Using Fuzzy Reasoning to Support a System of Diagnosis of Skin Disease

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Summary

We herein present a fuzzy reasoning approach for a computer-aided diagnostic scheme using medical imaging. The scheme is utilized in skin color images to identify skin disease and to detect and classify clustered microcalcifications. The fuzzy membership functions are initially generated using various texture-based features obtained from reference images. After optimization, the classifier is used for disease identification. The results of this experiment are very promising and demonstrate that our proposed fuzzy reasoning approach is an effective method for computer-aided diagnosis in disease classification.

Keywords

skin color images, computer-aided diagnosis, fuzzy reasoning, skin disease

Introduction

Research in computer-aided diagnosis is a rapidly growing, dynamic field with new computer techniques, imaging modalities, and interpretation tasks. Computer-aided diagnosis is defined as a diagnosis made by a radiologist who uses a computerized analysis of medical images as a second opinion in detecting lesions, assessing the extent of a disease, and making diagnostic decisions (Giger et al., 2001). Most computer-aided diagnosis studies have involved either mammograms (Chen and Lee, 1997; Bruce and Adhami, 1999; Huo et al., 2000; Lo et al., 2002) or chest radiographs (Carreira et al., 1998; Catariou et al., 2001; Ginneken and Katsuragawa, 2002); however, recent reports show that computer-aided diagnosis research has now been extended to other fields such as colonography (Gokturk et al., 2001; Yoshida and Nappi, 2001).

The skin is a unique organ that is highly accessible to direct visual inspection with light. Skin color is an important clinical parameter for the dermatologist and cosmetic scientist. The perceived color of the skin depends on a number of variables, including pigmentation, blood microcirculation, surface texture, sweating, and sebum secretion. Visual inspection of cutaneous morphology is the mainstay of clinical dermatology, although it relies heavily on subjective assessment by skilled dermatologists. Digital imaging methods are now being used to visualize, document, monitor, measure, and classify morphologic manifestations of various cutaneous processes. The appearance of human skin is a major descriptive parameter in both clinical and scientific evaluations. For example, skin color may be associated with susceptibility to the development of skin cancer, changes in color characterize erythema, and the observation of color variegation is an important clinical criterion for differentiating between cutaneous malignant melanoma and benign nevi. However, visual observations and subjective assessments lack precision in regard to the communication of color information. Human skin is a textured medium with a multilayered structure. Various pigments such as melanin and hemoglobin are present in the medium, and slight changes in structure and pigment construction produce rich skin color variation. It is therefore necessary to analyze skin color on the basis of structure and pigment construction in discerning various skin colors. The visual inspection of cutaneous morphology is the mainstay of clinical dermatology, but it relies heavily on subjective assessment by skilled dermatologists. With the recent progress in various imaging systems such as multimedia, computer graphics, and telemedicine, skin color becomes increasingly important for communication, medical diagnosis, cosmetic development, and so on.

In this paper, we present a generalized computer-
aided diagnosis scheme based on our previously reported computer-aided diagnosis scheme (Farkas et al., 1998; Alfano et al., 1988; Ercal et al., 1993). The proposed computer-aided diagnostic scheme involves four stages: image preprocessing, feature extraction, classifier training, and classification. This scheme can be applied to various imaging modalities and diseases with minor modifications. In our system, we employ fuzzy logic for classification. We herein report the experimental results of applying the proposed technique to real data. The evaluation compares this diagnostic strategy with a technique that uses layered neural networks.

**Physical basis of skin color**

The skin is divided into three layers; namely, the epidermis, the dermis, and the subcutaneous tissue. The epidermis is the outermost portion of the skin and is composed of stratified squamous epithelia. The innermost layer of the epidermis consists of a single layer of cuboidal cells called basal cells, which differentiate and migrate towards the skin surface. The outer layer of the epidermis is called the stratum corneum and is composed of flattened dead cells. Various pigments such as melanin, hemoglobin, bilirubin, and β-carotene are present in the layers. The most common pigments are melanin and hemoglobin, which are predominantly found in the epidermal and dermal layer, respectively. Although combined variations of cutaneous melanin and hemoglobin essentially account for the entire range of normal skin colors, distinctive changes in color also result from the presence of abnormal pigments, high concentrations of normally minor pigments, or abnormal anatomical distributions of normal pigments. Hemochromatosis and tattoos are examples of the presence of abnormal pigments. Blue nevi result from melanin and the purpura result from extravascular blood in the dermis. Cutaneous pathologies can also change skin color due to variations in the normal amount of epidermal melanin (vitiligo, epidermal melanocytic nevi, melanoma) or blood in the superficial dermis (inflammation, atrophy, hemangioma). Atopic dermatitis, acne vulgaris, comedo, solar keratosis, senile pigment freckles, malignant melanoma, nevi, and melasma are other sources of abnormal skin color variation.

