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REVIEW ARTICLE

Various Techniques for Detecting Skin Lesion: A Review

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Abstract*t— *Segmentation is an important step in computer aided diagnostic systems for pigmented skin lesions, since that a good definition of the lesion area and its boundary at the image is very important to distinguish benign from malignant cases. Segmentation of skin lesion is one of the biggest tasks to do along considering under and over segmentation. One of the biggest huddles is to merge segmented objects after over segmentation due to its large number of probabilities. In this paper numbers of techniques are described from which researcher can get idea of an efficient technique. The objective of this review paper is to summarize and compare some results of well known methods of various stages in detecting skin lesion.

Keywords— Lesions; Dermoscopy; IHP; TDLS; LOG Edge Detector

I. INTRODUCTION

Pigmented skin lesions include both, benign and malignant forms. Just in United States of America occur about 10000 deaths per year from the 40000 to 50000 diagnosed cases of melanoma, a dangerous kind of malignant pigmented skin lesions. Early diagnosis is of fundamental importance to improve the patient prognosis; nevertheless discriminating benign from malignant skin lesions has been proven to be a challenging task.

To facilitate the diagnosis, physicians often use dermoscopy, which is a non-invasive technique that magnifies sub macroscopic structures with the help of an optical lens (a dermoscope) and liquid immersion. The early diagnosis of melanomas is very important for the patient prognosis, since most malignant skin lesion cases can be treated successfully in their early stages.

However, even with the help of dermoscopy, differentiating malignant and benign lesions is a hard task. In fact, specialists affirm that in the early stages of the evolution of malignant lesions, dermoscopy may be useless as a tool to help the diagnosis.

Still considering early stage cases, there are practical situations where a non-specialist (e.g. a physician not trained on Dermatology) wishes to have a qualified opinion about a suspect skin lesion, but only standard camera imaging is available on site. In such situations, telemedicine is justifiable, and the non-specialist can capture an image of the suspect skin lesion and send it to an specialist, who can analyze it in higher detail. In this particular situation, a tele-dermatology consultation brings benefits, like the easier access to health care and faster clinical results.

As a result of this, interest is growing to find out methods for remotely diagnosing skin lesion, and in this context there is great importance of segmentation because before the lesion is analyzed and diagnosed, it must be correctly located.

II. TECHNIQUES OF DETECTING SKIN LESIONS

A. Independent Histogram Pursuit (IHP)

An unsupervised algorithm, called the Independent Histogram Pursuit (IHP), for segmenting dermatological lesions is mentioned here. The algorithm estimates a set of linear combinations of image bands that enhance different structures embedded in the image.

Let X be an m x n image with N bands. Then the (i, j) th pixel of this image can be considered as an N-vector

$X_{ij=}$ $\left(x_{ij}^{(1)}, \ldots, x_{ij}^{(N)}\right)^{T}$

All the pixels X_{ij} of a given image constitutethe input data. The IHP estimates a sequence of orthogonal-vectors, or components, that constitute a linear transformation of the original color space of the given image. We obtain these orthogonal components based on the fact that a typical dermatological image contains two large classes of pixels: the lesion and the normal skin. Therefore, the histogram of pixels which is projected onto the optimal component would have two large maximally separated modes (groups of two pixels). Based on this observation, the first component is computed so that the histogram of projected pixels, is bimodal and there is a maximum area of the concavity between the two modes (the hatched area as shown in Fig. 1). In the second step,using the same criterion, the remaining (N-1) IHP components are estimated, requiringeach component to be orthogonal to those previously estimated.

Formally, the set of IHP components is estimated by solving the following optimization problem for each k:

$$\tilde{\mathbf{u}}_k = \arg\max_{\mathbf{z}\in\Re^N} f\left[\left\{\mathbf{z}^T\tilde{\mathbf{x}}_{ij} \middle| i = 1,\ldots,m; j = 1,\ldots n\right\}\right] \quad (1)$$

$$\tilde{\mathbf{u}}_k^T\tilde{\mathbf{u}}_l = 0, \quad \text{for } k > 1 \text{and } l = 1,\ldots,k-1 \quad (2)$$

where $\tilde{\mathbf{x}}_{ij}$ are the whitened pixels of X_{ij} [1]. To eliminate the correlations in the data whitening is needed, which is a necessary condition for making estimated components independent. The function $f[\{\mathbf{z}^T\tilde{\mathbf{x}}_{ij}\}]$ on the right-hand side of (1) is defined as the area of the concavity between the two modes of the histogram of data $\tilde{\mathbf{x}}_{ij}$ projected onto z , as in Fig. 1. It is important to note that the histogram has to be smoothed in order to eliminate insignificant local extrema.

