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Comparative analysis of segmentation techniques for foot thermogram

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ABSTRACT

The prevalence of diabetes mellitus in the Indian population is approximately 8.9% which is 77 million people. One of the most recognized issues in diabetic Mellitus patients is foot ulceration which is indicated by an abnormal rise in the temperature of the foot plantar. According to the International diabetic federation, every 15 people out of 100 get affected and there is a 6 percent of chance getting foot ulcers. Early identification and treatment of ulcers of the plantar skin will be beneficial to reduce the treatment cost and avoids amputation. Thermal imaging methods are one of the best, easiest and repeatable techniques to monitor the progress of foot ulcerations. Image processing enables doctors to make quick decisions in diagnosing the severity of the infection. In this paper, a sample foot thermogram is utilized for applying segmentation techniques such as region growing, clustering, and active contour for the extraction of the region of interest. The segmented results are compared for the performance using the Jaccard index, Similarity index Dice coefficient, and Volume similarity. The results show that the Snakes algorithm as a segmentation technique gave 85 % accuracy in extracting the RoI successfully.

Keywords: *Diabetes Foot, Thermography, Segmentation Techniques, Active Contours, Region Growing, Clustering*

1. INTRODUCTION

Diabetic mellitus is one of the global health care concern which is growing rapidly day by day. The reason for occurrence of diabetes is due to low or no production of insulin in the human body. Reasons for causing foot ulceration are peripheral neuropathy in normal words nerve damage and lower extremity ischemia also called as lack of blood flow. 90% of foot ulcerations are caused by peripheral neuropathy. Here nerves are damaged because of presence of high glucose levels in the blood. Mainly the motor, sensory and autonomic nerves are damaged because of high glucose levels [1]. This damages the immune system and resist the immune power to fight with the infection. This usually happens when there is a nerve destruction which may cause pain and weakness or the loss of senses. Many people have different level of burning sensation. Diabetic foot ulcer can lead to limb amputation. Early diagnosis of diabetic foot ulcers can reduce the treatment cost and prevent the limb amputation. Temperature variation in foot plantar region could be an indication of presence of neuropathic foot problems. Infrared thermal imaging methods is a potentially an easiest and reliable technique to identify the foot ulcerations. Thermography is a technique applied to study the diabetic foot by analysing thermal changes [2]. This technique is very advantageous for its non-invasive and repeatable technique. Thermography provides the distribution of temperature on the surface of the object and because of its ability to perform with high precision makes its widely used technique. The accuracy of using thermography in the treatment of diabetic foot ulcers is very high and the patient can be self-monitored by checking whether they are changes in the temperature in the plantar region.

2. LITERATURE REVIEW

There is various literature study carried out in the past where foot thermograms have been used for segmentation to extract the region of interest (ROI). The following papers are discussed to highlight the works carried out by various authors in this field. The literature review table is also tabulated in the Table 1.

The authors in [1], obtained the foot thermograms from 15 diabetes mellitus patients with and without complications of ulcers. In the pre-processing stage they have used manual annotations to extract the boundaries of the foot. The manual segmentation in their process has deteriorated the accuracy in classifying the patients from diabetes mellitus with complications. In [2], the authors have used histogram-shape based foot positioning system to position the feet in the right positions to avoid redundancy in the classification process. The authors succeeded with the automated angiosome extraction through this segmentation technique. The authors in [3], apply snakes algorithm as active contour technique to segment the plantar regions of the DM foot. The algorithm is automated and is carried out in three stages. The first part of the algorithm separates the two feet from each other, the second stage requires evolving of the contours in the region selected and the third part boundaries are detected to segment the ROI.

