Using Texture Analysis for Medical Diagnosis

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An automated system for recognizing human skin disease conditions analyzes skin texture images using texture recognition techniques based on gray-level co-occurrence and wavelet decomposition matrices.

Texture analysis is one of the fundamental aspects of human vision by which we discriminate between surfaces and objects. In the digital-image-processing field, 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. 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. (See the ''Related Work on Texture Analysis'' for more details.)

In recent years, computer vision methodologies have been applied to the health informatics and telemedicine fields to help automatically diagnose diseases. The huge collection of medical images generated every day all over the world has helped fuel interest in automated health diagnosis. For example, the Radiology Department of the University Hospital of Geneva alone produces more than 12,000 images a day.[1] Moreover, automated diagnosis measures have shown great potential for reducing diagnostic errors. One of the most important predictors of healthcare performance is the accuracy and efficiency of medical diagnosis. One Harvard study reported that diagnostic errors have a substantial negative impact on patient care, such as an incremental cost per patient of $4,685 and an increase in average length of stay by 4.6 days.[2] In the US alone, medical errors result in 44,000 to 98,000 unnecessary deaths each year and 1 million excess injuries.[3]

Ironically, most diagnostic errors are preventable. Research shows that diagnosis errors often occur when clinicians are inexperienced and new procedures are introduced. Furthermore, age, complex care, urgent care, and prolonged hospital stay have been found to be correlated with diagnostic errors. The two types of diagnostic errors include *errors of omission*, or failures of action such as a missed diagnosis or a delayed evaluation, and *errors of commission*, or incorrect actions such as administering the wrong drug to the wrong patient at the wrong time. Applying automated information systems in medical analysis has shown great promise in reducing both types of human-based errors.[4]

This article proposes a scheme for automated detection of three classes of skin diseases by analyzing textures obtained from a collection of medical images. This approach uses features based on a gray-level co-occurrence matrix (GLCM) and wavelet decomposition matrix (WDM) with various types of classifiers, including neural networks.

Computing a GLCM

Introduced by Robert Haralick,[5] a GLCM is a popular statistical method for texture analysis. A GLCM indicates the probability of gray-level i occurring in the neighborhood of gray-level j at distance d and direction θ. GLCMs can be computed from texture images using different values of d and θ, and these probability values create the co-occurrence matrix $G(i, j \mid d, \theta)$.

Consider a 4×4 section I of an image having four gray-level intensities:

$$I = \begin{bmatrix} 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 1 \\ 0 & 2 & 2 & 2 \\ 2 & 2 & 3 & 3 \end{bmatrix}$$

To compute the frequency of one gray tone in the neighborhood of others, we form a 4×4 matrix (because there are four distinct gray

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Related Work on Texture Analysis

Researchers have proposed numerous methodologies to automatically analyze and recognize textures. One of the first studies involved derivation of texture-energy measures using a set of simple masks (vertical, horizontal, diagonal, and antidiagonal).[1] Other work attempted to define a set of visually relevant texture features,[2] including coarseness, contrast, directionality, line likeness, regularity, and roughness. Alex Pentland reported a high degree of correlation between fractal dimensions and human estimates of roughness.[3] Two-state Markov models have been used to detect texture edges characterized by changes in first-order statistics.[4] Gabor filters have been used in several image analysis applications, including texture classification and segmentation.[5]

In health informatics, researchers have applied computer vision techniques involving texture analysis to predict and characterize skin diseases. N.K. Al abbadi and his colleagues proposed a method for skin-texture recognition using a three-layer neural network using both skin color and texture features.[6] Another research team proposed a method of diagnosing pigmented skin lesions using a digital dermoscopy analyzer to evaluate a series of clinically atypical, flat-pigmented skin lesions.[7] Fractal parameters such as lacunarity and fractal dimensions have been used in skin cancer diagnoses.[8] Bayesian networks have also been used for skin texture recognition.[9] (A review of image analysis techniques for medical diagnoses is available elsewhere.[10])

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tones), indicating them with sequential numbers along the left (reference) and top (neighbor). We then compute the frequencies with which each pair (reference, neighbor) of gray tones occurs together in I. That is, for a reference gray tone i, how many times does the neighbor gray tone j occur near it within I? This constitutes the (i, j)th element of GLCM matrix G:

$$\mathbf{G} = \begin{array}{c} \\ 0 \\ 1 \\ 2 \\ 3 \end{array} \begin{array}{c} \begin{array}{cccc} 0 & 1 & 2 & 3 \end{array} \\ \begin{bmatrix} 2 & 2 & 1 & 0 \\ 0 & 2 & 0 & 0 \\ 0 & 0 & 3 & 1 \\ 0 & 0 & 0 & 1 \end{bmatrix} \end{array}$$

For simplicity's sake, we consider the distance d as 1 (only considering adjacent pixels) and angle θ as 0° (along the positive x-axis from left to right).

For example, 0 (reference) adjacent to 0 (neighbor) in I occurs twice (rows 1 and 2), so we put 2 at position (0, 0) of G. Likewise, 0 adjacent to 1 occurs twice (rows 1 and 2), so (0, 1) contains 2; and 0 adjacent to 2 occurs once (row 3), so (0, 2) contains 1; and so on. This procedure repeats for all pairs of intensities.

If we had moved along the negative x-axis—that is, if 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