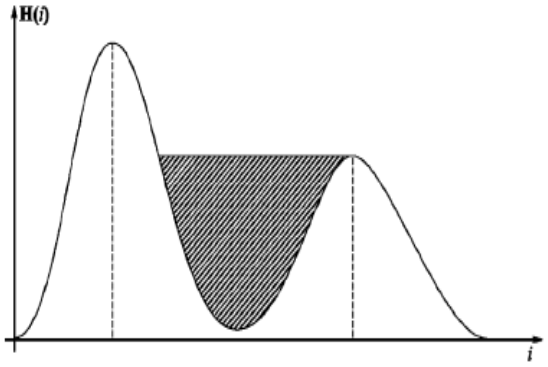

Fig. 1. Sample bimodal histogram of pixels projected onto z during optimization. The hatched pattern indicates the area maximized by the algorithm.

B. LOG Edge Detector

Using LOG edge detector is a robust and efficient image segmentation algorithm [2] to extract the true border of noisy clinical skin images containing lesions in whichthe global structure irregularity is revealed, which may suggest regression or excessive cell growth of a melanoma.

An image segmentation algorithmwhich may suggest regression orexcessive cell growth of a melanoma, to extract the true border that reveals the global structure irregularity, This algorithm is applied to the image containing the lesion, where the RGB image is converted to gray-scale intensity image by eliminating the hue and saturation information while retaining the luminance and adds salt and pepper noise to the image and uses background noise reduction techniques which filters the noise. The LOG Edge Detector algorithm (using LOG method) converts an image to a binary image, based on threshold and finds edges in the image and traces the object in the image by determining the co-ordinates of the pixel on the border of the object using the binary image and the image got from edge detection using LOG method and usingthat pixel on the border of the object as the starting point traces the border of the object effectively.

1) Median filtering: Median filtering used in image processing is a nonlinear operation often to reduce "salt and pepper" noise. In comparison to convolutionMedian filtering is more effective when the goal is to preserve edges and simultaneously reduce noise.

2) Edge detection: Understandably, an edge is a set of connected pixels that lie on the boundary between two regions [3].An image can be segmented by detecting those discontinuities. The key to a satisfactory segmentation result lies in keeping a balancebetween detecting accuracy and noise immunity. If the accuracy detecting level is too high, noise may make the outline of image unreasonable bringing in fake edges . Otherwise, if the degree of noise immunity is excessive some parts of the image outline may get undetected and the position of objects may be mistaken [2].

Edge detection is a most common approach for detecting meaningful discontinuities in grey level. Such discontinuities are detected using first order and second order derivatives [4]. The first order derivative of choice is the gradient. The gradient of the 2D function f(x, y), is defined as a vector.

The vector's magnitude is given by

$g = [Gx2+Gy2]1/2$ (3)

Where $Gx = \partial f/\partial x$ and $Gy = \partial f/\partial y$

The second derivative in image processing is computed using the laplacian. As second order derivative the laplacian is unacceptably sensitive to noise therefore it is seldom used by itself for edge detection and its magnitude produces double edges and it is unable to detect edge direction. However Laplacian can be a powerful complement when used in combination of other

edge detection techniques. The basic idea behind edge detection is to find places in an image where the intensity changes very rapidly using one of the two general criteria:

1. Find places where the first derivative of the intensity is greater in magnitude than a specified threshold.
2. Find places where the second derivative of the intensity has zero crossing.

3) Laplacian of Gaussian Detector: Consider the Gaussian function

$$h(r) = -e^{-r2/2\sigma 2} \tag{4}$$

Where $r^2=x^2+y^2$

This is a smoothing function, which if convolved with an image, will blur it. The degree of blurring is determined with the value of σ.

The Laplacian of this function (the second derivative with respect to r is

$$- [(r^2-\sigma^2) /\sigma^4] e^{-r2 / 2\sigma 2} \tag{5}$$

This function is called Laplacian of Gaussian. Because the second derivative is a linear operation, convolving the image with the above said function, is the same as convolving the image with the smoothing function first and then computing the Laplacian of the result. This is the key concept underlying the LOG detector. The LOG detector finds the edges by looking for zero crossing after filtering f(x, y) with a Gaussian filter [5].

C. Texture Distinctiveness

The TDLS algorithm [6] consists of two main steps

First, a set of sparse texture distributions that represent skin and lesion textures are learned. A texture distinctiveness metric is calculated to measure the dissimilarity of a texture distribution from all other texture distributions. Second, the texture distinctiveness metric is used to classify regions in the image as part of the skin class or lesion class. In this section, the first step is described in detail and Fig. 2[6] illustrates the overall process to learn the representative texture distributions and calculate the texture distinctiveness metric.