Table 1: Literature Review

Ref. No.	Pre-processing Methodology	Limitations	Future Scope
1.	Manual annotation for foot boundaries	Boundaries were manually drawn	Optimized system for patient positioning required
2.	Histogram-shape based thresholding, Feet position correction and automated angiosome extraction	--	--
3.	Snakes algorithm to segment the plantar foot regions from the background	--	--
4.	Manual segmentation	Semi-automated segmentation technique	Deep Learning techniques suggested
5.	R-CNN to segment semi-automatically using the mask	Error from Mask R-CNN mask added as background to the image	-
6.	Segmentation using region growing method	-	-
7.	Automated segmentation using Shannon entropy and fuzzy entropy	-	

The authors in [4] used advanced techniques in feature extraction using DD-DT-CWT and deep learning neural techniques for classification but failed to segment the foot regions using automated algorithm. Hence, their manual annotations of extracting the boundaries failed to produce the accurate results. In [5], the authors used R-CNN model as automated procedure to segment the ROI from the foot thermograms. The R-CNN facilitated in generating the mask that helped the user to annotate the boundaries of the feet. Using region growing technique, the authors in [6], segmented the foot ROI by giving seed point in the region and their results using SVM for classification succeeded with region growing method. The authors in [7], automated the segmentation process by using Shannon entropy method for extracting the ROI. This technique played a crucial role in separating the hottest spot in the plantar region of the foot thermograms as the hot spots can be an indication of tissue damage for the DM patients.

3. METHODOLOGY

Pre-processing techniques are a very important stage in the computer aided detection techniques to make decisions in the medical images. The right diagnosis of the disease can lead to proper treatment and timely prognosis for the patients. Segmentation of foot thermograms is essential as only the foot regions are required in the feature extraction process. Accurate segmentation can lead to relevant features to be extracted in the process. Hence, this paper deals with some of the major technique selected from the literature study for comparison and their performance is evaluated to proceed in further analysis of pattern recognition. The sample foot thermogram [8] used for the following three methods is given in figure 1.

Fig. 1: Sample foot thermogram

3.1 Region Growing

Region growing in an image segmentation method follows pixel-based image segmentation method. In this method the segmentation happens with the neighboring pixels of the initial seed which is given on choice based on the priority of the region in the foreground to be extracted and decides whether the pixel neighbor should be added to the region or not be added. This process works iteratively in the same manner as the data clustering algorithms. The main mechanism of this segmentation technique is to segment or divide the foot images into regions and achieve its thresholding level. It is the kind of segmentation technique in which the desired regions are obtained directly after the segmentation. This segmentation should work with every pixel in the region if not happen the segmentation is incomplete. This needs the points in that region to relate to some predefine sense.

The first step of region growing is to initialize the set of seed points and that seed point selection can be based on pixels in certain grey scale range or pixels arranged evenly. This seed points grow to the adjacent points which satisfy the criteria that is color, texture, and intensity. This mainly used in the foot thermograms to identify the temperature variations by initializing seed point so that the seed point grows to the adjacent point whether it is of same intensity value on gives us the region where the temperature is high [6].

3.2 K Means Clustering

Clustering is a process of separating the data points into the required number of clusters or groups with similar details. There are different types of clustering in which two methods are widely popular, they are K means and fuzzy C means clustering. K means clustering is a method for identifying K number of clusters. It is an iterative algorithm which assigns data points to any one of the groups based on the similarities. Centroids of the K clusters are used to label the data. Each cluster is divided by its center point that is centroid. The distance is calculated from the centroid to each data point when the distance is less between the data point and centroid it will be assigned to that cluster. The required number of cluster K and initial starting point set of K and the number of required cluster and the centroid for each cluster each consider as a data set. It will be repeated by giving another set of centroid and result is taken from the better performed [9].

