

A COMPARISON OF ACTIVE CONTOUR PRIOR SHAPE SEGMENTATION METHODS: APPLICATION TO DIABETIC PLANTAR FOOT THERMAL IMAGES

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ABSTRACT

The segmentation of diabetic plantar foot thermal images that are taken with no constraining setup is a challenging problem. The present paper is dedicated to the comparison of three active contour-based methods with prior shape information that are well suited to the given problem. The first method was recently proposed by the present authors. It is based on the Kass et al. method and on a new extra term that minimizes the difference between the curve curvature of the active contour and the prior shape one. The second method is the Ahmed et al. one, a Fourier-based method with prior shape matching. The third one was suggested by Chen et al. where a geodesic snake is associated with a prior shape energy function. Using a database of 50 plantar foot thermal images, results show that our proposed method outperforms the two others with a root-mean-square error (RMSE) equal to 5.12 pixels and a Dice Similarity Coefficient (DSC) score of 93.9%. In addition, our method is robust to initial contour variations and fast, therefore suitable for smartphone application in the context of diabetic foot problem.

KEYWORDS

Prior shape-based segmentation, active contours, plantar foot thermal images, diabetic foot.

1. INTRODUCTION

Diabetes is a growing health problem all over the world. It can damage many parts of the body such as the heart, blood vessels, eyes, kidneys, nerves, and feet. The foot ulcer is of particular concern. The occurrence of foot ulcer is often associated with foot hyperthermia. In [1], foot hyperthermia was defined as a temperature difference higher than 2.2°C between a foot region and the same region on the contralateral foot. According to [1], foot ulcer occurrence can be reduced by 70% if the foot hyperthermia is early detected. To this end, the plantar foot temperature can be measured by using a thermal camera, as reported in several studies[2][3]. Such images are segmented in order to extract the thermal information to detect hyperthermia. To ensure good image quality and therefore a high-quality segmentation, constraining acquisition setups with the use of isolation systems were required. The acquired image is similar to the one shown in Figure 1.1 (left column). Thus only the plantar foot surface is present allowing an easy segmentation task.

Since our aim is to develop a user-friendly technology for thermal image analysis of plantar foot, Dhinaharan Nagamalai et al. (Eds) : WIMO, ICAIT, ICDIPV, NC, CRYPIS - 2019 pp. 33-41, 2019. © CS & IT-CSCP 2019 DOI: 10.5121/csit.2019.90404

we, therefore, free ourselves from the use of an isolation system. Plantar foot images are acquired without special isolation objects and are freehandedly taken using a smartphone equipped with a dedicated thermal camera (FlirOne Pro for example). The segmentation of such images is a difficult task because of the occurrence of the other parts of the body in addition to the plantar foot surface as shown in Figure 1.1 (right column).

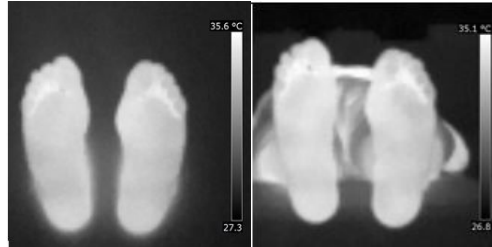


Figure 1.1. Thermal images acquired with an isolation system (left column) and without it (right column).

Because we seek a single closed contour of the plantar foot, and because the shape of a human foot is known, we will focus on segmentation approaches based on active contour with prior shape information. Recently, we have proposed in [4] to add an extra term to the snake energy functional of Kass *et al.*[5]. This term guides the snake to the desired contour by minimizing a curvature difference between the snake curve and the prior shape curve. In [6], an active contour model with a greedy implementation was presented by Ahmed *et al.* The shape matching was performed in the Fourier domain. In [7], Chen *et al.* proposed a variational method based on a geodesic active contour model of Caselles[8].

In the present paper, we propose to compare our proposed method [4] to Ahmed *et al.*[6] and Chen *et al.*[7] methods. Our aim is to qualitatively and quantitatively characterize the performance of those methods when segmenting diabetic foot plantar images that are taken without special constraining setups and freehandedly with a smartphone.

The remainder of the paper is organized as follows. Section 2 presents a brief review of the tested methods. In Section 3, a comparison to Ahmed *et al.* method [6] and Chen *et al.* method [7] is carried out by applying all the three methods on a database of 50 plantar foot thermal images. Finally, conclusions and perspectives are presented in the last section.

