Facial Skin Monitoring System Based on Image Processing

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Abstract. The facial skin quality tester can give reasonable skin care recommendations for the replication situation, so it has a broad market prospect. The current domestic testers have shortcomings such as single detection function, low detection accuracy, complicated operation, expensive price and large volume. This paper studies the image processing algorithm for skin quality index detection, including oil and pigment detection based on HSV color space, pore detection based on dual threshold segmentation and morphological operations, and roughness index detection based on gray-level co-occurrence matrix. And based on the CBS-1800 detection system as the standard, the skin quality index detection algorithm in this paper has been effectively verified.

Keywords: Facial Skin, Oil Detection, Pigment Detection, Pore Detection

1. Introduction

With the progress of society, the value of appearance has become the criteria for selecting talents by major companies. Therefore, people pay more attention to appearance. People hope to have healthy skin, not only free of diseases, but also moist and bright skin. Skin diagnosis and care methods have been diversified, and a more accurate and effective method for assessing skin conditions is needed. Existing diagnostic tools and management do not have sufficient evidence to prove their effects. So far, skin diagnosis has been carried out by dermatologists based on their personal experience and knowledge, so the diagnosis results of different dermatologists may be different.

There are very few researches related to pore detection algorithms. Literature [1] indicates that fast fuzzy mean clustering algorithm can be used to realize pore detection by first zooming in on the original image, and then using the global brightness method to analyze the pore pattern. Perform equalization, then segment the image, and finally use the fast fuzzy mean clustering algorithm to calculate the position of the pores. Literature [2] detects nasal hair follicles based on the relationship between the direction of the eigenvector corresponding to the maximum eigenvalue of the Hessian matrix and the direction of the gradient, and the module image of the nose of the face needs to be input first. Nazre Batool et al. proposed a mark-point process wrinkle detection algorithm based on retrograde Markov chain Monte Carlo [3], Zou Yaobin proposed a data-driven and model-driven hybrid control strategy algorithm [4].
Aiming at the problems existing in the current market skin detectors and combining customer needs, this paper studies a human facial skin detection and analysis system with high accuracy, easy operation and diversified detection indicators. The system detects pores, oil content, roughness, pigment and skin color on the collected skin images, and comprehensively evaluates the skin. It can quickly and easily analyze people's skin conditions, so as to detect anytime and anywhere. It is convenient for everyone to choose later skin care products and evaluate the efficacy of long-term skin care products.

2. Skin Image Preprocessing

2.1. Image Acquisition
The skin image in this article was taken with Galaxy A3 (SM-A310NZKAKOO, Samsung Electronics Co., Ltd.), the camera specification is 1.3MP back camera, aperture F1.9, 8-bit color image. In order to obtain the skin image, we take a 2.0x image at a certain distance from the moving camera. The object of this study is healthy non-smokers, aged between 20 and 60 years old. The captured images are facial skin images. The skin texture and age changes can be confirmed with the naked eye. Because the moving camera is affected by the light when collecting the image, it is necessary to preprocess the image, including histogram equalization, Gaussian smoothing filter and morphological transformation.

2.2. Grayscale Processing
The collected skin image is a 24-bit full-color skin image. For the calculation of the program, the color image will greatly increase the time complexity of the algorithm, which is not conducive to ensuring the operating efficiency of the program. To further improve the image processing speed, it needs to be changed.

Aiming at the problems existing in the above methods, a third gray processing method: weighting method is proposed. First, the corresponding value of RGB color component in each color channel is obtained, and then a certain weight is assigned to each color component [5]. By assigning different weights to the two color components and added together, and then the sum value is rounded up. The final integer is the gray value of the pixel position. The formula is as follows:

\[
R = G = B = w_r \times R + w_g \times G + w_b \times B
\]

where \(w_r\) represents the weight assigned to the red channel, \(w_g\) represents the weight assigned to the green channel, and \(w_b\) represents the weight assigned to the blue channel. Considering the adaptability of human vision to color, \(w_r, w_g, w_b\) are usually set at 0.299, 0.587 and 0.114 respectively.

2.3. Histogram Equalization
Due to the different skin type of each person, when the curvature image of oily skin and moist skin is taken with the camera, there will be highlights related to mirror and shadow, and the distribution of histogram of corresponding image is uneven.

Adaptive histogram equalization with limited contrast divides the image into fixed-size blocks and applies image equalization to each block. Adjacent blocks use bilinear interpolation to remove artificial boundaries. We can obtain a uniform image and improve the details of features such as wrinkles and wrinkled cells. Adaptive histogram Equalization (AHE) is a computer image processing technique used to improve image contrast. Unlike ordinary histogram equalization algorithms, the AHE algorithm changes the image contrast by calculating the local histogram of the image and then redistributing the brightness. Therefore, the algorithm is more suitable for improving the local contrast of the image and obtaining more details.

