Human Skin Texture Analysis using Image Processing Techniques

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Abstract: ***The skin properties like skin dryness, fungus and allergic symptoms i.e. etching kind of problem correlation with skin texture profile is discussed in the proposed thesis work. In the existing scenario, the skin images are analyzed in frequency domain. However, it is observed that the skin color in texture images does not vary over a wide range. Hence, the histogram profile of the skin texture remains almost flat. In the proposed work, we have shifted the skin texture analysis towards the gray level profile analysis. The gray color profile of the skin texture may give fair idea about the skin sensitivity and is a new emerging skin texture analysis tool. In the proposed work, skin gray color profile has been taken as the input parameter in order to ascertain the skin profile. In the proposed thesis work, Gray Level Co-occurrence Matrix of the skin image is computed. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix. Further, the image entropy and energies are also computed in order to correlate the skin symptoms to the skin texture images.***

Keywords: GLCM, Gray Level Co-occurrence Matrix

1. Introduction

According to dermatologist, the skin texture has close relation with the individual’s diet, hormones, hydration and any allergic symptoms. Therefore, by analyzing the skin texture by acquiring the skin texture image by exposing the human skin to imaging devices, the skin’s health may be defined. Texture analysis in image processing is an important tool in analyzing the image of textural nature.

The skin texture is the appearance of the skin smooth surface. To the features of this texture, many factors are occurring, for instance diet and hydration, amount of collagen and hormones, and, of course, skin care. A gradual decline in skin is moreover superimposed by age. As skin ages, it becomes thinner and more easily damaged, with the appearance of wrinkles. The deterioration is also accompanied by a darkening of skin color for an over absorption of the natural coloring pigment, melanin, by the top most cell layer in skin. The skin texture also depends on its body location. In the case of image processing, we have to consider the fact that texture appearance is changing with image recording parameters, that are camera, illumination and direction of view, a problem common to any real surface. The task to have a quantitative evaluation of the skin features is quite complex, as in all the cases where image analysis must be applied to surfaces with irregular non-periodic patterns.

In the digital image processing, several methods have been developed to classify images and define statistical distances among them, with the aim to decide whether, in a set of many images, there exist some which are close to any arbitrary image previously encountered. The texture discrimination can be obtained by choosing a set of attributes, the texture features, which account for the spatial organization of the image.

2. Related Works

A practical skin color and texture analysis/synthesis technique is introduced for this E-cosmetic function. Shading on the face is removed by a simple color vector analysis in the optical density domain as an inverse lighting technique. The image without shading is analyzed by a previously introduced technique that extracts hemoglobin and melanin components by independent component analysis. The comparison shows an excellent match between the synthesized and actual images of changes due to tanning and alcohol consumption. We also proposed a technique to synthesize the change of texture in pigment due to aging or the application of cosmetics. [1]

Grain size and anisotropy are evaluated with proper diagrams. The possibility to determine the presence of pattern defects is also discussed. [2]

The skin color image is decomposed to the four texture components by multi-resolution analysis using wavelet transform. A variety of skin images with different conditions of skin color and texture are created in a linear combination of the texture components. Experimental results show good separation of skin textures by wavelet analysis and realistic synthesized images. [3]

To make improvement in this regard, we propose a new texture analysis synthesis framework that combines two main ideas. Firstly, in material space we decompose the texture contents into units with "basic shape" and 'feature vector ". Based on this, the space spanned by a set of sampled textons is constructed to help introduce additional changes upon textons. Secondly, in pattern space, using the idea of 'feature texture “acquired from texture swatch for different properties especially for distribution rules of textons, we may capture and manipulate the global structure flexibly. By this formulization, we are able to obtain a satisfactory texture appearance, and also a rich control ability as well. [4]

