AUTOMATED DETECTION OF SKIN DISEASES USING TEXTURE FEATURES

ANAL KUMAR MITTRA*
Masters Research Scholar
School of Education Technology
Jadavpur University, Kolkata 700032, India
anal2007.mittra@gmail.com

DR.RANJAN PAREKH
Asst. Professor
School of Education Technology
Jadavpur University, Kolkata 700032, India
rparekh@school.jdvu.ac.in

Abstract:

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 $\theta$. Directional GLCMs are computed along four directions: horizontal ($\theta = 0^\circ$), vertical ($\theta = 90^\circ$), right diagonal ($\theta = 45^\circ$) and left diagonal ($\theta = 135^\circ$), and a set of features computed from each, are averaged to provide an estimation of the texture class. 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.

Keywords: Grey-level Co-occurrence Matrix (GLCM), skin disease detection, medical imaging, neural network

1. Introduction

Texture analysis is one of the fundamental aspects of human vision by which we discriminate between surfaces and objects. In the field of digital image processing, computer vision techniques can take advantage of the cues provided by surface texture to distinguish and recognize objects. Texture refers to visual patterns or spatial arrangement of pixels that regional intensity or color alone cannot sufficiently describe.

Many methodologies have been proposed to analyze and recognize textures in an automated fashion. In [3] A.C. Bovik et. al. proposes a computational approach for analyzing visible textures by localizing spatial changes in the frequency, orientation, or phase of the textures using 2-D Gabor filters. Information extracted from the Gabor phase responses are used to detect phase discontinuities within a texture. In [4] Haralick introduced a statistical and structural method to model texture based patterns based on the symmetric Grey Level Co-occurrence Matrix (GLCM). GLCM defines the probability of one grey tone occurring in the neighborhood of another grey tone at a specified distance and along a specified direction. Authors like Tamura [12] made an attempt at defining a set of visually relevant texture features which includes coarseness, contrast and directionality. Coarseness is the measure of granularity of an image, or average size of regions that have the same intensity, contrast is the measure of vividness of the texture pattern affected by the use of varying black and white intensities, directionality is the measure of directions of the grey values within the image. In [6] Lepisto proposed a method to retrieve non-homogenous, directional texture features based on texture...

In recent years, computer vision methodologies have been applied to the fields of health informatics and telemedicine for automated diagnosis of diseases. Research shows that diagnosis errors often occur when clinicians are inexperienced and new procedures are introduced. Application of automated information systems in medical analysis has shown great promise in reducing human based errors [5]. N. K. Al abbadi et. al. [1] proposed a method for skin texture recognition using both color & texture features and a three layer neural network. In [2] J.M. Blackledge et al. has proposed an approach to detect and recognize skin cancers with the help of texture features involving fractal parameters such as Lacunarity and fractal dimensions. In [8] Rubegni et. al. proposed a method of diagnosis of pigmented skin lesions based on digital dermoscopy analysis. In [9] F. Smach et. al. implemented a classifier using MLP neural network for face detection using different features like shape, skin texture and skin color.

2. Proposed Approach

The present paper proposes a scheme for automated detection of three classes of skin diseases by analyzing textures obtained from a collection of medical images, using features based on Grey Level Co-occurrence Matrix (GLCM) and using neural networks as classifiers.

2.1. Computation of GLCM

GLCM is a popular statistical method of texture analysis. Originally proposed by R.M. Haralick [4], GLCM defines the probability of gray level \( i \) occurring at a distance \( d \) in direction \( \theta \) from gray level \( j \) in a grey-scale texture image. These probabilities create the co-occurrence matrix as indicated in Eq. (1).

\[
G = Pr(i, j | d, \theta)
\]  

