Volume 6, Issue 2, February 2016 ISSN: 2277 128X

International Journal of Advanced Research in Computer Science and Software Engineering

Research Paper

Available online at: www.ijarcsse.com

Detection of Diabetic Wounds Based on Segmentation Using Accelerated Mean Shift Algorithm

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Abstract—Diabetic foot ulcers represent a significant health issue. Currently, clinicians and nurses mainly base their wound assessment on visual examination of wound size and healing status, while the patients themselves seldom have an opportunity to play an active role. Hence, a more quantitative and cost-effective examination method that enables the patients and their caregivers to take a more active role in daily wound care potentially can accelerate wound healing, save travel cost and reduce healthcare expenses. This proposed novel has a wound image which is captured by the camera. After that, the system performs wound segmentation by applying the accelerated mean shift algorithm. Specifically, the outline of the foot is determined based on the wound boundary is found using a simple connected region detection method. Within the wound boundary, the healing status is next assessed based on red–yellow–black color evaluation model. Moreover, the healing status is quantitatively assessed, based on trend analysis of time records for a given patient. Experimental results on wound images collected in UMASS—Memorial Health Center Wound Clinic (Worcester, MA) following an Institutional Review Board approved protocol show that our system can be efficiently used to analyze the wound healing status with promising accuracy.

Keywords— Mean shift algorithm, Wound segmentation, Healing status, Maximum Likelihood principle, Risk analysis.

I. INTRODUCTION

For individuals with type 2 diabetes, foot ulcers constitute a significant health issue affecting 5–6 million individuals in the US [1], [2]. Foot ulcers are painful, susceptible to infection and very slow to heal [3], [4]. According to published statistics, diabetes-related wounds are the primary cause of nontraumaticlower limb amputations with approximately 71 000such amputations in the US in 2004 [5]. Moreover, the cost of treating diabetic foot ulcers is estimated at $15 000 per year per individual. Overall diabetes healthcare cost was estimated at $245 billion in 2012 and isexpected to increase in the coming years [5].

There are several problems with current practices for treating diabetic foot ulcers. First, patients must go to their wound clinic on a regular basis to have their wounds checked by their clinicians. This need for frequent clinical evaluation is not only inconvenient and time consuming for patients and clinicians, but also represents a significant health care cost because patients may require special transportation, e.g., ambulances. Second, a clinician's wound assessment process is based on visual examination.

Bob Zhang [1] has described about Diabetes mellitus (DM) and its complications leading to diabetic retinopathy (DR) are soon to become one of the 21st century's major health problems. This represents a huge financial burden to healthcare officials and governments. To combat this approaching epidemic, this paper proposes a noninvasive method to detect DM and nonproliferative diabetic retinopathy (NPDR), the initial stage of DR based on three groups of features extracted from tongue images. They include color, texture, and geometry

Lucas [2] has said that in telemedicine environments, a standardized and reproducible assessment of wounds, using a simple free-handled digital camera, is an essential requirement. However, to ensure robust tissue classification, we introduce the key steps including color correction, and segmentation-driven classification based on support vector machines. The tool thus developed ensures stability under lighting condition, viewpoint, and camera changes, to achieve accurate and robust classification of skin tissues. Clinical tests demonstrate that such an advanced tool, which forms part of a complete 3-D and color wound assessment system, significantly improves the monitoring of the healing process. It achieves an overlap score of 79.3 against 69.1% for a single expert.

Gui and Xu .C. F. [3] has used Level set methods in image processing and computer vision. In conventional level set formulations, the level set function typically develops irregularities during its evolution, which may cause numerical errors and eventually destroy the stability of the evolution. This paper proposes a new variational level set formulation in which the regularity of the level set function is intrinsically maintained during the level set evolution.

Comaniciu and P. Meer [4] said that Numerous nonparametric clustering methods can be separated into two parts: hierarchical clustering and density estimation. Hierarchical clustering composes either 23 aggregation or division based on some proximate measure. The concept of the density estimation-based nonparametric clustering method is that the feature space can be considered as the experiential probability density function (p.d.f.) of the represented parameter. The mean shift algorithm can be classified as density estimation. It adequately analyzes feature space to cluster them and can provide reliable solutions for many vision tasks.