2. TESTED METHODS

2.1. Our Method [4]

Our method is a parametric method based on the snake method proposed by Kass *et al.*[5]. The total energy of the Kass model is given by the following energy function:

$$E_{\text{Total}} = \int_0^1 (E_{\text{intern}}(C) + E_{\text{image}}(C) + E_{\text{con}}(C)) ds, \quad (1)$$

where an element $C(s, t) = (x(s), y(s))$ along the contour depends on the curvilinear abscissa $s \in [0, 1]$ and on time t ; x and y are the pixel coordinates. The internal energy E_{intern} contains two terms: length and curvature terms. The image energy E_{image} is given by the gradient information. The external constraint E_{con} could be for example the balloon energy.

We propose to modify the snake functional (equation 1) by adding an extra energy E_{PS} . This prior shape energy function assesses the difference between the curve curvature C_{SS} and the prior shape curvature C_{SS}^* during the contour evolution. This extra term imposes the shape of the foot during the snake evolution. The numerical expression of E_{PS} is given by equation 2 and the total energy of the model is in equation 3.

$$E_{PS} = \gamma |C_{SS}(s) - C_{SS}^*(s)|^2, \quad (2)$$

$$E_{Total} = \int_0^1 (E_{intern}(C) + E_{image}(C) + E_{con}(C) + E_{PS}(C)) ds, \quad (3)$$

where $C_{SS} = \frac{\partial^2 C}{\partial s^2}$ (the same for C_{SS}^*). Minimizing the E_{Total} (equation 3) leads to solving the Euler Lagrange equation 4:

$$\alpha C_{SS} + (\beta + \gamma) C_{SSSS} - \gamma C_{SSSS}^* + \frac{\partial(E_{image} + E_{con})}{\partial C} = 0, \quad (4)$$

where $C_{SSSS} = \frac{\partial C^4}{\partial s^4}$, $C_{SSSS}^* = \frac{\partial C^{*4}}{\partial s^4}$ and α, β, γ are ponderation parameters.

2.2. The Ahmed *Et Al.* Method [6]

The method proposed by Ahmed *et al.* is a Fourier-based active contour model with a greedy implementation. The energy functional of this model is the same function of Kass *et al.* model (equation 1) but the minimization process differs. Indeed, an extra prior shape term is added to the total energy function of the snake. This term assesses the shape matching performed directly in the Fourier descriptor space. The distance between the curve C and a prior shape curve C^* is then calculated based on normalized Fourier descriptors. Let $C = (x_i, y_i)$ be the curve where $i = 0, 1, \dots, n-1$, n is the number of points on C , and $z_i = x_i + j \cdot y_i$ the complex coordinates of C . The Discrete Fourier Transform is applied to give a set of Fourier coefficients $Z_k = R_k e^{-j\theta_k}$, where R_k is the amplitude and θ_k is the phase. The normalized descriptor is then $\hat{Z}_k = \hat{R}_k e^{-j\hat{\theta}_k}$ where:

$$\hat{Z}_k = 0 \quad (k = 0), \quad \hat{R}_k = \frac{R_k}{R_1}, \quad \hat{\theta}_k = \theta_k - \theta_1, \quad (k \neq 0) \quad (5)$$

By exploiting the Parseval theorem, the extra prior shape energy is given by equation 6 and added to the functional equation 1. This energy is controlled by a parameter γ .

$$E_{PS} = \gamma \sqrt{\sum_{k=-\frac{n}{2}}^{\frac{n}{2}-1} |\hat{Z}_k - \hat{Z}_k^{ref}|^2}, \quad (6)$$

\hat{Z}_k and \hat{Z}_k^{ref} are the normalized descriptors of the curve C and C^* , respectively.