The color of normal human skin depends on the interactions of incident light upon it. The spectrum of visible light extends between the wavelengths of approximately 400 nm and 700 nm. The blue region of this spectrum lies between about 400 nm and 500 nm and the red region lies between 600 nm and 700 nm. However, when more than one wavelength is present (as is almost always the case), human color vision is to a large extent comparative. The essentially infinite number of possible hues derives from the different balances between spectral regions of the visible spectrum and also to some extent from the intensity of the light reaching the eye. Color vision is also comparative in the sense that rather subtle color judgments of a given site are made in reference to the rest of the visual field. Therefore, decreased spectral reflectance in the shorter wavelengths relative to the surroundings may be perceived as a red or brownish hue. Conversely, decreased reflectance in the longer wavelength region in comparison to the visual surroundings can give rise to bluish colors. In the case of blue skin lesions, their color derives not from increased spectral reflectance in the blue region, but rather from decreased spectral reflectance in the red region in comparison to normal skin.

Visible light returning from the skin is composed of two easily separable components, one reflected from the skin surface and the other back-scattered from within the tissue. These two components carry vastly different information about the skin. Roughly 5% of incident light is reflected from the skin surface due to the large increase in the refraction index in traveling from the air to the stratum corneum. This regular reflectance component is essentially independent of wavelength and therefore has little or nothing to do with our appreciation of skin color. It does, however, allow an assessment of fine skin surface contours. Surface reflection obeys Fresnel's classic law of reflection, which states that the angle of reflection is equal to the angle of incidence. This surface reflection component gives oily or stretched skin a shine. It is simple to eliminate the surface reflection component from one's view of skin by using a linearly polarized source of light and viewing the skin through a second polarizer in crossed orientation to the source. One's ability to discern surface detail is lost, but deeper tissue structures often become more apparent. Allowing for 5% surface reflectance, about 95% of normal incident light penetrates the skin, where it is absorbed by tissue pigments and scattered by nonhomogeneous tissue structures. Skin colors derive from the spectral character of visible radiation backscattered from within the tissue.

A simple, clinically useful model can be used to describe the backscattered radiation. The thick, strongly reflective, opaque dermis is overlain by and viewed through the thin, melanized epidermis. Whereas melanin absorption dominates the optical properties of the epidermis, scattering by collagen fibers largely determines dermal optics. Aside from the surface reflection discussed above, the stratum
corneum and epidermis do not normally backscatter more than a small percentage of the incidental light. In traversing this thin outer layer, there is simply insufficient backscattering of visible wavelengths to account for a significant contribution to skin reflectance, regardless of the melanin content. For example, after correction for its surface reflectance component, isolated albino or vitiliginous epidermis diffusely backscatters only about 5% of incident visible radiation, and pigmented epidermis backscatters even less. The vast majority of visible incident light entering the epidermis is therefore either absorbed or transmitted to the dermis, but not directly backscattered by the epidermis. In this manner, the epidermis acts as an absorption filter through which one views the underlying dermis, and therefore most of the backscattered radiation from the skin traverses the epidermis twice.

Transmission spectra confirm the dominant role of melanin as the major epidermal absorber of visible wavelengths. Transmittance through isolated epidermis is strongly dependent upon the melanin content, with the shorter wavelengths being attenuated more than longer, yellow/red wavelengths, which leads to brown coloration. Traditionally, the color of human skin has been evaluated visually and with various types of instruments (after the advent of electronic light transducers). All instrumental approaches to skin color evaluation depend on the illumination of the skin site by a standard light source at a fixed relative angle that minimizes the spectral reflected light from the stratum corneum. The detector collects light backscattered by the skin site from a particular angle with a chosen filter that mimics a specific selected response. Instrumental evaluation thus yields a number or a series of numbers that describe some aspect of skin appearance.

