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Human Skin Texture Analysis Using Neural Networks

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Abstract: Skin recognition is used in many applications like face detection, hand gesture analysis, and to objectionable image filtering. In this paper a skin recognition system was developed and tested. There are many skin segmentation algorithms which focuses only on skin color, our work focuses on both skin color and texture features to give a better and efficient recognition accuracy of skin textures.
We used neural networks to classify input textures images for skin or non skin textures. This technique gave very encouraging results during the neural network generalization face. Skin texture analysis is one of the feature in Digital image processing used to analyze the images that is captured by the imaging devices on human skin.

Keywords:

- Digital Image Processing.
- Skin Recognition.
- Texture Analysis.
- Neural Networks.
- Skin Texture Analysis.

1. Introduction

Skin is very complex that is difficult to model for many reasons. The skin texture features depends up on many variables such as body location (knuckle vs. torso), subject parameters (age/gender/health) and imaging parameters (lighting and camera). Also with many real world surfaces, skin appearance is strongly affected by the direction from which it is viewed and illuminated.

Recognition of human skin is an important task for computer vision and graphics. For computer vision, accurate recognition of skin texture can greatly assist algorithms for human face recognition or face feature tracking. In computer graphics, face animation is an important problem which is necessary reliable skin texture recognition.

In addition to computer vision and graphics, skin recognition is useful in dermatology and several medical fields. In dermatology, the skin recognition can be used to develop methods for computer-assisted diagnosis of skin disorders, and in the pharmaceutical industry quantification is useful when applied to measuring healing progress.

Many skin segmentation methods depend up on skin color which will have many difficulties. The skin color will depend on human race and on lighting conditions, although this can be avoided in some ways using YCbCr color spaces in which the two components Cb and Cr depends only up on chrominance, there are still many problems with this method because there are many objects in the real world that have a chrominance in the range of the human skin which are wrongly considered as skin. For the above reasons combining the texture features of skin with its color features will increase the accuracy of skin recognition.

2. Related Works

Most existing skin segmentation techniques involves the classification of individual image pixels into skin and non-skin categories on the basis of pixel color. There are number of studies of skin color pixel classification has been reported.

Jones and Rehg created the first large skin database as Compaq database and used the Bayesian classifier with the histogram technique for skin detection. Brand and Mason compared three different techniques on the Compaq database as thre sholding the red/green ratio, color space mapping with 1D indicator, and RGB skin probability map.

Terrillon et al. compared Gaussian and Gaussian mixture models across nine chrominance spaces on a set of 110 images of 30 Asian and Caucasian people. Shin et al. compared skin segmentation in eight color spaces. In their study, skin samples were taken from the Aleix Martinez and Robert Benavente (AR) and the

University of Oulo face databases and non-skin samples were taken from the University of Washington image database.

3. Feature Extraction

3.1. Color Features (Color Moment)

Color moment is a representation of the color feature to characterize a color image. It has shown that most of the color distribution information is captured by the three low-order moments. The first order moment (μc) captures the mean color, the second order moment (σc) captures the standard deviation, and the third-order moment captures the skew ness (θc) of color. These three low-order moments (μc, σc, θc) are extracted for each of three color planes (R G B), using the following mathematical formulation.

$$\mu_c = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} p_{ij}^{c} \qquad \ldots(1)$$

$$\sigma_c = \left[\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(p_{ij}^{c} - \mu_c)^2\right]^{1/2} \qquad \ldots(2)$$

$$\theta_c = \left[\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(p_{ij}^{c} - \mu_c)^3\right]^{1/3} \qquad \ldots(3)$$

Where M and N are the image dimensions, pc ij is value of the color c, component of the color pixel in the row i and column of the image. For a result, we need to extract only nine parameters (three moments for each of the three color planes) to characterize the color image.

3.2. Texture Features

Texture is a very interesting image feature that has been used for characterization of images, a major characteristic of texture is the repetition of a pattern over a region in a image. The elements of pattern are sometimes called textons.

The size, shape, color, and orientation of the textons can vary over the region. The difference between two textures can be in the degree of variation of the textons. It can also be due to spatial statistical distribution of the textons in the image.

Texture is an innate property of virtually all surfaces, such as bricks, fabrics, wood, papers, clouds, trees, lands and skin. It contains important information regarding the underlying structural arrangement of the surfaces in an image. Texture analysis has been an active area of research in the pattern recognition.

A variety of techniques have been used for measuring textural similarity. In 1973, Haralick et al. proposed co-occurrence matrix (GLCM) representation of texture features to mathematically represent the gray level spatial dependence of texture in an image. In this method the co-occurrence matrix is constructed based up on the orientation and distance between image pixels.