2.3. The Chen *Et Al.* Method [7]

Chen *et al.* [3] presented a variational method using prior shapes based on a geodesic active contour model of Caselles *et al.* [8]. The total energy of the model is the following equation:

$$E_{\text{Total}} = \int_0^1 g(|\nabla I|(C)) |C'| ds, \quad (7)$$

where $C = (x(s), y(s))$ ($s \in [0, 1]$) is a differentiable parametrized curve in the image I ,

$g(|\nabla I|) = \frac{1}{1+b|\nabla G_{\sigma} * I|}$, $b > 0$ is a ponderation parameter and G_{σ} is a Gaussian kernel with standard deviation σ . Authors proposed to find the curve C and the transformations μ , R and T (scale, rotation and translation parameters, respectively) such as the prior shape C^* is closely associated to the curve $\mu R(\Theta)C + T$. The curve C has to match a high gradient location in the image. The proposed energy function depended on the curve and the transformation μ , R and T . The curve C and the transformation parameters μ , R and T evolve to minimize equation 8.

$$E_{\text{Total}}(C(s), \mu, R, T) = \int_0^1 \{ g(|\nabla I|(C)) + \frac{\lambda}{2} d^2(\mu RC + T) \} |C'| ds, \quad (8)$$

where $\lambda > 0$ is a weight, and $d(x, y) = d(C^*, (x, y))$ is the fast marching distance between the point (x, y) on the image I from C^* .

3. RESULTS

The comparison between the 3 methods is performed on a database of 50 plantar foot thermal images. Images are taken with a Samsung S8 smartphone associated with the FlirOne Pro thermal camera. 25 healthy volunteers (no diabetes) from the University of Orleans were included. This sample group was composed of 10 women and 15 men. The dataset of 50 plantar foot images is then obtained after splitting each acquired image into two images containing one foot each.

The prior shape corresponds to the average of 10 contours manually segmented by an expert as shown in Figure 3.1 (first row). The prior shape contour is used as an initial contour, reduced by a scale factor of 2 and vertically placed inside the foot region. Its gravity center is assessed by binarizing the image with an adaptive threshold using the Otsu method followed by erosion and by dilation to suppress other parts than the plantar surface.

Parameters of each method are selected for optimal results.

3.1. Qualitative Results

We first qualitatively evaluate the performance of the 3 tested methods. Results are presented in Figure 3.1 for 3 images selected from the database.

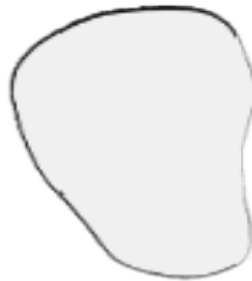
Results show that our method is qualitatively better than the two other ones for the 3 tested images. Next is a quantitative measures on the 50 images of the database.

3.2. Quantitative Results

Two metrics are used. The first one is the root-mean-square error (RMSE) between the ground truth contour and the final contours given by the three methods. At each point of the ground truth contour, the closest point of the contour is estimated to form the final RMSE. The second metric is the Dice Similarity Coefficient (DSC) [9]. This score assesses the similarity between the foot region given by the ground truth contour and the regions bounded by the segmentation contours given by the three methods. Table 1 shows the mean scores given by the methods with their respective standard deviations. Table 1 shows that our method is the best one with an RMSE of 5.12 pixels and a DSC of 0.939. One can note that 5 pixels corresponding to a value of about 5 mm on the image. This error is smaller than most of the wound dimensions that are usually observed in the diabetic foot.

Table 1. RMSE and DSC of the segmentation methods.

	RMSE (mean±STD)	DSC (mean±STD)
Our method	5.120 ±1.88	0.939 ±0.02
Ahmed <i>et al.</i>	10.990 ±4.24	0.850 ±0.07
Chen <i>et al.</i>	6.163 ±1.38	0.929 ±0.017