Materials and Methods

Data set

In an earlier paper, we described a portable rapid skin color meter using a video camera (Asaeda et al., 1997; Takata et al., 2001; Yang et al., 2003). We demonstrated that the instrument could be applied to the quantification of hemoglobin and melanin. In the present work, the images were captured from an image-colorimeter. The basic hardware components of the system were a CCD camera, a light source, a real-time image processing board, a magneto-optics disk, and a personal computer that controls the entire system. The block diagram of the system is illustrated in Fig. 1. Both the camera and projector were housed in a portable box and the illumination was provided by a halogen lamp connected with a color temperature conversion filter. The light from the halogen lamp was transmitted and delivered onto the surface at an angle of 45° to the normal angle. The reflected light is collected by the camera at 0° to the surface normal. The picture obtained provided a set of data which offers a spatial resolution of 768 (horizontal) × 494 (vertical) pixels and a color resolution of 256 levels for each band of red, green and blue (RGB), thus indicating that each band had an independent brightness in 256 gradations (0, darkest; 255, brightest), and that the color of each pixel was expressed by an additive mixture of the three basic colors. The RGB color spaces did not form any CIE recommended standard color spaces. Color quantification in established color notation, using the described system, required the conversion of the measured RGB values of the image to the CIE-XYZ tristimulus values. This conversion was performed using a transformation matrix between the RGB and XYZ color spaces. In the described system, the CIE-L′a′b′ uniform color space was used and the derivation of the L′, a′, b′, C′, and h° color parameters from the XYZ values was determined by the following formulas:

\[
L' = 116 \left( f\left( \frac{Y}{Y_0} \right)^{1/3} - 16 \right) \quad (1)
\]

\[
a' = 500 \left( f\left( \frac{X}{X_0} \right)^{1/3} - f\left( \frac{Y}{Y_0} \right)^{1/3} \right) \quad (2)
\]

\[
b' = 200 \left( f\left( \frac{Y}{Y_0} \right)^{1/3} - f\left( \frac{Z}{Z_0} \right)^{1/3} \right) \quad (3)
\]

\[
C' = \sqrt{a'^2 + b'^2} \quad (4)
\]

\[
h = \tan^{-1}\left( \frac{b'}{a'} \right) \quad (5)
\]

Fig. 1. System utilized for the color analysis of the skin consisting of a video camera and a personal computer.
where \(X_0, Y_0\) and \(Z_0\) were the tristimulus values of the reference white. Under these conditions, \(X_0, Y_0, Z_0\) were the tristimulus values of the standard illuminant with \(Y_0\) equal to 100. The psychometric chroma \(C^*\) and hue angle \(h^\circ\) were calculated as follows:

\[
C^* = (a^{*2} + b^{*2})^{1/2}
\]

\[
h^\circ = \tan^{-1}(b^*/a^*)
\]

The color space was expressed in a three dimensional space as shown in Fig. 2. In this color space, equal distances between color points represented approximately equal perceptual differences, as long as the distances are relatively small. For the present range of colors, \(L^*\) was related to brightness, the \(a^*\) index was related to redness (+) versus greenness (−) and the \(b^*\) index was related to yellowness (+) versus blueness (−).

**Feature extraction**

We thought that the CIE-L*a*b* color space would be suitable for the identification of skin disease. Therefore, we fuzzified the \(L^*, a^*, b^*, C^*,\) and \(h^\circ\), and then assumed them to be the characteristic parameters of the skin which we measured. In addition, the method of the membership functions of the data was that we assume it was size 1 mainly on the data which we measured and did it with three square shapes having suitable width. We fuzzified the typical data of every skin disease and make characteristic parameters. We performed the max operation of the membership function made of every characteristic parameter that we collected and made a dictionary. In addition, we could increase the diagnostic accuracy by the revision of a membership function when a new patient was seen for a specific skin disease. Table 1 shows the definitions of the representative diseases.

**Proposed Method**

**Fuzzy membership functions and fuzzy rules**

Fuzzy rule interpolation techniques are essential for sparse rule-based fuzzy systems. Triangular fuzzy membership functions were initially considered to demonstrate the basic ideas of the present work due to their simplicity and popularity (Nauck et al., 1997; Cordon et al., 1998; Fuller, 2000). This function is to be followed by more complex functions such as trapezoidal and Gaussian curves. To facilitate the discussion, the representative value of a triangular membership function was defined as the average of the \(x\) coordinates of its three key points: the left and right extreme points (whose membership values were 0) and the normal point (whose membership value was 1). Without losing generality, given a fuzzy set \(A\) (denoted as \(a_0, a_1, a_2\)) as shown in Fig. 3, its representative value was
Support System of Skin Disease by Fuzzy Reasoning

Disease Definition

**Acne vulgaris**
Acne is a skin condition caused by changes in the pilosebaceous units (skin structures consisting of a hair follicle and its associated sebaceous gland). Severe acne is inflammatory, but acne can also manifest in noninflammatory forms. Acne lesions are commonly referred to as pimples, blemishes, spots, zits, or acne.

