Contents lists available at ScienceDirect



Computerized Medical Imaging and Graphics





Enhanced 3D curvature pattern and melanoma diagnosis

Yu Zhou^{a, c,*}, Melvyn Smith^a, Lyndon Smith^a, Abdul Farooq^a, Robert Warr^b

^a Machine Vision Laboratory, University of the West of England, Bristol BS16 1QY, UK

^b Department of Plastic Surgery, North Bristol NHS Trust, Bristol BS16 1LE, UK

^c Faculty of Engineering, University of Leeds, Leeds LS2 9JT, UK

ARTICLE INFO

Article history: Received 6 September 2009 Received in revised form 13 October 2010 Accepted 14 October 2010

Keywords: Shape analysis Melanoma Convolution Curvature Ensemble classifier

1. Introduction

As the incidence of melanoma has been rising in the past decades around the world [1–3], enhancing clinical diagnosis of melanoma to make the diagnosis results more objective and reliable is increasingly critical for people's health. Thus in the literature, numerous inspection and diagnosis methods by clinicians and researchers have been published in a variety of journals [4–6].

In pigmented lesion clinics, the classic approach of melanoma diagnosis is usually through visual inspection of skin surfaces by surgeons with hand-held lenses. This visual inspection method is convenient to apply and it is relatively cost-effective as compared with other methods like biopsy, thus visual inspection is the dominant approach for skin inspection in clinics at present.

However, even if visual examination is still indispensable nowadays, it could be criticized in several ways. For instance, since visual inspection relies on experiences of the surgeons, subjectiveness of the surgeons can affect clinical decisions profoundly. In addition, as most lesions seen in the clinics are benign ones and inspecting them one by one can take a large share of the surgeons' working time, this wastes a lot of clinical resources which could be highly valuable.

Due to the presence of these disadvantages of visual examination, new alternatives are emerging recently. For example,

E-mail address: kylepub@gmail.com (Y. Zhou).

ABSTRACT

This article describes an enhanced curvature pattern based melanoma diagnosis system using convolution techniques and ensemble classifiers. We extract the 3*D* data of melanoma with a photometric stereo device first. Then differential forms of the melanoma surface can be extracted with the convolution method proposed. After extracting 3*D* based differential forms, statistical moments of enhanced principal curvatures of skin surfaces are calculated to describe the geometrical texture patterns. Finally, ensemble classifiers are constructed whose optimal mean sensitivity and specificity can reach 89.24 percent and 87.62 percent respectively. Comparisons with skin tilt/slant pattern based 3*D* shape characterization method and 2*D* methods like color variation and border irregularity are also included.

© 2010 Elsevier Ltd. All rights reserved.

researchers are designing various imaging devices to assist surgeons in pigmented lesion clinics [5–10]. These devices can acquire and/or analyze skin data automatically to assist surgeons in making diagnosis.

As compared with visual inspection, there are numerous advantages of machine based skin inspection. Firstly, it allows non-experts to conduct skin inspection and this can be very helpful to patients concerning their skin health. Secondly, it saves clinical resources as normally patients are less likely to visit clinics if they are advised with highly reliable clinical suggestions saying that their skin condition is healthy or non-critical. Thirdly, machine based skin inspection eliminates subjectiveness in visual inspection and thus the diagnosis results are of better repeatability thanks to its objectiveness.

A machine based melanoma diagnosis system usually works in four steps. These four typical steps include data acquisition of skin samples, segmentation, feature extraction and classification. It is well-known that a good diagnosis system requires all these steps working in good condition as they are highly inter-connected.

Among these steps, extracting good features is a key step for melanoma diagnosis. Many researchers are studying melanoma images to extract features from the perspective defined by *ABCD* rules [4] as they are probably the most convenient criteria in evaluating the skin conditions. For instance, [11–16] discuss asymmetry of lesion shapes. In Ref. [17–22], the border irregularities of suspicious lesions are investigated. Color based lesion studies are reported in Ref. [23–27]. In Ref. [28], lesion diameters are used to recognize melanoma. Nevertheless, methods orthogonal to *ABCD* rules are also emerging [29–34]. See Ref. [35] for a general review

^{*} Corresponding author at: Institute of Particle Science and Engineering, School of Process, Environmental and Materials Engineering, Faculty of Engineering, University of Leeds, Leeds, LS2 9JT, UK. Tel.: +44 0 11732 83550.