Wang .L, Pedersen .P .C, Strong .D, Tulu .B, and Agu .E [5] Considering the prevalence of smartphones with a high- resolution digital camera, assessing wounds by analyzing images of chronic foot ulcers is an attractive option. In this paper, we propose a novel wound image analysis system implemented solely on the Android smartphone. The wound image is captured by the camera on the smartphone with the assistance of an image capture box.

II. WOUND ANALYSIS METHOD

A. Wound Image Analysis System Overview

Our quantitativewound assessment system consists of several functional modules including wound image capture, wound image storage, wound image preprocessing, wound boundary determination, wound analysis by color segmentation and wound trend analysis based on a time sequence of wound images for a given patient.The functional diagram of our quantitative wound assessment system is shown as in Fig. 1

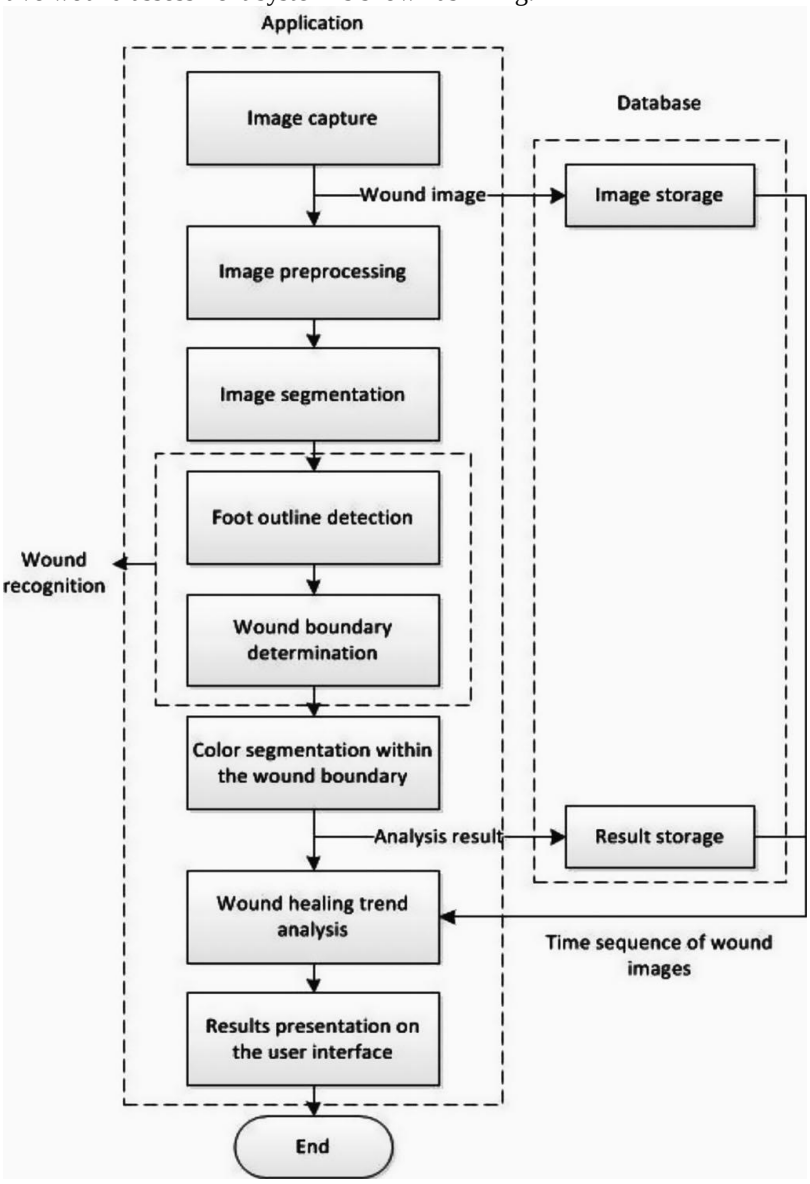

Fig.1. Woundimage analysis system software.