**Atopic dermatitis**
Atopic dermatitis is a chronic inflammatory skin disease of genetic origin. It is primarily due to the development of an inflammatory immune response in the skin, abnormalities in cutaneous permeability barrier function characterized by a significant increase in basal transepidermal water loss, and dysfunctions of the stratum corneum lipid metabolism.

**Lentigo**
Lentigo (plural lentigines) is generally described as a brown pigmented spot on the skin. The term “lentiginous” is used to describe a skin lesion that fits the description of a lentigo.

**Melasma**
Melasma is a tan or dark skin discoloration. Although it can affect anyone, melasma is particularly common in women, especially pregnant women and those who are taking oral or patch contraceptives or hormone replacement therapy medications.

### Table 1. Definitions of the representative diseases.

<table>
<thead>
<tr>
<th>Disease</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acne vulgaris</td>
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</tr>
</tbody>
</table>

\[
R(A) = \frac{a_0 + a_1 + a_2}{3} \quad (6)
\]

\[
\lambda_R = \frac{d(A_1, A^*)}{d(A_1, A_2)} = \frac{d(R(A_1), R(A^*))}{d(R(A_1), R(A_2))} \quad (8)
\]

This representative value happened to be the \( x \) coordinate of the center of gravity of such a triangular fuzzy set. Suppose that two adjacent fuzzy rules \( A_1 \Rightarrow B_1, A_2 \Rightarrow B_2 \) and the observation \( A^* \), which is located between fuzzy sets \( A_1 \) and \( A_2 \), are given. The case of interpolative fuzzy reasoning concerning two variables \( X \) and \( Y \) can be described through the following modus ponens interpretation (7) as illustrated in Fig. 4:

observation: \( X \) is \( A^* \)

rules: if \( X \) is \( A_1 \), then \( Y \) is \( B_1 \)

if \( X \) is \( A_2 \), then \( Y \) is \( B_2 \) \quad (7)

conclusion: \( Y \) is \( B^* \) ?

Here, \( A_i = (a_{i0}, a_{i1}, a_{i2}) \), \( B_i = (b_{i0}, b_{i1}, b_{i2}) \), \( i = 1, 2 \), and \( A^* = (a_0, a_1, a_2) \), \( B^* = (b_0, b_1, b_2) \).

To perform interpolation, the first step was to construct a new fuzzy set \( A' \) which had the same representative value as \( A^* \). The following was created first:

\[
a'_0 = (1 - \lambda_R) a_{10} + \lambda_R a_{20} \quad (9)
\]

\[
a'_1 = (1 - \lambda_R) a_{11} + \lambda_R a_{21} \quad (10)
\]

\[
a'_2 = (1 - \lambda_R) a_{12} + \lambda_R a_{22} \quad (11)
\]

which were collectively abbreviated to

\[
A' = (1 - \lambda_R) A_1 + \lambda_R A_2 \quad (12)
\]

Now, \( A' \) had the same representative value as \( A^* \). With (9)–(11) and (8),

\[
R(A') = (1 - \lambda_R) R(A_1) + \lambda_R R(A_2) - R(A^*) \quad (13)
\]

Consequently, \( A' \) was generated to be a convex fuzzy set as the following held given \( a_{10} \leq a_{11} \leq a_{12}, a_{20} \leq a_{21} \leq a_{22} \) and \( 0 \leq \lambda_R \leq 1 \):
The second step of interpolation was performed in a similar way to the first, such that the consequent fuzzy set $B'$ could be obtained as follows:

\begin{align*}
  a_1' - a_0' &= (1 - \lambda_R)(a_{11} - a_{10}) + \lambda_R(a_{21} - a_{20}) \geq 0, \\
  a_2' - a_1' &= (1 - \lambda_R)(a_{12} - a_{11}) + \lambda_R(a_{22} - a_{21}) \geq 0
\end{align*}

with the abbreviated notation:

$$B' = (1 - \lambda_R)B_1 + \lambda_R B_2$$

As a result, the newly derived rule $A' \Rightarrow B'$ involved the use of only normal and convex fuzzy sets. As $A' \Rightarrow B'$ was derived from $A_1 \Rightarrow B_1$ and $A_2 \Rightarrow B_2$, it was feasible to perform fuzzy reasoning with this new rule without further reference to its originals. The interpolative reasoning problem was therefore changed from expression (7) to the new modus ponens interpretation:

observation: $X$ is $A^*$

rules: if $X$ is $A'$, then $Y$ is $B'$

conclusion: $Y$ is $B^*$?