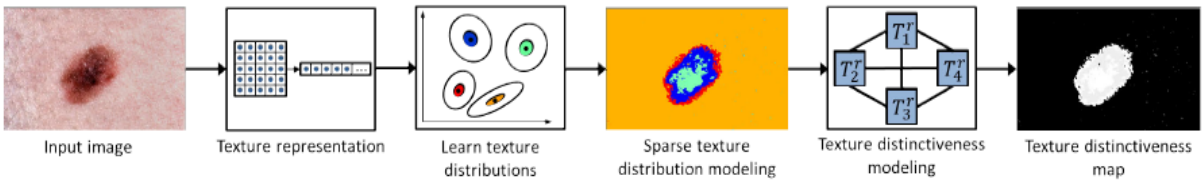

Fig.2 Algorithm flow chart displaying the steps to learn the representative texture distributions and calculate the texture distinctiveness metric

Convert the corrected image to the XYZ colour space. For each pixel s in image I, extract the texture vector ts to obtain the set of texture vectors T .

$$\mathcal{T} = \{\boldsymbol{t}_{\boldsymbol{s}_j} | 1 \leq j \leq N \times M\} \tag{6}$$

Cluster the texture vectors in T to obtain the representative texture distributions. Calculate probability that two texture distributions are distinct d j, k using Equation for all possible pairs of texture distributions.

$$d_{j,k} = 1 - L_{j,k} \tag{7}$$

Then Calculate the textural distinctiveness metric D_j for each texture distribution.

$$D_j = \sum_{k=1}^{K} d_{j,k} P(T_k^r | I) \tag{8}$$

Apply the statistical region merging algorithm to find the initial regions. Calculate the region distinctiveness metric DR for each initial region using Eqn.

$$\mathcal{D}_R = \sum_{j=1}^{K} D_j P(T_j^r | R) \tag{9}$$

After that Calculate the threshold T between the normal skin and lesion classes

$$\tau = \arg\min_{\tau} \left(\sigma^2_{C_1(\tau)} P\left(T^r | C_1(\tau)\right) + \sigma^2_{C_2(\tau)} P\left(T^r | C_2(\tau)\right) \right) \tag{10}$$

Classify each region as normal skin or lesion based on the previous equations.

$$y(R) = \begin{cases} 1 & \text{if } \mathcal{D}_R \geq \tau \text{ (lesion)} \\ 0 & \text{otherwise (normal skin)} \end{cases}$$

Apply a morphological dilation operator to the initial lesion classification. For each contiguous region in the initial segmentation, count the number of pixels in the region. As the final lesion segmentation, return the contiguous region consisting of the most pixels.

D. Iterative Stochastic Region Merging

Iterative stochastic region merging [7] method for skin lesion segmentation can be summarized as follows:

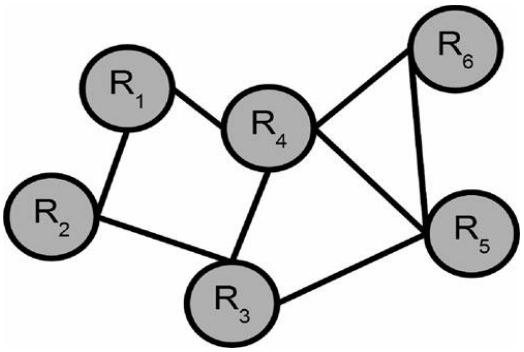

Fig. 3 Example of a region adjacency graph, where each vertex represents a region R, and the graph edges E connect each vertex (representing an individual region R) to its adjacent graph vertices (i.e., to the regions adjacent to R on the discrete lattice S).

The iterative stochastic region merging algorithm proposed for skin lesion segmentation includes assigning each pixel in the image to a unique region and these regions are subsequently merged with other regions in a stochastic manner [7]

Algorithm 1 Iterative Stochastic Region Merging

1: Assign each site s in the image f a unique region label (Note: order of assignment does not matter).
2: Construct an initial region adjacency graph, where each vertex represents a site s with eight adjacent vertices each (i.e., its eight neighbors).
3: **repeat**
4: Place all adjacent region pairs into a priority queue based on ascending regional expectation differences.
5: **repeat**
6: Remove region pair R_a and R_b from priority queue.
7: Merge region pair R_a and R_b with a probability $\alpha(R_a, R_b)$ based on the proposed region merging likelihood function in (3).
8: If merging occurs, update the adjacency graph.
9: **until** Priority queue is empty
10: Decrease Q by half.
11: **until** Convergence

