

According to the previous skin detection approaches, there is not a popular database of skins to evaluate the performance of its methods. Some of the researchers provide a database for itself by digital camera. Some ones use benchmarks which are provided for face identification or pose detection as test set. In this respect, in order to prove the quality of proposed approach, two different datasets are employed.

7.1. Hand captured database

50 images are captured by a digital camera with resolution 12 megapixels. Different skin color types are considered in hand captured database. The proposed skin detection approach is applied on them. Accuracy rate is computed using detection rate measure (equation (9)). Skin detection and surface defect detection can be categorized in visual two class classification problems. One of the efficient measures to evaluate performance of these problems is detection rate (equation 10). In [BBK00] and [TKS08], the authors are used this criterion to compute the accuracy rate for texture defect detection approaches. The detection rate equation (9), is used in [FT12] for surface defect detection, and respectively for texture classification [Fek12]. Many previous state-of-the-art skin detection approaches such as [FST12] and [KMB07], are used these criteria to evaluate their efficiency and performance.

$$Detection\ Rate = 100 \times \left(\frac{N_{DD}+N_{SS}}{m*n}\right) \quad (9)$$

Where, n and m are the size of test image. N_{SS} means the number of really skin pixels which detected as skin and N_{DD} means the number of pixels which are not skin and the proposed approach don't detects them as skin.

The accuracy rates for the entire test images in hand captured database is computed 90.73 ± 0.2. In order to compute the standard deviation Pair T-Test method is used.

High detection rate shows the power of our proposed approach to detect skin parts of input images in terms of every kind of human color skins. So, it can be used in many applications, which are needed a skin detection process. Low complexity in computation and run time are some of other advantages of the proposed approach. Using a train stage is provide, various skin kinds detection ability. According to the section 4, proposed approach can be used for skin kind's classification in complex images also. Complex images mean the images which are included two or more kinds of skins. Some of the visual results are shown in Figure 4. Some other methods such as wavelet filtering, histogram analysis and Gabor filter are applied on test images, and the results are compared by proposed approach in terms of detection rate, which is shown in the Table 1.The Sensitivity (equation (10)) and specificity (equation (11)) were measured for all of the skin detected results. Where TN, TP, FN and FP are means true negative, true positive, false negative and false positive. These are shown in Table 1.

$$Sensitivity = \frac{TP}{TP+FN} \quad (10)$$

$$Specificity = \frac{TN}{TN+FP} \quad (11)$$

7.2. Face recognition ICPR database

There are many benchmarks to evaluate the performance of face recognition or facial identification methods. Some researchers in skin detection scope use these databases to evaluate their quality and performance. In this respect, ICPR database is chosen here as a test dataset. ICPR consists of 15 sets of images. Each set contains of 2 series of 93 images of the same person at different poses. There are fifteen people in the database totally. Some features of the ICPR dataset are as follows:

- Wearing glasses in some images
- Various skin colors
- Different pose orientation
- Different head directions

The proposed approach is applied on this database images and detection rate is computed. The result is shown in table 2. The comparison results of some state-of-the-art skin detection methods are shown in table2 too using ICPR dataset. As it can be found, detection accuracy rate of the proposed approach on ICPR dataset is less than hand captured dataset. It may be occurred because of higher variety of pose or skin colors in ICPR. Some of the visual results on ICPR images are shown in Figure 5.