If \(f(i, j)\) is defined to represent the gray pixel value corresponding to \(x(i, j)\), ACE (adaptive histogram equalization) algorithm can be expressed as follows:
As AHE has the noise problem of the same area in the over-enlarged image, the contrast amplification around the specified pixel value is mainly determined by the gradient of the transform function, which is proportional to the gradient of the cumulative histogram of the field.

2.4. Gaussian Filtering

In the adaptive histogram equalization step with limited contrast, the noise (such as humidity, oil content) is obvious, and an over-segmentation factor will be generated [5]. Gaussian smoothing filter can eliminate this noise. The Gaussian distribution belongs to the normal distribution. If the random variable obeys a probability distribution (normal distribution) with a location parameter of \( \mu \) and a scale parameter of \( \sigma \) (normal distribution), denoted as: \( X \sim N(\mu, \sigma^2) \), then the probability density function is:

\[
G(x, y) = \frac{1}{2\pi \sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}
\]

\( \sigma \) is expressed as the standard deviation, also known as the Gaussian radius: \( \sigma^2 \) is the variance. \( \mu \) stands for mean value, also called mathematical expectation. In this paper, a Gaussian mask with \( \sigma = 10 \), \( 5 \times 5 \) is selected to obtain a uniform skin image.

3. Skin Quality Detection Algorithm

3.1. Grayscale Processing

In human facial skin, the distribution areas of pigment and oil are not the same. The pigmented areas in the skin tend to be darker in color, which is exactly different from the area where facial oils are located. The appropriate color model can be used cleverly to separate the two areas.

By detecting the proportion of the area occupied by pigments and oils, the indicators of pigments and facial oils can be detected [6]. HSV (hue, saturation, brightness) is a color space that separates brightness information from colors and can be expressed. It is a cone model. At the apex of the cone as shown in Figure 1, V=0, H and S are undefined, representing black. At the center of the top surface of the cone, V=max, S=0, H is undefined and represents white.

3.2. Method of Maximum Interclass Variance

The Otsu algorithm divides the image into background region and target region threshold by setting different thresholds. \( T \) is the assumed optimal segmentation threshold. The pixel value of the
foreground image is expressed as 0 compared with the pixel value of the whole image, and the average gray value is expressed as 0. The pixel value of the bottom image is expressed as $\omega_1$ compared with that of the overall image, and the average gray value is expressed as 1. Represents the average gray value of the whole image, and the inter-class variance is represented by $G$ [7]. The expression of inter-class variance is as follows:

$$\delta^2(t) = w_0(\mu_0 - \mu)^2 + w_1(\mu_1 - \mu)^2$$  \hfill (5)

By traversing the threshold $T$, when the inter-class variance $\sigma^2$ is maximized is obtained as the optimal segmentation threshold for the image, which can be expressed as:

$$T^* = \arg \max_{0 \leq t \leq L-1} f(t)$$  \hfill (6)

3.3. Gray Level Co-Occurrence Matrix

Skin roughness is mainly based on the analysis of the texture characteristics of the skin image. At present, the commonly used texture analysis methods are: statistical texture analysis, model texture analysis, spectral texture analysis and structural texture analysis. This paper uses the gray-level co-occurrence matrix method in statistical texture analysis to analyze and evaluate skin roughness.

The gray-level co-occurrence matrix refers to the joint probability distribution of two gray-level pixels that are separated by $\delta = (\Delta x, \Delta y)$ in an image at the same time [8]. It is expressed as the gray-level correlation of adjacent pixels. The mathematical description is:

$$P(i, j) = \frac{\#(x) \in M \times N | f(x_i, y_i) = i, f(x_j, y_j) = j}{N}$$  \hfill (7)

where $f(x, y)$ is the target image, its size is $M \times N$, and $\#(x)$ is the number of elements in the set. In practical applications, the following four characteristic values are often used to characterize:

$$ASM = \sum_i \sum_j p(i, j)^2$$  \hfill (8)

The angular second-order moment is an index used to indicate the thickness of the image texture. When the value given in the co-occurrence matrix is the same, the angular second-order moment is small.

$$ENT = -\sum_i \sum_j p(i, j) \log_2[p(i, j)]$$  \hfill (9)

The value of entropy is used to indicate the complexity of the texture in the image and the uncertainty of the texture gray distribution, and it can also measure the amount of information in the image [9].

$$CON = \sum_i \sum_j p(i, j)(i - j)^2$$  \hfill (10)

Contrast can be understood as the sharpness of the image, which measures how much the local gray level of the image changes.

$$COR = \frac{\sum_i \sum_j p(i, j) (i+1)(j+1) - u_x u_y}{d_x d_y}$$  \hfill (11)

Correlation measures the correlation of local gray levels of an image, that is, the degree of similarity of gray values in the row and column directions.
4. Skin Image Feature Extraction

4.1. Determination of Oil Content and Pigment

The extraction of oil content and pigment is mainly based on the color model. An image acquisition device is used to take a face skin image, as shown in Figure 2(a). First, the sample image is converted into HSV space, and then the S-space and V-space of the sample image are binarized by the maximum intercategory method. The oil and pigment on the skin can be distinguished by the degree of light and shade on the image. For the oil on the skin, the color should be brighter and the saturation should be smaller, i.e., V should be larger and S smaller. For skin pigments, the color should be darker and more saturated, that is, V is smaller and S is larger. The S and V binarization space after threshold segmentation is logically calculated to obtain the oil content and pigment region in the image. where the threshold value of S space is 0.37 and the threshold value of V space is 0.74.