The prior shape

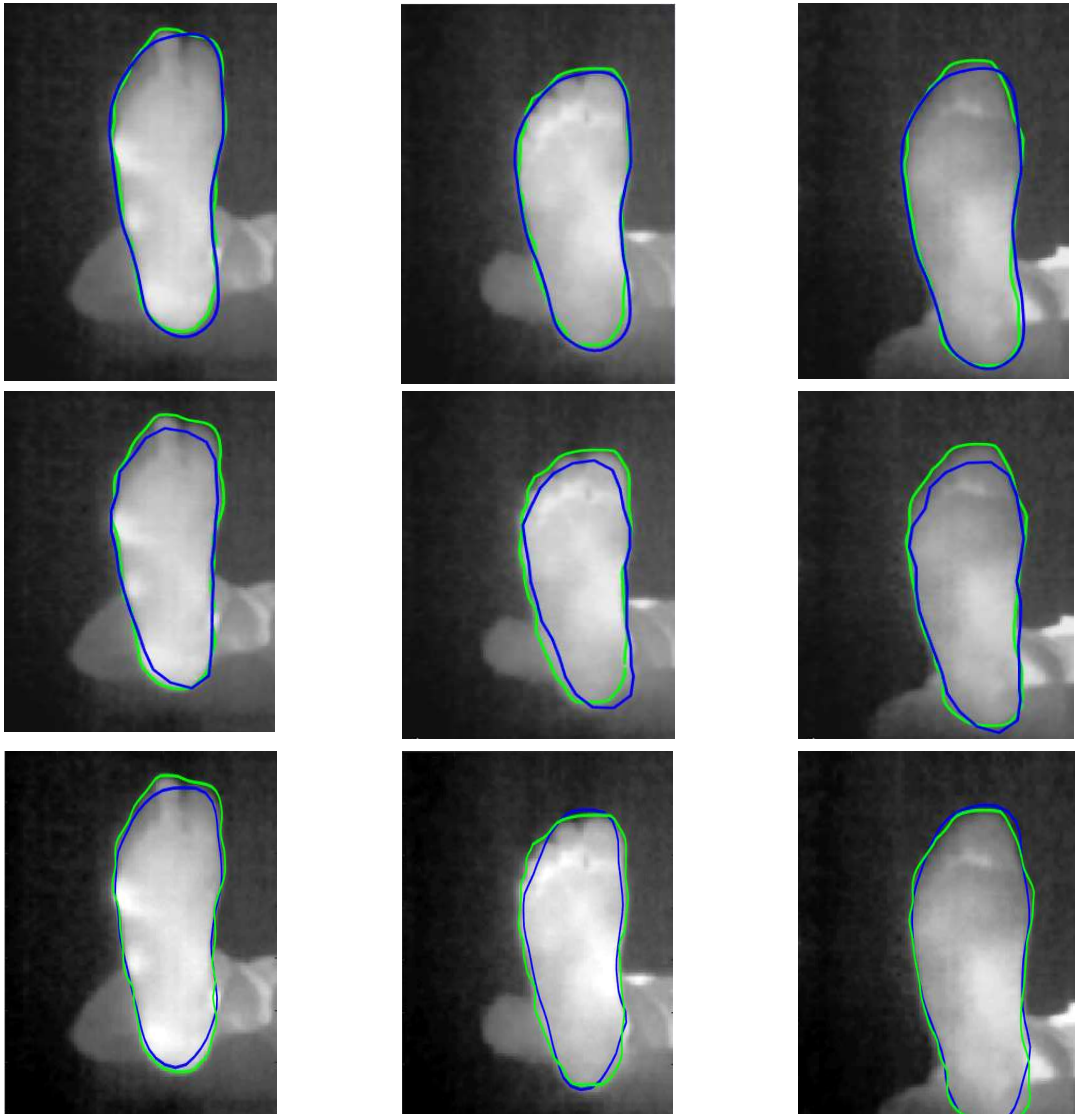


Figure 3.1. Segmentation of 3 plantar foot thermal images. The first row presents the prior shape. The second row corresponds to our method, while the third row shows the Ahmed *et al.* method. While Chen *et al.* method is presented in the last row. The blue curve corresponds to the contour found by the methods while the green curve represents the ground truth contour.

3.3. Robustness and Speed

In order to evaluate the robustness of these 3 methods, we test them to initial contours variations as shown in Figure 3.3. We can see that the methods proposed by Ahmed *et al.* and Chen *et al.* are sensitive to the position of the initial contour. At the opposite, our method is robust to the initialization variations.