Texture refers to visual patterns or spatial arrangement of pixels that regional intensity or color alone cannot sufficiently describe. Researchers have proposed numerous methodologies to automatically analyze and recognize textures, from deriving texture energy measures using a set of simple masks to using Gabor filters, for several image analysis applications, including texture classification and segmentation. [5]
To be adaptive to the dynamic illumination and chrominance, face detection is used to customize the skin color model to each image. The proposed method has achieved promising performance over our dataset, which is a challenging set with a great part of hard images. Our True Positive Rate is 81.2% under False Positive Rate 8.2%, which out performs all eight state-of the- art algorithms. [6]

The filtering method introduced here is applied to dermoscopic skin image in a non-linear manner and allows selective image filtering. This feature is highly desirable due to the fact that in most cases of computer aided diagnostic, input images need to be pre-processed (e.g. for brightness normalization, histogram equalization, contrast enhancement, color normalization) and this can results in unwanted artifacts or simply may require human verification. Introduced method was developed specially to recognize one of the differential structures (pigmented network texture) used for calculating the Total Dermoscopy Score (TDS) of the ABCD rule. [7]

A method is proposed that tracks the skin's recovery optically from an initial strain made using a mechanical indentor, diffuse side-lighting and a CCD video-capture device. Using the blue color plane of the image it is possible to examine the surface topography only, and track the decay of the imprint over time. Two algorithms are discussed for the extraction of information on the skin's displacement and are analyzed in terms of reliability and reproducibility. [8]

ANIL KUMAR MITTRA et. al. This paper proposes an automated system for recognizing disease conditions of human skin in context to health informatics. The disease conditions are recognized by analyzing skin texture images using a set of normalized symmetrical Grey Level Co-occurrence Matrices (GLCM). GLCM defines the probability of grey level I occurring in the neighborhood of another grey level j at a distance d in direction θ. The system is tested using 180 images pertaining to three dermatological skin conditions viz. Dermatitis, Eczema, Urticaria. An accuracy of 96.6% is obtained using a multilayer perceptron (MLP) as a classifier. [9]

The geometric, random field, fractal, and signal processing models of texture are presented. The major classes of texture processing problems such as segmentation, classification, and shape from texture are discussed. The possible application areas of texture such as automated inspection, document processing, and remote sensing are summarized. A bibliography is provided at the end for further reading. [10].

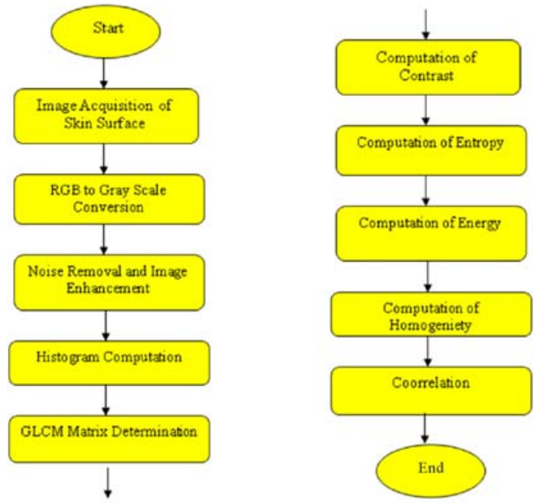
The relation between the nonlinear results by Monte Carlo simulation (MCS) and the modified Lambert Beer's law (MLB) is also clarified, emphasizing the importance of the absolute values of skin pigments and their influence on the mean path-length used in MLB. Images of oxygenated hemoglobin with a newly-developed four wavelength camera are presented to demonstrate the advantages of a multi wavelength system. [11]

3. Methodology

A statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix.