![Skin image sample](image1.png) ![Out segmentation of sample images](image2.png)

*Figure 2. Determination of oil content and pigment*

The above algorithm is realized by MATLAB software programming, and the simulation results are shown in Figure 2(b), where the green area represents oil and the red area represents pigmentation. Through the realization of the algorithm in this paper, it can be observed that the regional distribution of oil and pigment in the skin image can be accurately obtained and the proportion of the two occupying the skin surface can be calculated as shown in Table 1. And compared with other algorithms, it also proves the reliability of this algorithm. Due to the limited amount of image data in this research, if more relevant image data can be obtained, the feasibility of this algorithm can be better verified.

| Index | Other algorithms | This algorithm |
|-------|------------------|----------------|
| Oil   | 16%              | 17%            |
| Pigment | 35%            | 34%            |

4.2. Pore Detection

The detection of pores in this algorithm is mainly based on the double threshold segmentation performed by Otsu and basic morphological operations. From the observation of the skin image, it can be seen that the position of the pores is mainly where the color is darker and the color saturation of the image is greater. Based on this feature, an algorithm can be designed to extract the areas with darker color and greater saturation.

When dividing the $S$ color space, set its threshold to $K_1$ times the original threshold $Ths$ ($K_1 > 1$), so that the hair and pore regions can be better separated in the S space. At the same time, when segmenting the V space, the segmentation threshold needs to be set to $K_2$ times the original threshold $Thv$ ($K_2 < 1$). When the threshold is divided into V space, the threshold is reduced to $K_3$
times the calculated threshold $Thv (K3 < K2)$. Here, the division of V space uses the double threshold OTSU algorithm, which can be effectively find out the location area of the pores in the skin image [10].

Connect the pixel areas, and use morphological methods to complete the extraction of pore blocks. Close operation can connect adjacent pixels, open operation is used to separate small pixel areas, smooth the pore prototype boundary, and eliminate noise to remove possible small pixel blocks.

$$S1 = Ths = K1 \cdot Ths$$

$$S1 = K3 \cdot Thv = K2 \cdot Thv = Thv$$

Figure 3. Threshold distribution

Since the pores have different shapes and most of them are approximately circular, the original picture as shown in Figure 4(a), the radius of the pores is first calculated, and then the roundness screening is performed to retain the valid detection results. The calculation formula for the pore radius is as follows:

$$R = \sqrt{\frac{N \cdot \text{pixel}}{\pi}}$$  \hspace{1cm} (12)

where $N$ is the number of pixels contained in each pore block, \text{pixel} is the actual size of each pixel, and this value is determined by the collection device. Define circularity as:

$$M = \frac{4 \pi \cdot \text{area}}{l^2}$$  \hspace{1cm} (13)

where $M$ is the circularity, \text{area} is the area, $l$ is the circumference, the closer $M$ is to 1, the closer the area is to the circle. Use the above formula to calculate the circularity of each pore and set a threshold. When the pore circularity is greater than the setting the threshold, calculate the radius. In this paper, the circularity threshold is set to 0.75. The detection is shown in Figure 4(d). In the above figure, each connected area with a + mark centroid is an area that meets the circularity threshold, that is, the area where the pore is located, and these areas that meet the requirements are calculated and marked in the vicinity of each connected area. This algorithm accurately identifies 18 areas with pores. And the average diameter of these connected regions is 0.3mm.

Figure 4. Two or more references
4.3. Skin Roughness Detection
First, the original image is converted into a gray-scale image, and the gray-level co-occurrence matrix at the four positions of A is calculated and normalized. According to the obtained gray-level matrix, four texture feature indexes such as angle second moment, entropy, contrast and correlation are extracted. The four eigenvalues of the gray-level co-occurrence matrix after calculation are shown in the following Table 2.

Table 2. Co-occurrence matrix feature calculation result

| Number | ASM | ENT | CON | COR |
|--------|-----|-----|-----|-----|
| 1      | 0.2346 | 1.7707 | 0.1832 | 0.2800 |
| 2      | 0.1100 | 2.6858 | 0.4007 | 0.3412 |
| 3      | 0.2528 | 1.7656 | 0.1806 | 1.2552 |

The results show that the roughness of the skin identified by the algorithm is basically the same as that observed by ordinary human eyes.

5. Conclusion
This paper studies the image processing algorithm of face and skin quality detection. The detection of oil content and pigment index is based on the color model of S and V in the HSV color space. The experimental results and analysis are given. Pore detection is combined with OTSU multi-threshold segmentation and morphological operations. The roughness index detection is based on the characteristics of the gray-level co-occurrence matrix, and the roughness detection experimental results are given based on these indexes.

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