After the wound image is captured, the JPEG file path of this image is added into a wound image database.To determine the boundary of the wound area, we first determine an outline of the foot within the image. Hence the initial *Image*

segmentation operation is to divide the original image into pixel groups with homogeneous color values.Based on the standard color checkers provided in [20], both the light and dark skin color thresholds in CIE LAB space are incorporated into the system, which means that our algorithm is expected to work for most skin colors.

Afterwards,we carry out a *Wound boundary determination* basedon the foot outline detection result. If the foot detection resultis regarded as a binary image with the foot area marked as"white" and rest part marked as "black," it is easy to locate thewound boundary within the foot region boundary by detectingthe largest connected "black" component within the "white"part. If the wound is located at the foot region boundary, thenthe foot boundary is not closed, and hence the problem becomesmore complicated, i.e., we might need to first form a closedboundary.When the wound boundary has been successfully determinedand thewound area calculated, we next evaluate the healing stateof the wound by performing *Color segmentation*, with the goalof categorizing each pixel in the wound boundary into certainclasses labeled as granulation, slough and necrosis [21], [24].After the colorsegmentation, a feature vector including the wound area sizeand dimensions for different types of wound tissues is formedto describe the wound quantitatively. This feature vector, alongwith both the original and analyzed images, is saved in the resultdatabase.

B. Mean-Shift-Based Segmentation Algorithm

I chose the mean-shift algorithm, proposed in [16], overother segmentation methods. The mean-shift filtering algorithm is suitablefor parallel implementation since the basic processing unitis the pixel.The mean-shift algorithm belongs to the density estimationbasednonparametric clustering methods, in which the featurespace can be considered as the empirical probability densityfunction of the represented parameter. In general,the mean-shift algorithm models the feature vectors associatedwith each pixel (e.g., color and position in the image grid) assamples from an unknown probability density function $f(x)$ andthen finds clusters in this distribution. The center for each clusteris called the mode [25]. Given n data points xi, $i = 1,\ldots, n$in the $d$dimensional space Rd,the multivariate kernel densityestimator

$$fh,k(x) = \frac{C_{k,d}}{nh^d} \sum_{i=1}^{n} \mathrm{k}\left(\frac{x-x_i}{h}\right)^2 \qquad (1)$$

where$g(r) = -k_(r)$ and n is the number of neighbors takeninto account in the five dimension sample domain. We use thecombined kernel function where $hs$and $hr$are differentbandwidth values for spatial domain and range domain,respectively. The vector $k(x)$ defined in(1) is called the mean-shift vector, since it is the differencebetween the current value x and the weighted mean of theneighbors xi around x. In the mean-shift procedure, the currentestimate of the mode ykat iteration k is replaced by its locallyweighted mean

$yk+1 = yk+ m(yk)$ (2)

This iterative update of the local maxima estimation will becontinued until the convergence condition is met

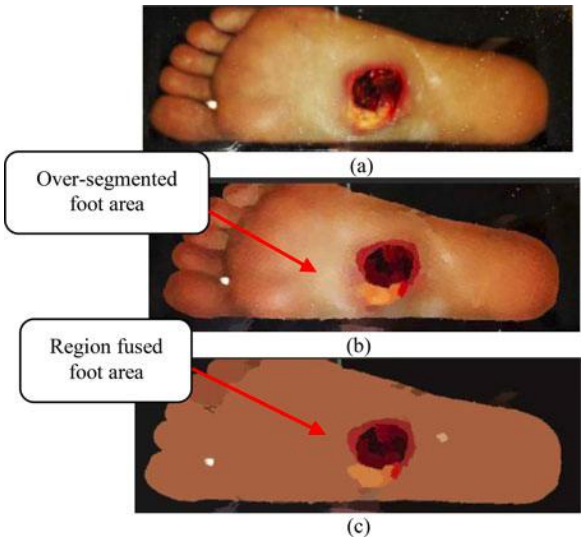

Fig.2. Mean-shift-based image segmentation sample result. (a) Original image.