The thesis work is divided into following stages:

- Image Acquisition
- Conversion to Gray Scale Image
- Image Enhancement using Histogram Equalization
- Histogram Computation of the enhanced image
- Computation of GLCM Matrix of skin texture image
- Computation of Contrast
- Computation of Entropy
- Computation of Energy
    - Computation of Homogeneity
    - Correlation with Skin Symptoms



4. Image Acquisition and Preprocessing

Skin images are acquired using the UV camera in order to get the deep skin images. The acquired image is in jpeg format and is read in matlab using the command imread(). The image is now converted to gray image using rgb2gray() function. The gray image is enhanced using the histogram equalization algorithm. Following figure show the result of image preprocessing operations:

Original Image **Histogram Equalized Images**

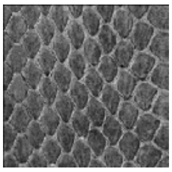


Fig. 1

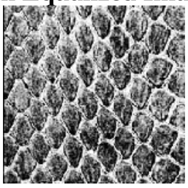


Fig. 2

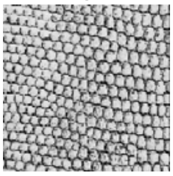
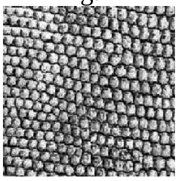


Fig. 3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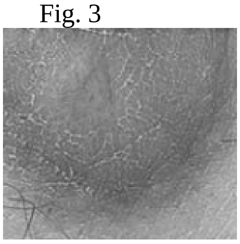


Fig. 5

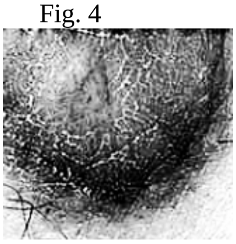


Fig. 6

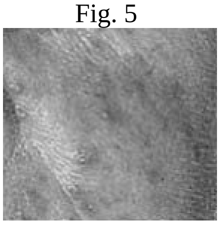


Fig. 7

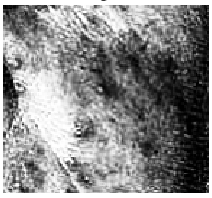


Fig. 8

5. GLCM Extraction

A statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix. The number of gray levels in the image determines the size of the GLCM. The gray-level co-occurrence matrix can reveal certain properties about the spatial distribution of the gray levels in the texture image. For example, if most of the entries in the GLCM are concentrated along the diagonal, the texture is coarse with respect to the specified offset.

To create a GLCM, use the graycomatrix function. The graycomatrix function creates a gray-level co-occurrence matrix (GLCM) by calculating how often a pixel with the intensity (gray-level) value i occurs in a specific spatial relationship to a pixel with the value j. By default, the spatial relationship is defined as the pixel of interest and the pixel to its immediate right (horizontally adjacent.

After you create the GLCMs, image contrast, energy, coorelation and homogeneity can be computed as:

Contrast → Measures the local variations in the gray-level co-occurrence matrix. Contrast is 0 for a constant image.

Correlation → Measures the joint probability occurrence of the specified pixel pairs. Correlation is 1 or -1 for a perfectly positively or negatively correlated image. Correlation is NaN for a constant image.

Energy → Provides the sum of squared elements in the GLCM. Also known as uniformity or the angular second moment. Energy is 1 for a constant image

Homogeneity → Measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. Homogeneity is 1 for a diagonal GLCM

6. Computation of Entropy

The expression of the information entropy of an image is given by:

$$H = -\sum_{i=0}^{L-1} p_i \ln p_i,$$

Where L denotes the number of gray level, pi equals the ratio between the number of pixels whose gray value equals i(0 i L _ 1) and the total pixel number contained in an image. The information entropy measures the richness of information in an image. If pi is the const for an arbitrary gray level, it can be proved that the entropy will reach its maximum.

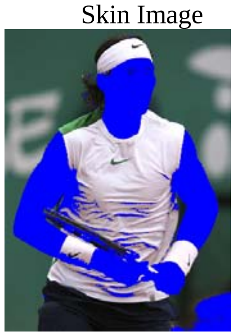
7. Results

For texture characterization, we consider a set of features derived from GLCM matrix: contrast (C), homogeneity (H), mean (M), energy (N), and variance (V). Images are obtained from Dermnet Skin disease atlas. Dermnet is the largest independent photo dermatology source. Dermnet provides information on a wide variety of skin conditions.