Meaningful statistics are extracted from the co-occurrence matrix, as the representation of texture. Since the basic texture patterns are governed by periodic occurrence of certain gray levels, co-occurrence of gray levels at predefined relative positions can be a reasonable measure of the presence of texture and periodicity of the patterns.

Several texture features are there such as entropy, energy, contrast, and homogeneity, can be extracted from the co-occurrence matrix of gray levels of an image.

The Gray Level Co-occurrence Matrix (GLCM) C(i,j) is defined by first specifying a displacement vector dx,y = (δx, δy) (where δx, δy are the displacements in the x and y directions respectively) and then counting all the pairs of pixels separated by displacement dx,y and having gray levels i and j .

The matrix C (i, j) is normalized by dividing each of the element in a matrix by the total number of pixel in pairs. Using this co-occurrence matrix, the texture features metrics are done as follows:

$$Entropy = \sum_i \sum_j C(i,j) \log(C(i,j)) \quad \ldots(4)$$

$$Energy = \sum_i \sum_j C^2(i,j) \quad \ldots(5)$$

$$Contrast = \sum_i \sum_j (i-j)^2 C(i,j) \quad \ldots.(6)$$

$$Homogeneity = \sum_i \sum_j \frac{C(i,j)}{1+|i-j|} \quad \ldots(7)$$

These four features are combined with the nine features computed for each color component resulting in 13 element features vector use to characterize the skin texture in this work.

4. The Proposed Skin Recognition Algorithm

Our proposed skin texture recognition algorithm consists of three main tasks as shown in fig 1:
(1) Creation of the library of representative skin features.
(2) Neural Network Training.
(3) Classification.

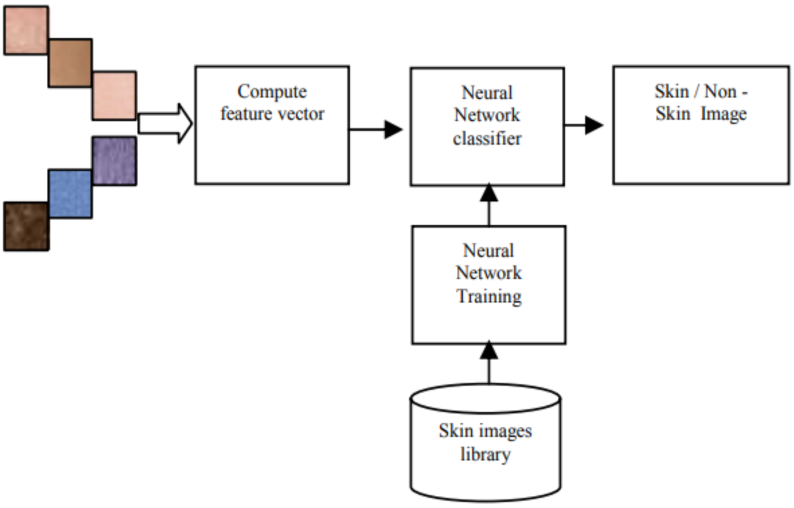

Fig 1: Skin texture recognition algorithm tasks.

4.1. Skin Texture Library

The library of skin texture is comprised of 300 images of skin textures of size 80X80 pixels. The library consists of variety of skin types of different human categories, different places of the human body and different lighting conditions. Samples of that library is shown in fig 2.

Fig 2: Skin library samples.

4.2. The Structure of Neural Network

We use a feed forward back propagation neural network with a adaptable learning rate. The NN have 3 layers as: an input layer (13 neuron), a hidden layer (50 neuron) , and output layer (1 neuron). The activation function which is used are the tan sigmoid function, for the hidden and the output layer. The input to the neural network is the feature vector contains 13 components these are the 4 texture features and the three color moments for each color component (R G B), the NN has only one output as shown in fig 3.

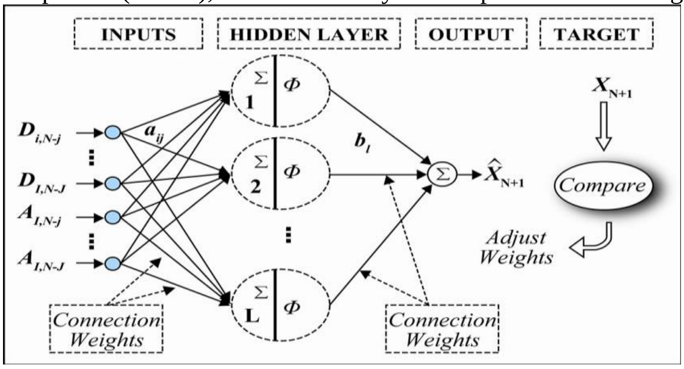

Fig 3: The neural network structure.