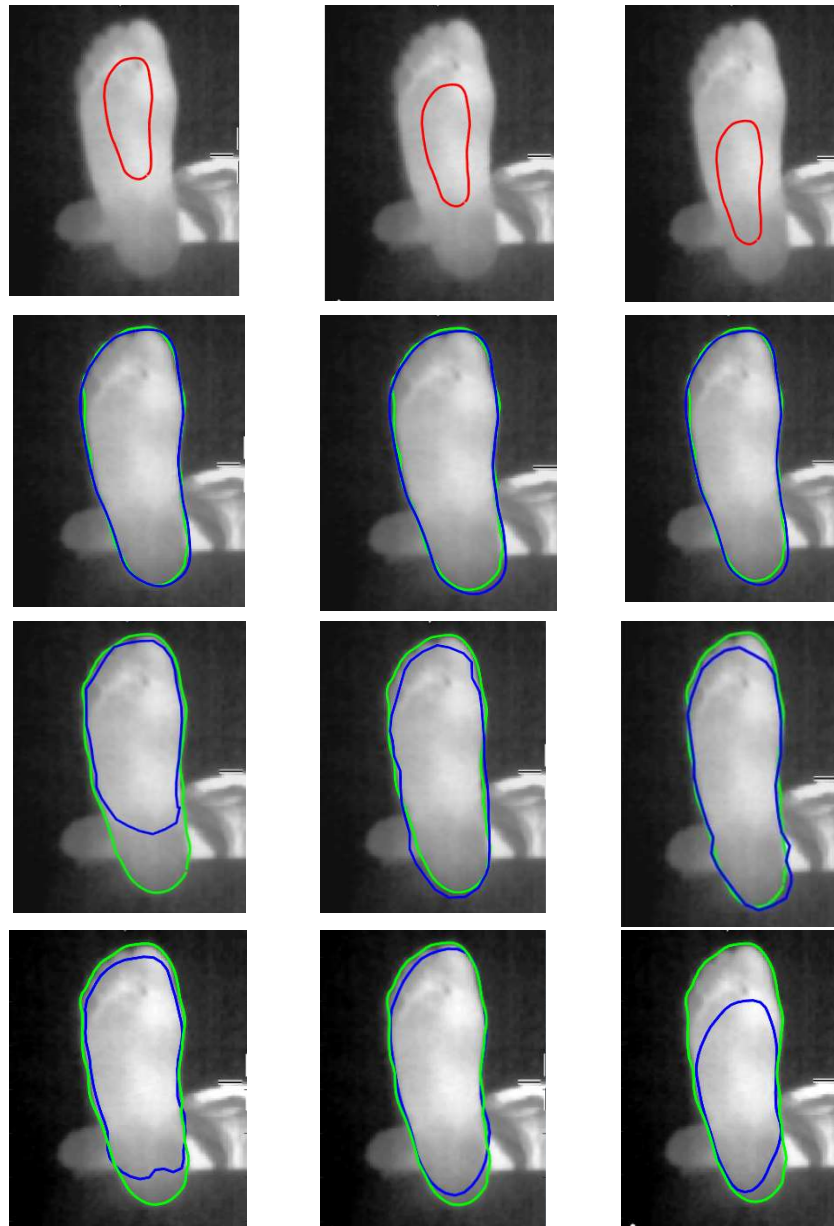


Figure 3.3. Segmentation of a plantar foot thermal image with different initial contours (row 1). Our method is in row 2, the Ahmed *et al.* method is shown in row 3, and the Chen *et al.* method is presented in the fourth row. The blue and green curves present the final contour and the ground truth contour, respectively.

An important criterion is the processing speed, especially in our application context for a smartphone deployment. To that end, we here measure the average CPU execution time on a Dell Precision Station 1700 with a Core i7-4790 CPU (3.60 GHz cycle frequency). Table 2 summarizes results obtained on the database of thermal images which dimensions are of 257×385 pixels.

Table 2. Average CPU time obtained with the different methods.

Our method	Ahmed <i>et al.</i>	Chen <i>et al.</i>
2.3 sec.	1.5 sec.	6.5 sec.

Table 2 indicates a superiority of Ahmed *et al.* method compared to the 2 other methods. Our method comes in the second position with a speed difference of less than 1 sec. The CPU time of our method is of 2.3 seconds which is suitable for smartphone applications we have in mind (8 cores with a CPU frequency of 2.3GHz).

4. CONCLUSIONS AND PERSPECTIVES

This paper has presented a comparative study of 3 active contour models with the prior shape for diabetic plantar foot thermal images segmentation: our method [4], Ahmed *et al.* [6] and Chen *et al.* [7] ones. The comparison of these three methods, carried out on a plantar foot thermal images database, showed the superiority of our method in term of RMSE (5.12 pixels) and DSC (93.9%). Moreover, our method converges rapidly toward the optimal solution and it is less sensitive to initial contour variations. The proposed method seems suitable to be implemented on smartphones for diabetic foot applications. Finally, we intend to improve the segmentation quality of our method using a multispectral approach by incorporating information contained in the color image. Furthermore, we are collaborating with the regional hospital of Orleans to acquire images of diabetic foot subjects. Therefore, we will apply our segmentation method in an embedded smartphone application in the clinical context.

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