This interpretation retained the same results as (7) in dealing with the extreme cases. If $A^* = A_1$, then it followed from (8) that $\lambda_R = 0$, and according to (12)
and (19), $A' = A_1$ and $B' = B_1$, so the conclusion $B^* = B_1$. Similarly, if $A^* = A_2$, then $B^* = B_2$. If a certain degree of similarity between $A'$ and $A^*$ was established, it was intuitive to require that the consequent parts $B'$ and $B^*$ attain the same degree of similarity.

The question was how to obtain an operator which could represent the degree of similarity between fuzzy sets $A'$ and $A^*$, and to allow transforming $B'$ to $B^*$ with the desired degree of similarity. Therefore, the third step of the interpolation process was to calculate the degree of similarity in terms of scale rate and to move ratio between $A'$ and $A^*$, and then to obtain the resulting fuzzy set $B^*$ by transforming $B'$ with the same scale rate and move ratio. Through interpolation steps 1 to 3, given a convex and normal triangular fuzzy set as the observation, a new convex and normal fuzzy set could be derived using two adjacent rules.

**Fuzzy inference process**

The fuzzy inference process could be described in the following five steps (shown in Fig. 5):

1. **Step 1: Fuzzy Inputs**
   The first step is to take inputs and determine the degree to which they belong to each of the appropriate fuzzy sets via membership functions.

2. **Step 2: Apply Fuzzy Operators**
   Once the inputs have been fuzzified, we know the degree to which each part of the antecedent has been satisfied for each rule. If a given rule has more than one part, the fuzzy logical operators are applied to evaluate the composite firing strength of the rule.

3. **Step 3: Apply the Implication Method**
   The implication method is defined as the shaping of the output membership functions on the basis of the firing strength of the rule. The input for the implication process is a single number given by the antecedent, and the output is a fuzzy set. Two commonly used methods of implication are the minimum and the product.

4. **Step 4: Aggregate all Outputs**
   Aggregation is a process whereby the outputs of each rule are unified. Aggregation occurs only once for each output variable. The input to the aggregation process is the truncated output fuzzy sets returned by the implication process for each rule. The output of the aggregation process is the combined output fuzzy set.

5. **Step 5: Defuzzify**
   The input for the defuzzification process is a fuzzy set, and the output of the defuzzification process is a crisp value obtained by using a defuzzification method such as the centroid, height, or maximum. We considered the input membership functions with different degrees of overlap. Here, the input $x$ denotes the quality of the service, which is represented by a number between 0 and 1 (1 designates very good and 0 very poor). The input $x$ is represented by the term set {very poor, poor, average, good, very good}. The output $y$ represents the tip, which varies between 5 and 30 percent, and is given by the term set {very cheap, cheap, average, generous, very generous}.

**Results and Discussion**

**Experimental results by fuzzy reasoning**

We performed this experiment by the proposed method using five parameters. We used data from 43 subjects (12 acne vulgaris patients, 7 atopic dermatitis patients, 6 senile pigment spot patients, 3 melasma patients, and 15 people with normal skin). We made the dictionary from these data and chose 9 patients with an unknown skin disease to perform the experiment. The results were correct in 8 out of 9 patients (Tables 2 and 3).
Experimental results by neural network

We used a three hierarchy model neural network for the diagnosis of skin disease. We performed the experiment on the same set of five parameters that were used in the proposed method. The constitution of the neural network was five input layer units, 30 hidden layer units, and five output layer units. We prepared $L^*$, $a^*$, $b^*$, $C^*$, and $h^*$ for the input data and prepared the name of skin disease – acne vulgaris, atopic dermatitis, old man-related pigment spot, stain and normal skin – in the output. We used the diagnosis from a doctor for the teacher signal. It learned with the data from patients with the representative skin diseases and estimated the state of skin after learning. Table 2 shows the experiment results. From these results, we know that the diagnoses using the fuzzy reasoning were more accurate than those obtained via the neural

Table 2. Distributions of calculated feature values.