(b) Mean-shift-filtered image
(c) Region fused image..

The colordifference between two adjacent nodes should not exceed hf,which is regarded as the region fusion resolution. The meanshiftfiltering and region fusion results of a sample foot wound are shown.We can see that the oversegmentation problem in (b) iseffectively solved by region fusion procedure.

C. Wound Boundary Determination and Analysis Algorithms

Based on the camera screen resolution, skin color feature and foot outline assumptions, the proposed wound boundarydetermination method is illustrated as in Fig. 3, and explainednext.The *Largest connected component detection* is first performedon the segmented image, using the fast largest connected componentdetection method introduced in [31] including two passes.

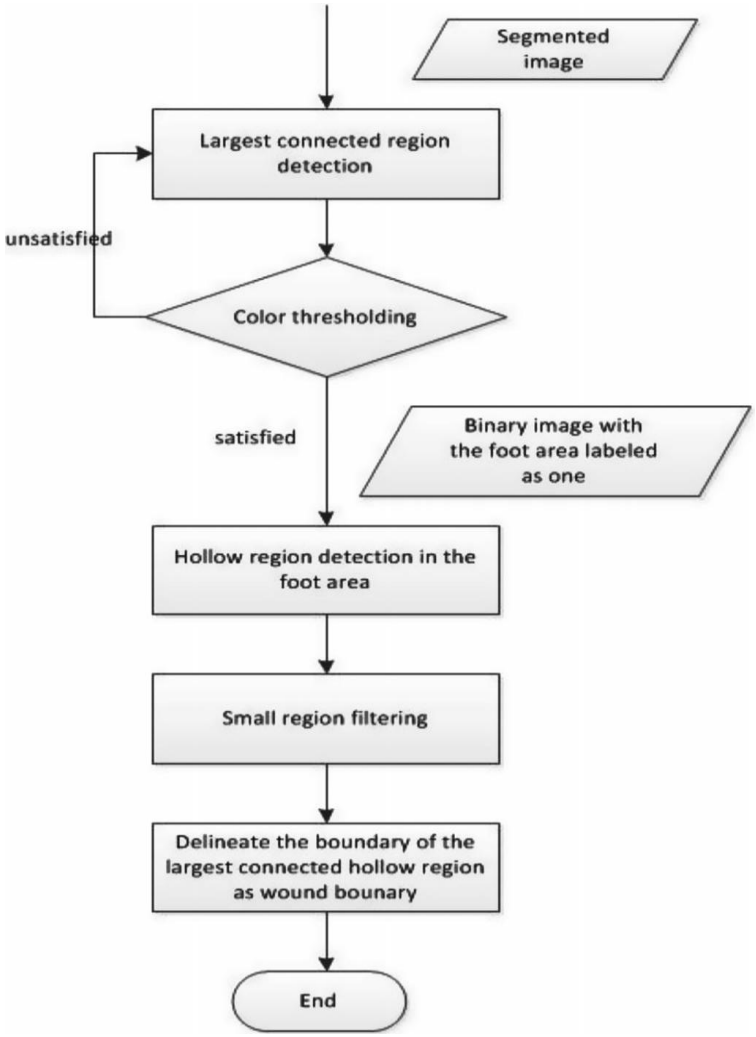

Fig.3. Largest connected component detection-based wound boundary determinationmethod flowchart

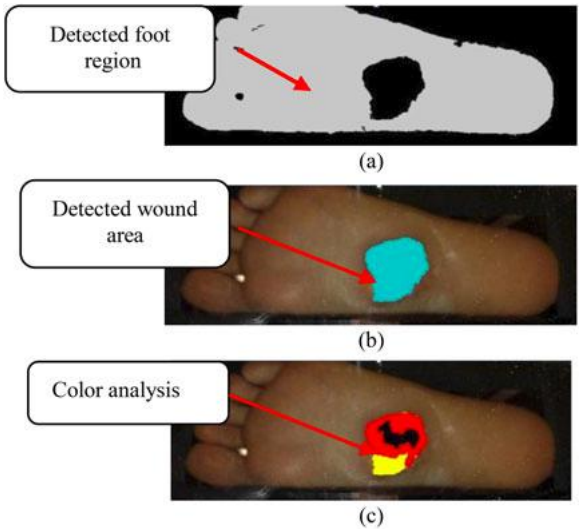

Fig.4. Wound boundary determination and analysis result. (a) Foot boundarydetection result. (b)Wound boundary determination result. (c) Color segmentationresult within the wound boundary

After the best estimate of the wound boundary is obtained,we analyze the wound area within the boundary using a wounddescription model.