3.3 Active Contours – Snakes Algorithm

The active contour model is used for representing an object delineation from the noise image. This model is accepted when computer vision and the active contours are used for recognizing the shapes, detection of edges, segmentation process and in the object tracking. The basic active contour model is controlled by the impact of forces which it includes the forces of the images and the forces obtained by the external sources. This internal force performs by giving piece wise smoothness constrain and which the images releases pressure on the contour line or the snake to the main features of the image which are edges, lines and contours which are important [3]. This process is done by positioning the snakes near to the local minimum which is due to external constrain forces. The snake can minimize the energy in which constrain, and forces of the image and the deformable spline is getting pulled over the object contours by the forces and it resist the deformation as energy reduction occurs and there is a special case being introduced has the deformable model to the image. If we assume the position of snake as.

$$s(k) = (x(k), y(k)) \qquad (1)$$

Energy function can be derived as follows.

$$E_{snake}^{total} = \int_0^1 E_{snake}\big(s(k)\big)dk$$

$$= \int_0^1 (E_{int}(s(k)) + E_{image}\big(s(k)\big) + E_{con}\big(s(k)\big))dk \qquad (2)$$

Here, E_{int}, E_{image}, E_{con} are related to the internal energy of the spline as a result of the bending, proceed to the image forces then proceed to the external damper forces, respectively.

$$E_{int} = (\alpha(k)|s_k(k)|^2 + \beta(k)|s_{kk}(k)|^2)/2 \qquad (3)$$

The spline energy, internal energy (E_{int}), having two terms: α(k), β(k). Due to the first order term α(k) snake works as a membrane and due to the second order term β(k) works as thin plate. By accommodating the α(k), β(k) the membrane and thin plate are self-regularizing to move the contour smooth. When β(k)=0, snake will become second order discontinuous and it can setup a corner. In this process the snakes ae applied to divide the feet from the background of thermograms.

E_{image} is image force, it is having 3 energy functions as we shown in Eq.

$$E_{image} = \omega_{line}E_{line} + \omega_{edge}E_{edge} + \omega_{term}E_{term} \qquad (4)$$

These three energies function the snake is enticing to edges, terminations and edges of the thermogram. These 3 energies (ω_{line}, ω_{edge}, ω_{term}) will control the activity of the snake.

$$E_{line} = I(x, y) \qquad (5)$$

Here, I(x, y) will be the image intensity of the snake which will drag the bright lines and the dim lines based on the sign and order of the snake to snatch the contours with image gradient.

$$E_{edge} = -|\nabla I(x,y)|^2 \qquad (6)$$

G(x, y) is a Gaussian function and S(x, y) is a rather smoothed image version as follows.

$$s(x,y) = G(x,y) * \; I\,(x,y) \qquad (7)$$

$$\theta_G = \tan^{-1}\left(\frac{s_y}{s_x}\right) \qquad (8)$$

$$n=(\cos\theta_G \,, \sin\theta_G) \qquad (9)$$

$$n_{\downarrow} = (-\sin\theta_G \,, \cos\theta_G) \qquad (10)$$

The derivatives of S(x, y)w.r.t x and y are S_x and S_y respectively. Gradient angle is denoted byθ_G, unit vectors are denote by n and $n_{\downarrow}$ is perpendicular (90°) to the gradient direction.

$$E_{term} = \frac{\partial \theta_G}{\partial n_{\downarrow}}$$

$$= \frac{\partial^2 S/\partial n_{\downarrow}{}^2}{\partial S/\partial n} \qquad (11)$$

Using this equation curvature of level contours in s(x, y) as follows.

$$= \frac{s_{yy}S_x^2 - 2s_{xy}s_x s_{y+}\, s_{xx}\, S_y^2}{\left(S_x^2 + S_y^2\right)^{3/2}} \qquad (12)$$

When the E_{term} and $E_{edge,}$ are combined then snake contour can be created that clutch the edges.