^{0895-6111/\$ -} see front matter © 2010 Elsevier Ltd. All rights reserved. doi:10.1016/j.compmedimag.2010.10.004

of ABCD rules and Ref. [36] for supplementing the evolutionary features into the ABCD rules.

Although these bio-imaging based techniques differ in detail with varying degrees, one common approach among most of them is using 2D data of the skin. Since real skin surfaces are 3D objects in space, it makes sense to expect that 3D data has descriptive power in describing shape and irregularity of melanoma. Nevertheless, instead of referring to 3D in space, '3D' can be used in a different way. For instance, a '3D' method proposed in [23] means 2D in image plane plus viewing the image intensity values as an elevation parameter.

Thanks to recent progresses in 3D imaging technologies, [37–39] use skin tilt/slant pattern to describe 3D surface shape irregularity. However, as proof of convergency of the nonlinear optimization problem involved in extracting skin tilt/slant pattern is missing, its reliability is jeopardized to a large extent. In Ref. [40], we give a direct method for computing 3D curvature which does not involve any optimization process. Although this method is simple to extract curvature features, it is sensitive to noise in computing curvatures.

In this article, we improve the method proposed in [40] using convolution method to suppress the noise involved in extracting features. We analyze why this method is more robust to noise and how to select the parameters effectively. After extracting curvature parameters, statistical moments including mean value and standard deviation of principal curvature of skin surface are used to characterize 3D shape irregularity as shown in [40].

This article is arranged as follows. Section 2 discusses how to obtain 3D data of skin and how to extract the curvature pattern effectively. In Section 3, experimental results are summarized using enhanced 3D curvature pattern and skin tilt/slant pattern. In addition, 2D methods such as border irregularity and color variation are also investigated as references to illustrate the validity of enhanced 3D curvature pattern in melanoma diagnosis. Section 4 concludes this paper.

2. 3D shape model of skin

2.1. Surface model

There are various approaches to build 3D surface models of melanoma. Here photometric stereo [41] is employed to model skin surface as it is an accurate, efficient and numerically stable method to extract skin surface data.

Denote the surface normal vector for a point P on the lesion surface as \vec{n} and $\vec{n}:=[n_x, n_y, n_z]$. The vectors of light sources are denoted as $\{\vec{L}^1, \vec{L}^2, \vec{L}^3\}$. Suppose the reflectance model for

$$\begin{bmatrix} \frac{\partial^2 z}{\partial x^2} & \frac{\partial^2 z}{\partial x \partial y} \\ \frac{\partial^2 z}{\partial y \partial x} & \frac{\partial^2 z}{\partial y^2} \end{bmatrix} = \frac{1}{2}$$

the skin surface is Lambertian, i.e., satisfying a linear reflectance model, the following equation can be obtained:

$$\rho \begin{bmatrix} \vec{L}^1 \\ \vec{L}^2 \\ \vec{L}^3 \end{bmatrix} \vec{n} = \begin{bmatrix} I^1 \\ I^2 \\ I^3 \end{bmatrix},$$
(1)

 I^{3} } are image intensities of *P* corresponding to $\{\vec{L}^{1}, \vec{L}^{2}, \vec{L}^{3}\}$ respectively.

If $\{\vec{L}^1, \vec{L}^2, \vec{L}^3\}$ are not lying on one plane, solving (1) yields a unique solution of the surface normal vector \vec{n} as follows,

$$\vec{\boldsymbol{n}} = \frac{1}{\rho} \begin{bmatrix} \begin{bmatrix} \vec{\boldsymbol{L}}^1 \\ \vec{\boldsymbol{L}}^2 \\ \vec{\boldsymbol{L}}^3 \end{bmatrix}^{\prime} \begin{bmatrix} \vec{\boldsymbol{L}}^1 \\ \vec{\boldsymbol{L}}^2 \\ \vec{\boldsymbol{L}}^3 \end{bmatrix}^{-1} \begin{bmatrix} \vec{\boldsymbol{L}}^1 \\ \vec{\boldsymbol{L}}^2 \\ \vec{\boldsymbol{L}}^3 \end{bmatrix}^{\prime} \begin{bmatrix} \boldsymbol{l}^1 \\ \boldsymbol{l}^2 \\ \boldsymbol{l}^3 \end{bmatrix}, \qquad (2)$$

since \vec{n} is of unit length.