5. Results

The NN training process is done by using skin and non skin texture images from the image library. The output of the neural network assumed to be 1 for the skin input image and -1 for non-skin input image. The system where implemented using Matlab 7.0.

The performance criterion used is SSE (sum square error) and the goal was 10-6 which is proved to be very acceptable goal. The performance goal has reached after 23039 training iteration. As shown in fig 3.

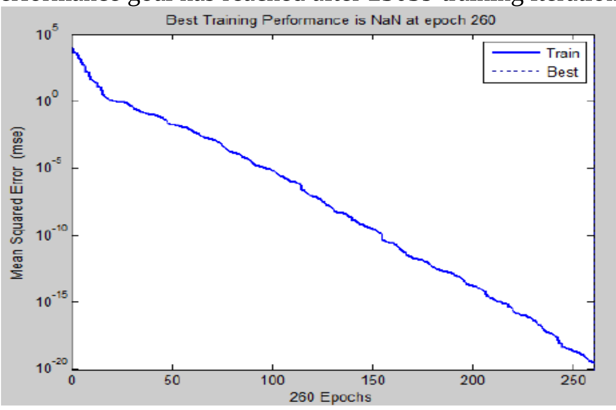

Fig 3: Neural Network Performance

To test our system we used 50 skin texture images and 50 non-skin texture images. These images were not used in the training phase and they are taken under different lighting conditions, for different human races. The images are input to the neural network after training to obtain the generalization results as shown in figures 4 and 5.

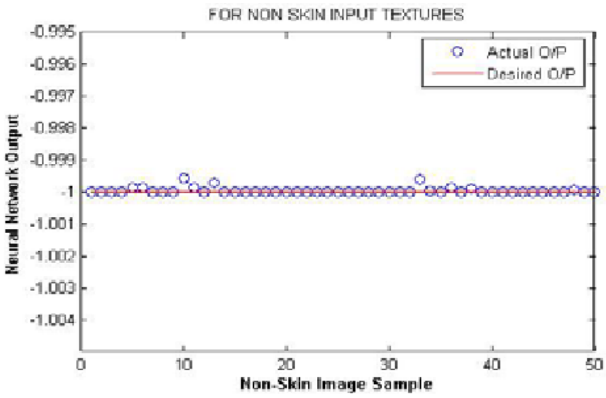

Fig 4: Neural network generalization O/P for skin input images

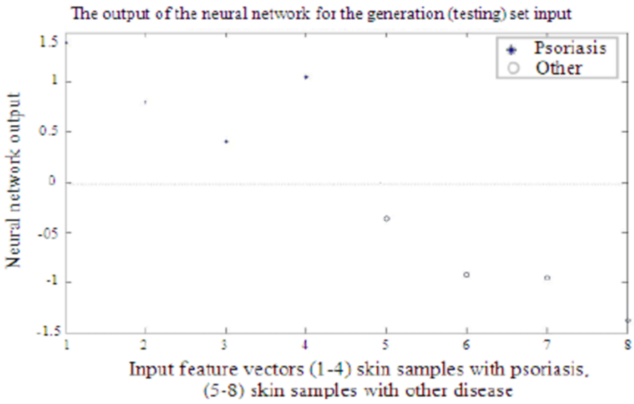

Fig 5: Neural Network Generalization O/P for non-skin input images

Fig 6: The undetected skin image samples

6. Conclusion and Future Enhancement

It can be concluded from the figures above that the system gave very encouraging results for both skin and non-skin inputs. The use of texture and color feature enhanced the performance of our system and gave recognition accuracy of 96% in the generalization test. This accuracy proves that the texture features are very useful as recognition features for skins in addition to the color features that are used in many applications.

Figure 4 shows the output from the actual output form the neural network and the desired output which is 1 since the input images are all the skin image. It can be seen that only four samples is wrongly recognized as non-skin form 50 skin samples, these four samples are shown in figure 6. It can be seen from figure 6 that the images are either taken under lighting conditions that are very different under which that training set is taken, or they are not plane skin texture i.e. they contain 3D shadow. This shows the limitations of this method.

Figure 5 shows that all the non-skin image samples are truly detected as non skin (NN output of -1) with a small error that is negligible. The ultimate goal of this paper is a system for objectionable image filtering. The future work is to develop the algorithms for skin classification (classifying for which part of the body the skin belongs to), and to investigate for appropriate features that can serve for this purpose.

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