The proposed algorithm produce a skin map of a given image and highlights patches of skin like pixels. The function reads an image file given using Matlab command imread. A skin map overlayed onto the image with skin pixels marked in blue color is generated by using the GLCM matrix. Following figures shows the output of the algorithm. Once the skin pixels are extracted,, than it is easier to analyze the skin diseases.

Input Image

Skin Image



Results for contrast, correlation, energy and homogeneity are summarized in below given table.

Image No.	Contrast	Correlation	Energy	Homogeneity
2	4.5224	0.4846	0.0222	0.5306
4	4.5385	0.4814	0.0218	0.5226
6	2.5239	0.7105	0.0300	0.6175
8	1.5620	0.8212	0.0341	0.6526

8. Conclusion

The main focus of this paper is on analyzing the texture of skin thereby using it to diagnose the skin diseases. Various skin diseases can be analyzed based on the combination of feature vector set of contrast, correlation, energy and homogeneity. From the experimental results discussed above, we infer that the multi-class classification can serve as an effective tool in identifying skin diseases. The future work will be based on developing algorithms to identify various other skin diseases, to improve the overall efficiency and also to further reduce the computational time.

References

[1] Norimichi Tsumura* Nobutoshi Ojima† Kayoko Sato* Mitsuhiro Shiraishi† Hideto Shimizu* Hirohide Nabeshima† Syuuichi Akazaki† Kimihiko Hori† Yoichi Miyake*, "Image-based skin color and texture analysis/synthesis by extracting hemoglobin and melanin information in the skin", IEEE-2012

[2] Motonori Doi, Shoji Tominaga, "Image Analysis and Synthesis of Skin Color Textures by Wavelet Transform", 1-4244-0069-4/06/$20.00/©2006 IEEE.

[3] Yuanting Gu and Enhua Wu, "Feature Analysis and Texture Synthesis", 978 -1-4244-1579-3/07/$25.00 C) 2007 IEEE

[4] Ranjan Parekh , "Using Texture Analysis for Medical Diagnosis", Jadavpur University, India

[5] Lei Huang1,2, Tian Xia1, Yongdong Zhang1, Shouxun Lin1, 'HUMAN SKIN DETECTION IN IMAGES BY MSER ANALYSIS", IEEE-2011

[6] Leszek A. Nowak, Maciej J. Ogorzałek, Marcin P. Pawłowski, "Texture Analysis for Dermoscopic Image Processing", IEEE 2012

[7] Neil T. Clancy*a, Martin J. Leahya, Gert E. Nilssonb, Chris Andersonc, "Analysis of skin recovery from mechanical indentation using diffuse lighting and digital imaging", Proc. of SPIE-OSA Biomedical Optics, SPIE Vol. 6629, 66291G, © 2007 SPIE-OSA · 1605-7422/07/$18

[8] ANIL KUMAR MITTRA, DR.RANJAN PAREKH, " AUTOMATED DETECTION OF SKIN DISEASES USING TEXTURE", International Journal of Engineering Science and Technology (IJEST) ISSN :

[9] Mihran Tuceryan and Anil K. Jain, "Texture Analysis", The Handbook of Pattern Recognition and Computer Vision (2nd Edition), by C. H. Chen, L. F. Pau, P. S. P. Wang (eds.), pp. 207-248, World Scientific Publishing Co., 1998.

[10] Manami Kobayashi, Yasunobu Ito, Naofumi Sakauchi, Ichiro Oda, Ikuo Konishi, and Yoshio Tsunazawa, 2001 Optical Society of America, OCIS codes: (170.0170) Medical optics and biotechnology, (170.3880) Medical and biological,

[11] Dr. S.Arivazhagan, 2Mrs. R.Newlin Shebiah, 3Ms. K.Divya, 4Ms. M.P.Subadevi, "Skin Disease Classification by Extracting Independent Components", VOL. 3, NO.10 Oct, 2012 ISSN 2079-8407 Journal of Emerging Trends in Computing and Information Sciences

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