III. WOUND COLOR FEATURES

The following section describes how color features are extracted from tongue images. Every foreground tongue pixel is compared to 12 colors representing the tongue color gamut and assigned its nearest color. This forms the color features.

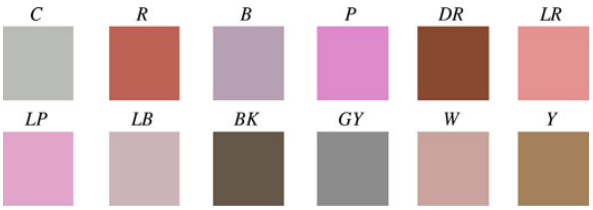

Table I RGB and CIELAB Values of the 12 Colors

Color	[R G B]	[L A B]
C (Cyan)	[188 188 185]	[76.0693 -0.5580 1.3615]
R (Red)	[189 99 91]	[52.2540 34.8412 21.3002]
B (Blue)	[183 165 180]	[69.4695 9.5423 -5.4951]
P (Purple)	[226 142 214]	[69.4695 42.4732 -23.8880]
DR (Deep red)	[136 72 49]	[37.8424 24.5503 25.9396]
LR (Light red)	[227 150 147]	[69.4695 28.4947 13.3940]
LP (Light purple)	[225 173 207]	[76.0693 24.3246 -9.7749]
LB (Light blue)	[204 183 186]	[76.0693 7.8917 0.9885]
BK (Black)	[107 86 56]	[37.8424 3.9632 20.5874]
GY (Gray)	[163 146 143]	[61.6542 5.7160 3.7317]
W (White)	[200 167 160]	[70.9763 10.9843 8.2952]
Y (Yellow)	[166 129 93]	[56.3164 9.5539 24.4546]

A. Color Feature Extraction

For the foreground pixels of a tongue image, correspondingRGB values are first extracted, and converted to CIELAB [29]by transferring RBG to CIEXYZ using

$$[X \quad Y \quad Z]= \begin{bmatrix} 0.4124 & 0.3576 & 0.1805 \\ 0.2126 & 0.7152 & 0.0722 \\ 0.0193 & 0.1192 & 0.9505 \end{bmatrix} [R \quad G \quad B]$$

followed by CIEXYZ to CIELAB via

$$L* = 166 \cdot f(Y/Y0) - 16$$
$$a* = 500 \cdot [f(X/X0) - f(Y/Y0)]$$
$$b* = 200 \cdot [f(Y/Y0) - f(Z/Z0)]$$

where $f(x) = x1/3$ if $x > 0.008856$ or

$f(x) = 7.787x + 16/116$ if $x \leq 0.008856$.

$X0$, $Y0$, and$Z0$ in (2) are theCIEXYZ tristimulus values of thereference white point. The LAB values are then compared to 12colors from the foot color gamut (see Table I) and assigned thecolor which is closest to it (measured using Euclidean distance).After evaluating all foot foreground pixels, the total of eachcolor is summed and divided by the total number of pixels.This ratio of the 12 colors forms the foot color feature vector$v$, where $v = [c1, c2, c3, c4, c5, c6, c7, c8, c9, c10, c11, c12]$ and cirepresents the sequence of colors in Table I. The original image is decomposed into one of the 12. Only seven colors are listed out of the 12 asthe remaining five have ratios less than 1%