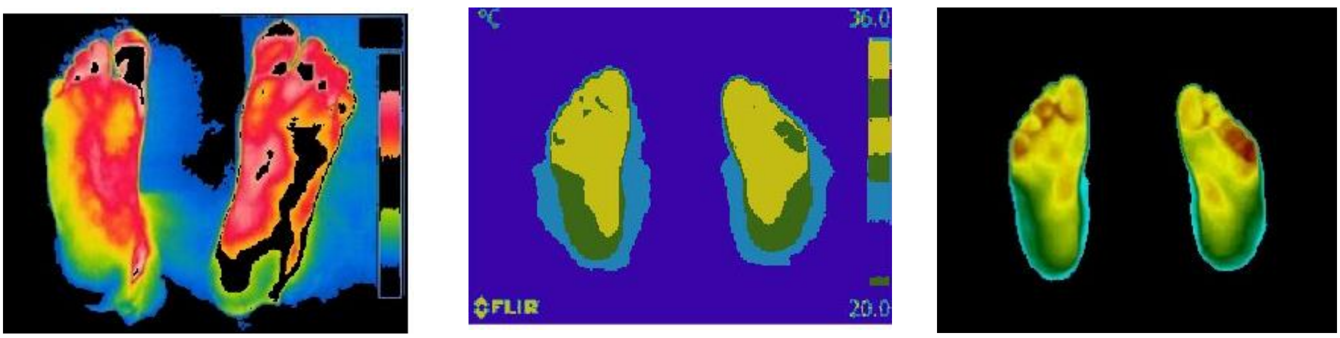
However, this algorithm is developed for grey scale images then further developed and made it implementable for pseudo colour images. We use snake algorithm because the active contours are the snakes can be controlled by the user which can remove noise and make sure the snake is insensitive to the noise. This is used instead of algorithms like Canny method, Sobel algorithm as is more time taken and noise sensitive, respectively.

4. EXPERIMENTAL RESULTS

Region growing algorithm was applied to the sample foot thermogram as shown in the figure 1. The primary purpose of segmentation is to extract the foot regions from the thermogram leaving behind the company logo, temperature scale and Celsius symbol. All the image processing algorithms are applied using Matlab 2020a version. The sample image was first converted to greyscale image. The pixel values in the greyscale image were normalized to a scale from 0 – 1. The seed point was chosen using the maximum peak values in the histogram of the greyscale image. The seed point obtained in the coordinates were (x, y) = (290, 310). The threshold value chosen was 0.09. The result shown in figure 2(a) shows the region growing algorithm has extracted the neighboring background pixels along with the boundaries of the foot regions. The high frequency components could not be well defined to extract the ROI precisely.

The sample foot thermogram is also applied to the K mean algorithm to separate the similar data points that group the ROI pixels together. The steps followed in this algorithm are the colour seed points in the foreground and background are classified as different datapoints, mean values of the data points in the foreground and background are evaluated and the minimum distance between the pixels nearby are calculated. Even though accurate results were not obtained using K means algorithm, the foot regions could be delineated effectively as shown in figure 2(b).

Snakes algorithm works best when there are too many color pixels to segregate. The region of boundary was manually suited around the closed edges of the foot. The evolution of the internal and external forces enabled in the extraction of the ROI. The results are shown in figure 2(c).



(a) (b) (c)

Fig. 2: Segmentation of ROI from foot thermograms, (a) Region growing method for ROI extraction, (b) K means clustering method for ROI extraction, (c) Snakes algorithm method for ROI extraction

Performance evaluation

In-order to check whether the ROI are correctly segmented, it is compared with the ground truth image created by the radiologist. The performance is calculated by using Dice, Jaccard and SSIM. Two sets A and B for Dice similarity coefficient is expressed as:

$$\text{dice}\,(A, B) = 2 * |\,\text{intersection}\,(A, B)\,| \,/\, (|\,A\,| + |\,B\,|) \qquad (13)$$

where the cardinal of set *Ais represented by* $|A|$. Jaccard similarity coefficient, belongs to numeric scalar. If input arrays are binary images, then similarity is a scalar. If similarity is a vector then images are label images, where the label 1 and label 2 belongs to first coefficient, the second coefficient, and so on. If similarity is a vector then images are categorical images, where the label 1 and label 2 are first coefficient, second coefficient, and so on. The Jaccard similarity coefficient of two sets A and B is expressed as:

$$jaccard\,(A, B) \;=\; |\,intersection\,(A, B)\,| \,/\, |\,union\,(A, B)\,| \qquad (14)$$