Table 1. Skin detection rates using Hand captured database

Approach	Detection rate	Sensitivity	Specificity
Proposed Approach	**90.73±0.2**	**89.17± 0.3**	**91.54± 0.2**
Statistical Features [JR02]	81.22±0.9	79.54± 0.7	82.81± 0.8
Structural Features [PBC03]	88.62±0.8	85.32± 0.3	89.01± 0.5
Image retrieval technique [FST12]	89.47±0.6	89.28± 0.7	91.02± 0.6

Table 2. Skin detection rates using face recognition databases

Approach	Detection rate	Sensitivity	Specificity
Proposed Approach	**89.62 ±0.4**	**88.41± 0.4**	**89.92± 0.5**
Statistical Features [JR02]	77.96± 0.6	79.54± 0.8	79.55± 0.7
Structural Features [PBC03]	87.76± 0.6	82.29± 0.4	87.90± 0.4
Image retrieval technique [FST12]	88.91± 0.5	87.83± 0.3	89.75± 0.2

CONCLUSION

The aim of this paper was to propose an accurate approach to detect skin in color human facial images. According to this aim, an approach is proposed based on combination of probabilistic distribution estimation techniques and single scale retinex. The proposed approach included two steps. In the train stage, system learned the pure skin intensities distribution using mean and standard deviation of some pure skin images. In the test stage, the skin area of the test image was detected using a Gaussian model. In the result part, the detection rate was compared by some well known methods in this literature. Results proved the performance quality of our proposed approach for skin detection. Some other advantages of the proposed approach can be numbered as follows:

A. The proposed approach can be used to detect every colors of skin. It's enough to train intensities distribution of desired skin color by using some pure skin images in desired color.
B. The proposed approach is a general visual areas classification that can be used for some other image processing applications such as surface defect detection, image segmentation and etc.
C. The computational complexity of proposed approach is low, because of using train step one times in all cases
D. Sensitivity of our proposed approach to impulse noise is low. In the distribution estimation technique, the whole image is considered rather than local features. So, little impulse noises on pixels cannot disturb entire mean or standard deviation
E. The extracted feature vector in section 2 is rotation invariant. Because of using mean and standard deviations as feature dimensions.

FUTURE WORK

One of the good directions for future works may be to analysis this approach in other color spaces like HSV or YC_bC_r. Also, using relation between each pixel and his neighbors may provide more severability between skin and non-skin pixels.


(a)

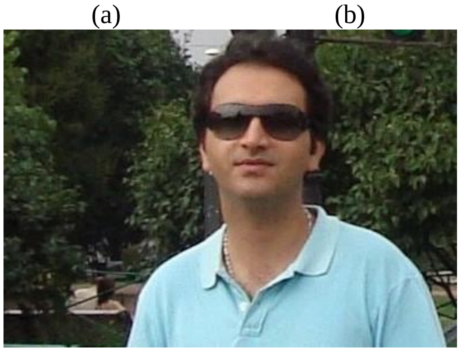
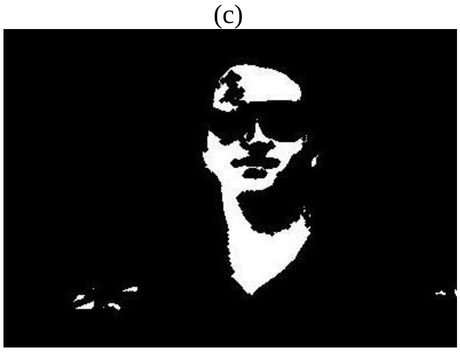
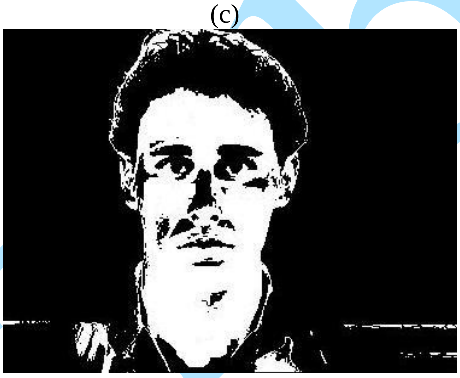
(b)

(c)

(d)

Fig. 4. (a) Original Image (b) skin detected using proposed approach (c) Original Image (d) skin detected using proposed approach

(a)

(b)

(c)



(d)

Fig. 5. (a) Original Image (b) skin detected using proposed approach (c) Original Image (d) skin detected using proposed approach

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