B. Foot Texture Features

` Texture feature extraction from wound images is presentedin this section. To better represent the texture of wound images,eight blocks of size 64 × 64 strategically located onthe foot surface are used. A block size of 64 × 64 was chosendue to the fact that it covers all eight surface areas very well,while achieving minimum overlap. Larger blocks would coverareas outside the wound boundary, and overlap more with otherblocks. Smaller block sizes would prevent overlapping, but notcover the eight areas as efficiently. The blocks are calculatedautomatically by first locating the center of the wound using asegmented binary foot foreground image. Following this, theedges of the wound are established and equal parts are measuredfrom its center to position the eight blocks. The Gabor filter is a linear filters used in image processing,and is commonly used in texture representation. To compute thetexture value of each block, the 2D Gabor filter is applied and defined asGk

$$(x, y) = \exp\_x\_2 + \gamma 2 \cdot y\_2 - 2\sigma 2 \qquad (3)$$

Where$x_ = x \cdot \cos\theta + y \cdot \sin\theta,$

$y\_ = -x \cdot \sin\theta + y \cdot \cos\theta,$

σisthe variance, λ is the wavelength, γ is the aspect ratio of thesinusoidal function, and θ is the orientation. A total of three σ(1, 2, and 3) and four θ (0◦, 45◦, 90◦, and 135◦) choices wereinvestigated to achieve the best result. Each filter is convolvedwith a texture block to produce a response $Rk(x, y)$:

$$Rk(x, y) = Gk(x, y) * im(x, y) \qquad (4)$$

where$im(x, y)$ is the texture block and $*$represents 2-D convolution.Responses of a block are combined to form FRi, and its final response evaluated as follows:

$FRi(x, y) = \max(R1(x, y), R2(x, y), \ldots, Rn(x, y))$ (5)

which selects the maximum pixel intensities, and represents thetexture of a block by averaging the pixel values of *FRi*.In the end, σ equal to 1 and 2with three orientations (45◦, 90◦,and 135◦) was chosen. This is due to the fact that the sum of alltexture blocks between Healthy andDMhad the largest absolutedifference.

C. Wound Geometry Features

In the following section, we describe geometry features extracted from wound images. These features are based on measurements,distances, areas, and their ratios.

Width: The width *w* featureis measured as thehorizontal distance along the *x*-axis from a wound's furthestright edge point (*x*max) to its furthest left edge point (*x*min):

$w = x\max - x\min.$ (6)

Length: The length *l* feature is measured asthe vertical distance along the *y*-axis from a wound's furthestbottom edge (*y*max) point to its furthest top edge point (*y*min):

$l = y\max - y\min.$ (7)

Length–width ratio: The length–width ratio *lw*is the ratio ofa wound length to its width

$lw = l/w.$ (8)

Smaller half-distance: Smaller half-distance *z* is the half distanceof *l* or *w* depending on which segment is shorter

$z = \min(l, w)/2.$ (9)

Center distance: The center distance (*cd*) is distance from *w*_s*y*-axis center point to the center point of

$l(ycp)cd = (\max(yx\text{m ax}) + \max(yx\text{m in}))2 - ycp$ (10)

where*ycp*= (*y*max + *y*min) /2.

Center distance ratio: Center distance ratio (*cdr*) is ratio of*cd* to *l*:

$cdr = cdl.$ (11)

Area: The area (*a*) of a wound is defined as the number offoot foreground pixels.

Circle area: Circle area (*ca*) is the area of a circle within thewound foreground using smaller half-distance *z*, where $r = z$

$ca = \pi r2$. (12)

IV. EXPERIMENTAL RESULTS

The goal of the experimental work has been:

1) to assessthe accuracy of the wound boundary determination based onthe mean-shift algorithm and the color segmentation basedon the mean shift algorithm; and

2) to perform an efficiencycolour feature extraction and analysis the healing status of the wound in a foot area by comparing the values to the CIE LAB values.

V. CONCLUSION

we plan to apply machine learning methodsto train the wound analysis system based on clinical input andhopefully thereby achieve better boundary determination resultswith less restrictive assumptions. Furthermore, we plan to computea healing score to be assigned to each wound image tosupport trend analysis of a wound's healing status.

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