SSIM quality comes under assessment index. The overall index is a combination of the product of the three terms.

$$SSIM\,(x, y) = [l\,(x, y)]^{\alpha} \cdot [c\,(x, y)]^{\beta} \cdot [s(x, y)] \qquad (15)$$

Where,

$$I\,(x, y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_2} \qquad (16)$$

$$S\,(x, y) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3} \qquad (17)$$

where the local means, standard deviations, and cross-covariance of x, y are μ_x, μ_y, σ_x, σ_y, and $\sigma_{x\,y}$.

$$SSIM\,(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \qquad (18)$$

The performance was evaluated using dice coefficient, Jaccard coefficient, Similarity index and Volume similarity. The results were plotted for the graph. The graph is shown in figure 3. It is evident from the graph that, the Snakes algorithm has given promising results in extracting the ROI successfully on par with the ground truth annotated by the radiologist.

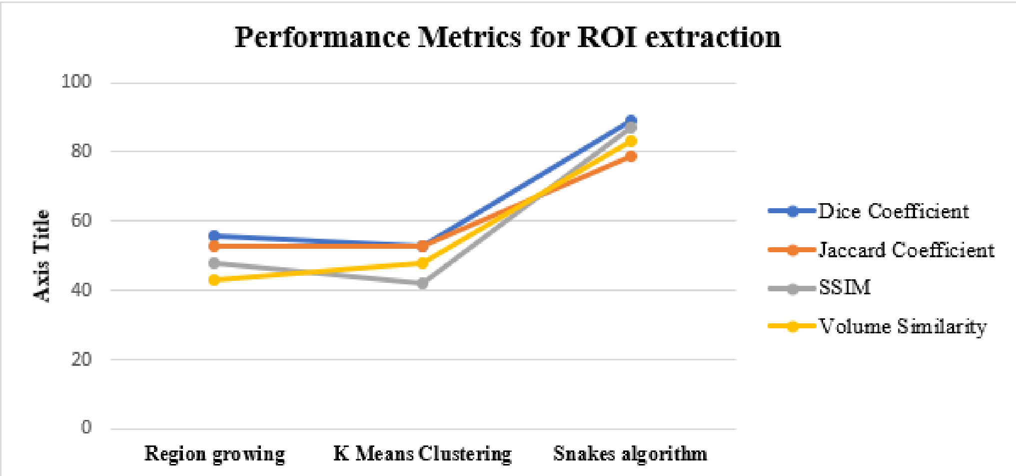


Fig. 3: Graph plot for performance metrics

5. CONCLUSION

In the recent times, there has been many developments in the field of medical thermography. With arising technology in the IR imaging methodologies, high resolution thermograms lead to effective way of decision making and image processing. DM is an arising concern in global statistics and treatment in early stages has improved the mortality rate in a big way. DM patients are prone to foot infection and ulcers which lead to unnecessary amputation. To avoid this, foot thermograms provide functional information of the underlying infection in terms of the surface temperature in the plantar regions of the foot. This paper has dealt with comparing three types of segmentation techniques such as region growing, k means and snakes algorithm for extraction the left and right feet from the background. The results show that snake algorithm with user's intervention, robust solution. The performance metric measures the highest similarity for the snakes algorithm as compared to the other two. Thus, the snakes algorithm can be chosen to extract the ROI without having to include the background pixel values from the patient's legs. Even in the fuzzy circumstances of thermograms obtained, this algorithm produces promising results pertaining to decision making system in pattern recognition.

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