Fig. 4 Algorithm of Iterative Stochastic Region Merging

III. EVALUATION PARAMETERS

The evaluation parameters measure the sensitivity, specificity and accuracy of each segmentation algorithm. This is done after the algorithm determines each pixel of lesion skin. The results of each algorithm are compared to the ground truth which is the manually drawn result of the segmentation [6]

Sensitivity also called the *true positive rate* measures the proportion of actual positives which are correctly identified as such. Sensitivity relates to the test's ability to identify a condition correctly [6]

$$Sensitivity = \frac{TP}{TP + FN} \tag{11}$$

Specificity also called the *true negative rate* measures the proportion of negatives which are correctly identified as such .Specificity relates to the test's ability to exclude a condition correctly[6]

$$Specificity = \frac{TN}{TN + FP} \tag{12}$$

Accuracydetermines the true value, the repeatability or reproducibility of the measurement, the proximity of measurement to theprecision results.

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \tag{13}$$

Here

TP= True Positive

TN= True Negative

FN= False Negative

FP= False Positive

IV. EXPERIMENTAL RESULTS

After comparing the segmentation results with the parameters like sensitivity, selectivity and accuracy , the results so obtained are shown in Table I. Table I specifies that the TDLS algorithm has the highest value of accuracy across all tested photographs, followed closely by the Otsu-PCA algorithm and TDLS has second highest sensitivity and specificity[6]

TABLE I

SEGMENTATION ACCURACY RESULTS FOR ALL LESION PHOTOGRAPHS

Segmentation Algorithm	**Sensitivity**	**Selectivity**	**Accuracy**
L-SRM	89.4%	92.7%	92.3%
Otsu-R	87.3%	85.4%	89.4%
Otsu-RGB	93.6%	80.3%	80.2%
Otsu- PCA	79.6%	99.6%	98.1%
TDLS	91.2%	99.0%	98.3%

V. CONCLUSION

Detection of melanoma at an early stage is very important in today's practice of dermatology, which can be done with segmenting the skin lesion accurately. For diagnosing skin lesion, the lesion must be correctly located before it is analyzed and diagnosed. Various techniques have been proposed to detect the lesion: Independent Histogram Pursuit (IHP), Log Edge Detector, Texture Distinctiveness, Iterative Stochastic Region Merging. But the biggest hurdle that comes in the path of detection is over segmentation and under segmentation.

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REFERENCES

[1] David Delgado Gomez, ConstatineButakoff, BjarneKjaerErsboll and William Stoecker "Independent Histogram Pursuit for Segmentation of SkinLesions" IEEE Transactions on Biomedical Engineering, Volume 55, No. 1, January 2008.

[2]J.H. JaseemaYasmin, M. Mohamed Sathik, S. ZulaikhaBeevi "Robust Segmentation Algorithm using LOG Edge Detector for Effective Border Detection of Noisy Skin Lesions"ICCCET 2011, 18th & 19th March, 2011 pg 60-65

[3] Rafael C. Gonzalez, Richard E. Woods, "Digital Image Processing" Second Edition, Prentice-Hall, India.

[4] M. EmreCelebia, Hitoshi Iyatomib, Gerald Schaeferc, William V. Stoecker d. "Lesion Border Detection in Dermoscopy Images", Computerized Medical Imaging and Graphics, 33 (2009) pp. 148-153.

[5] Rafael C. Gonzalez, Richard E. Woods, Stevan L. Eddins, "Digital Image Processing using Matlab".

[6]Jeffrey Glaister, Alexander Wong and David A. Clausi "Segmentation of skin lesions from digital images using joint statistical texture distinctiveness"0018-9294 (c) 2013 IEEE Transactions on Biomedical Engineering

[7]Alexander Wong, Jacob Scharcanski and Paul Fieguth "Automatic Skin Lesion Segmentation via Iterative Stochastic Region Merging"IEEE Transactions on Information Technology in Biomedicine, Vol. 15, No. 6, November 2011

[8] Stefan Fischer, Philippe Schmid,JoelGuillod "Analysis Of Skin Lesions With Pigmented Networks" Image Processing 1996 IEEE proceedings Pg323 - 326 vol.1

[9] Gregory A. Hance , Scott E. Umbaugh, Randy H. Moss and William V. Stoecker "Unsupervised Color Image Segmentation With Application to Skin Tumor Borders" IEEE Engineering in Medical and Biology, January/Febuary 1996.

[10] Anil K. Jain, Robert P. W. Duin and Jianchang Mao "Statistical Pattern Recognition: A Review" IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 22, No. 1, January 2000.

[11] Brian D' Alessandro and Atam P. Dhawan "3-D Volume Reconstruction of Skin Lesions for Melanin and Blood Volume Estimation and Lesion Severity Analysis" IEEE Transactions on Medical Imaging, Volume 31, No. 11, November 2012.