At first an input image \( I \) is converted to grayscale by eliminating the hue and saturation information. Let there be \( k \) distinct grey levels in the image. To compute the frequency of one grey tone in the neighbourhood of others, a \( k \times k \) matrix is formed and sequential numbers along the left (reference) and top (neighbour) are used to indicate them viz. \( 1, 2, ..., k \). The frequencies in which each pair (reference / neighbour) of grey-tones, occur together in \( I \) is now computed i.e. for a reference grey-tone \( i \), how many times the neighbour grey-tone \( j \) occurs near it within \( I \), and this constitutes the \((i, j)\)-th element of GLCM matrix \( G \). For simplicity’s sake we consider the distance \( d \) as 1 i.e. only adjacent pixels are considered, and angle \( \theta \) as 0\(^\circ\) i.e. along the positive x-axis from left to right. If we had moved along the –ve x-axis, i.e. we had looked from right to left, then the matrix formed would have been the transpose matrix \( G^T \). To make the matrix independent of this factor, the transpose is added to the original to make it symmetrical viz.

\[
S = G + G^T
\]  

The symmetrical GLCM is finally normalized by dividing each element by the sum of all elements to form \( S^N_0 \). The ‘0’ in the subscript indicates angle \( \theta = 0^\circ \).

\[
S^N_0 = \frac{1}{\sum_i \sum_j S(i, j)} S
\]  

Directional GLCMs can also be computed along three other directions: vertical (\( \theta = 90^\circ \)), right diagonal (\( \theta = 45^\circ \)) and left diagonal (\( \theta = 135^\circ \)) generating matrices \( S^N_{45}, S^N_{90}, S^N_{135} \).
2.2. GLCM based Features

A set of features derived from four directional normalized symmetrical GLCMs are considered for texture characterization as defined in Eq. (4) and (5). Here $S^N(i, j)$ represents the element $(i, j)$ of a normalized symmetrical GLCM, and $k$ the number of grey levels.

$$F_1 = \sum_{i=1}^{k} \sum_{j=1}^{k} i(i-j)S^N(i, j)$$  \hspace{1cm} (4)

$$F_2 = \sum_{i=1}^{k} \sum_{j=1}^{k} \left[ S^N(i, j) \right]^2$$  \hspace{1cm} (5)

2.3. GLCM based Classification

A texture class $i$ consists of a set of $n$ member images : $T_i = \{t_1, t_2, \ldots, t_n\}$. For each member image, four directional symmetrical normalized GLCMs are computed as indicated below :

$$\{(t_{G_0}^G, t_{45}^G, t_{90}^G, t_{135}^G), (t_{G_0}^G, t_{45}^G, t_{90}^G, t_{135}^G), \ldots, (t_{G_0}^G, t_{45}^G, t_{90}^G, t_{135}^G)\}_i$$

For each directional GLCM, features in Eq. (4) and (5) are computed. Each feature is averaged over the four directional GLCMs, for each member image viz.

$$\{(\overline{F}_1^G), \ldots, (\overline{F}_n^G)\}_i \quad \text{where}, \quad \overline{F}_X = \frac{f_{X,0}^G + f_{X,45}^G + f_{X,90}^G + f_{X,135}^G}{4} \quad \text{and} \quad X \in \{F_1, F_2\}.$$  

A texture class is characterized by the collection of its feature values obtained during a training phase. A test image $s_j$ with its computed average features $(\overline{S}_j^G)$ is said to belong to a specific texture class if the probability of its feature values being a member of that training class is maximum.

3. Experimentations and Results

Skin images collected from the DERMNET (http://www.dermnet.com) image collection are used for experimentations. The total media-set used in this work consists of 180 images, divided into three disease classes with 60 images per class. The disease classes are as follows :

(1) Atopic Dermatitis (henceforth referred to as Class D), an allergic skin condition where the skin becomes red, flaky and itchy
(2) Eczema (henceforth referred to as Class E), an inflammation of the epidermis with symptoms like dryness, swelling, itching, blistering
(3) Urticaria (henceforth referred to as Class U) a kind of skin rash notable for dark red, itchy bumps.