<table>
<thead>
<tr>
<th>Dictionary patients</th>
<th>Acne vulgaris</th>
<th>Atopic dermatitis</th>
<th>Pigment spot</th>
<th>Melasma</th>
<th>Normal skin</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (Acne vulgaris)</td>
<td>0.88</td>
<td>0.52</td>
<td>0.58</td>
<td>0.30</td>
<td>0.68</td>
</tr>
<tr>
<td>2 (Acne vulgaris)</td>
<td>0.84</td>
<td>0.58</td>
<td>0.42</td>
<td>0.18</td>
<td>0.37</td>
</tr>
<tr>
<td>3 (Atopic dermatitis)</td>
<td>0.83</td>
<td>0.61</td>
<td>0.41</td>
<td>0.18</td>
<td>0.32</td>
</tr>
<tr>
<td>4 (Atopic dermatitis)</td>
<td>0.75</td>
<td>0.84</td>
<td>0.38</td>
<td>0.41</td>
<td>0.69</td>
</tr>
<tr>
<td>5 (Pigment spot)</td>
<td>0.71</td>
<td>0.53</td>
<td>0.75</td>
<td>0.39</td>
<td>0.36</td>
</tr>
<tr>
<td>6 (Pigment spot)</td>
<td>0.75</td>
<td>0.76</td>
<td>0.79</td>
<td>0.27</td>
<td>0.61</td>
</tr>
<tr>
<td>7 (Melasma)</td>
<td>0.72</td>
<td>0.57</td>
<td>0.52</td>
<td>0.81</td>
<td>0.67</td>
</tr>
<tr>
<td>8 (Normal skin)</td>
<td>0.70</td>
<td>0.66</td>
<td>0.43</td>
<td>0.52</td>
<td>0.88</td>
</tr>
<tr>
<td>9 (Normal skin)</td>
<td>0.49</td>
<td>0.31</td>
<td>0.39</td>
<td>0.26</td>
<td>0.87</td>
</tr>
</tbody>
</table>

Table 3. Performance comparison of various methods used to diagnose dermatological disease.

<table>
<thead>
<tr>
<th>Unknown patient (skin disease)</th>
<th>Fuzzy reasoning</th>
<th>Neural network</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diagnosis result</td>
<td>True or false</td>
<td>Diagnosis result</td>
</tr>
<tr>
<td>1 (Acne vulgaris)</td>
<td>Acne vulgaris</td>
<td>○</td>
</tr>
<tr>
<td>2 (Acne vulgaris)</td>
<td>Acne vulgaris</td>
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</tr>
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network. These results were due to the fact that the dictionary is made considering the patient differences in regard to a certain skin disease.

We evaluated the performance of the proposed method in terms of sensitivity, specificity, and overall accuracy. Sensitivity is the probability that a diagnostic test is positive when the patient does indeed have the disease, whereas specificity is the probability that a diagnostic test will be negative when the person does not have the disease. Overall accuracy is the probability that a diagnostic test is correctly performed. The benignancy rule and malignancy rule are used in our fuzzy logic, and the min-max compositional rule of fuzzy inference is employed for defuzzification. The results suggest that our proposed fuzzy method for determining the fuzzy membership functions is useful, especially in the case of limited availability of training data. Future studies increasing the sample sets for further feasibility tests on the proposed method are needed.

Conclusions

We have herein proposed a fuzzy approach for a computer-aided diagnostic scheme for disease classification. The proposed method exploited training for optimization of membership functions, and triangular-shaped membership functions were employed. The effectiveness of our proposed method has been demonstrated through two applications, namely, the identification of dermatological disease from skin color images and the classification of clustered microcalcifications from skin images. We have compared the proposed methods with another method, the neural network approach. The fuzzy classification approach exploited the optimization of membership functions, and the proposed method demonstrated 100% accuracy in disease classification. This result suggests that our method has the potential to become clinically useful in regard to the computer-aided diagnosis of skin disease. The accuracy has validated the superiority of the proposed method in the identification of dermatological disease. In the classification of microcalcifications, the receiver operating characteristic analysis was employed to compare the performance of the neural network method, and the results revealed the possibility of greater accuracy by using the proposed method. Our future studies will involve increasing the number of sample images for further feasibility tests on the proposed method, modifying the shape of the consequent-part membership function, and exploring more powerful image features.

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References