By denoting the coordinates of any point *P* on the skin as (x, y, y)z(x, y)), it yields

$$\begin{pmatrix} n_x \\ n_y \\ n_z \end{pmatrix} = \frac{1}{\sqrt{(\partial z/\partial x)^2 + (\partial z/\partial y)^2 + 1}} \begin{pmatrix} -\frac{\partial z}{\partial x} \\ -\frac{\partial z}{\partial y} \\ 1 \end{pmatrix},$$
(3)

as \vec{n} is a unit normal vector. Thus after obtaining \vec{n} from photometric stereo, the partial derivatives of surface relief z with respect to x and y can be obtained from Eqs. (2) and (3) as:

$$\begin{cases} \frac{\partial z}{\partial x} = -\frac{n_x}{n_z}, \\ \frac{\partial z}{\partial y} = -\frac{n_y}{n_z}, \end{cases}$$
(4)

if $n_z \neq 0$. For simplicity, $\partial z / \partial x$ and $\partial z / \partial y$ are denoted as p and q in Section 2.3.

Fig. 1 shows one benign lesion and one melanoma including their 3D modeling results. Fig. 1(a) is an intensity image of a benign lesion and Fig. 1(b) shows the 3D rendering result with the surface relief information of Fig. 1(a). Fig. 1(c) is an intensity image of a malignant melanoma. Fig. 1(d) shows the corresponding 3D rendering result of Fig. 1(c).

2.2. Differential forms - direct method

- 2

After obtaining the normal vectors, i.e., n_x , n_y and n_z , as shown in Eq. (2), second order partial derivatives of surface relief z with respect to x and y can be calculated from Eq. (4) as:

$$\begin{bmatrix} \frac{\partial^2 z}{\partial x^2} & \frac{\partial^2 z}{\partial x \partial y} \\ \frac{\partial^2 z}{\partial y \partial x} & \frac{\partial^2 z}{\partial y^2} \end{bmatrix} = \begin{bmatrix} -\frac{\partial}{\partial x} \left(\frac{n_x}{n_z} \right) & -\frac{\partial}{\partial x} \left(\frac{n_y}{n_z} \right) \\ -\frac{\partial}{\partial y} \left(\frac{n_x}{n_z} \right) & -\frac{\partial}{\partial y} \left(\frac{n_y}{n_z} \right) \end{bmatrix}.$$
(5)

Suppose *x* is along the direction from top to bottom and *y* is along the direction from left to right on the image plane. A direct method proposed in [40] is to approximate the second order partial derivatives of surface relief as follows:

$$\begin{bmatrix} -\frac{n_x(x+1,y)}{n_z(x+1,y)} + \frac{n_x(x-1,y)}{n_z(x-1,y)}, & -\frac{n_y(x+1,y)}{n_z(x+1,y)} + \frac{n_y(x-1,y)}{n_z(x-1,y)} \\ -\frac{n_x(x,y+1)}{n_z(x,y+1)} + \frac{n_x(x,y-1)}{n_z(x,y-1)}, & -\frac{n_y(x,y+1)}{n_z(x,y+1)} + \frac{n_y(x,y-1)}{n_z(x,y-1)} \end{bmatrix},$$
 (6)

where (x,y) is the coordinate of point *P* on the image plane.

This method, called *direct method* in this article, is simple to apply. However, it is poor in suppressing noise as illustrated in Fig. 2.

2.3. Differential forms – convolution method

As direct method relies on difference equations between first order partial derivatives of surface relief, second order partial derivatives obtained in this manner involve high noise. A convolution method appeared in [42] offers an approach to alleviate this problem. This method uses the obtained noisy surface relief data to extract high order partial derivatives with a 2D Gaussian kernel Download English Version:

https://daneshyari.com/en/article/504464

Download Persian Version:

https://daneshyari.com/article/504464

Daneshyari.com