The images are scaled to standard dimensions of $100 \times 100$ and stored in JPEG format. The resolutions of these images are 72 pixels per inch. A sample of the images is shown in Fig. 1.
Fig: 1: Sample Images belonging to three skin disease conditions (a) D, (b) E, (c) U

The following legends are used in this work:

TD1  Training set, Dermatitis, Feature 1
TE1  Training set, Eczema, Feature 1
TU1  Training set, Urticaria, Feature 1
TD2  Training set, Dermatitis, Feature 2
TE2  Training set, Eczema, Feature 2
TU2  Training set, Urticaria, Feature 2
SD1  Testing set, Dermatitis, Feature 1
SE1  Testing set, Eczema, Feature 1
SU1  Testing set, Urticaria, Feature 1
SD2  Testing set, Dermatitis, Feature 2
SE2  Testing set, Eczema, Feature 2
SU2  Testing set, Urticaria, Feature 2

Out of the 60 images per class, 30 images are chosen as the training set. Fig. 2 and Fig. 3 show the plots for the variation of the features $F_1$ and $F_2$ for the training dataset.
90 remaining images are chosen as the testing set, out of which the first 30 belong to Class-D, the next 30 to Class-E, and last 30 to Class-U. The testing plots are shown in Fig. 4 for feature $F_1$ and in Fig. 5 for feature $F_2$. 
Class probability of each test sample is estimated using a neural network (multi-layer perceptron: MLP). The neural network architecture used is 1-31-3, i.e., 1 input node (for each individual feature F1 or F2), 31 nodes in the hidden layer and three output nodes (for D, E, U), log-sigmoid activation functions for both the neural layers, learning rate of 0.01 and Mean Square Error (MSE) threshold of 0.005 for convergence. The convergence plot and MLP output for F1 are shown in Fig. 6. The MLP output indicates that number of images along the X-axis of which the first 30 belongs to Class-D, the next 30 to Class-E and the last 30 to Class-U.
The recognition accuracies are tabulated in Table 1. The overall accuracy (O) for the three classes is 96.6% with F₁ and 82.2% with F₂. F₁ is observed to provide the best recognition rates for all classes. By comparison the accuracy obtained by classification using Manhattan distance is 82.2% for F₁ and 78.8% for F₂.

Table 1: Recognition Accuracies

<table>
<thead>
<tr>
<th>Feature Used</th>
<th>D</th>
<th>E</th>
<th>U</th>
<th>O</th>
<th>Accuracy Using Manhattan Distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>F₁</td>
<td>30</td>
<td>29</td>
<td>28</td>
<td>96.67%</td>
<td>82.22%</td>
</tr>
<tr>
<td>F₂</td>
<td>29</td>
<td>25</td>
<td>21</td>
<td>82.22%</td>
<td>78.88%</td>
</tr>
</tbody>
</table>
4. Conclusions & Future Scopes:

The system proposed in this paper can be used to provide a low cost and effective solution for automated recognition of skin diseases. On one hand this would be useful for dermatologists to reduce diagnostic errors, while on the other it can serve as the initial test bed for patients in rural areas where there is a dearth of good medical professionals. In contrast to approaches like ASSERT [10] which require a physician to manually specify regions of interest, this system works entirely in an automated fashion, which makes it less costly and faster. Approaches like [13] based on fusion of several features like texture, color and shape, are computation intensive and require powerful systems which might not be available in remote and rural areas. Finally systems like Archimedes [11] use relational databases for image storage implying the need for textual descriptors, whereas the current system can store and search for similar images directly using feature vectors.

The accuracy of the current system is comparable to those reported in contemporary works. To put the above results in perspective with the state-of-the-art, the best results reported in [10] for identifying disease classes from 302 lung section images involving texture features homogeneity, contrast, correlation and cluster, in addition to other features like grey-level histogram, is 76.3%. Accuracy for classification of 800 endoscopic images in [13] using a fusion of color, texture and shape features ranges from 77% to 90% but only about 25% involving texture features alone. Accuracy results reported in [1] tested on 300 skin texture images is 96% but uses 9 color features in addition to 4 texture features, entropy, energy, contrast, homogeneity.

The accuracy of the current system can be improved upon by along the following directions:
1. Combining several GLCM based features together for better modeling possibilities
2. Considering color information by employing GLCMs on individual R, G, B color channels
3. Using other texture discrimination techniques like Wavelet decomposition

References