Analysis of Algorithms used in Wound Assessment for Diabetic Patients

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ABSTRACT

Now-a-day's we know that many people face Foot ulcers. Here we considering the prevalence of Smartphone with high resolution digital camera, a more quantitative and cost-effective method that enables the patients and caregivers to take more active role in daily wound care. The analysis of various wound assessment is done in this paper also we discuss why the level-set algorithms used in earlier detection methods are avoided and the reason why we opt the Mean Shift based algorithm for the wound analysis processes. Through the Smartphone camera the wound image is captured. After that, the wound segmentation is done by applying the accelerated mean shift algorithm. Using simple connected region detection method, the outline of the foot is determined based on skin color. The healing status is then next assessed based on red-yellow-black evaluation model.

Index Terms— Mean Shift and Image Analysis.

1. INTRODUCTION

Foot ulcers constitute a significant health issue affecting 5-6 million individuals in every country. These foot ulcers being painful, susceptible to infection and very slow to heal. Moreover it is estimated at $15,000 per year per individual as the cost of treating these diabetic foot ulcers [1]. The overall healthcare cost is expected to increase in the coming years [1]. There are several issues with the current practice for treating the diabetic foot ulcers. Patients must go to their wound clinic to have their wounds checked by their clinicians or doctors on a regular basis. Frequent clinical evaluation is needed which is not only inconvenient and time consuming for both patients and clinicians, but it also represents significant cost as patients require special transportation. Then a clinician's wound assessment process is based on visual examination. He/she describes the wound by its physical dimensions and the color of its tissues, providing important indications of the wound type and the stage of healing [2]. Because the visual assessment does not produce objective measurements and quant able parameters of the healing status, tracking a wounds healing process across consecutive visits is a difficult task for both clinicians and patients [3].

The wound image is captured by the camera on the Smartphone with the assistance of an image. After that, the Smartphone performs wound segmentation by applying the accelerated mean-shift algorithm. Specifically, the outline of the foot is determined based on skin color, and the wound boundary is found using as implementation connected region detection method. Within the wound boundary, the healing status is next assessed based on red–yellow–black color evaluation model.

For the wound boundary and classification of tissues, researches have applied image segmentation and supervised machine learning algorithm for wound analysis [4]. A support vector machine (SVM) based wound classification was proposed by the French research. Even though SVM classifier provide good results on typical wound images, it is not feasible to implement the training process and feature extraction. Moreover the learning of supervised algorithm requires large number of training images, which are both difficult and costly [4].

So we provide the solution of image analysis algorithms that run on a smartphone with a low cost and easy-to-use. We have to design a highly efficient and accurate algorithm for real-time wound analysis that operates the computational constraints of the smartphone.[1] The solution to this was to implement by utilizing an accurate and efficient algorithm such as mean shift algorithm, for wound boundary determination, followed by color *seg*mentation within the wound area assessing healing status. [1]

2. ANALYZING OF ALGORITHMS

2.1. Level Set Algorithm

Level set methods have been widely used 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. The level set evolution is derived as the gradient flow that minimizes energy functional with a distance regularization term and an external energy that drives the motion of the zero level set toward desired locations. The distance regularization term is defined with a potential function such that the derived level set evolution has a unique forward-and-backward (FAB) diffusion effect, which is able to maintain a desired shape of the level set function, particularly a signed distance profile near the zero level set. This yields a new type of level set evolution called distance regularized level set evolution (DRLSE) [6].

This present a novel wound image analysis system, utilizing the distance regularization level set evolution for wound boundary determination and the K-mean color segmentation algorithm for assessing healing status. The DRLSE algorithm is implemented as a narrow-band restricted version based on both the GPU and CPU. The fast K-mean algorithm is used to segment the wound area based on color and the size of each type of tissue is computed.

The key element in image analysis is wound area segmentation because it provides the subsequent processes. Thus the segmentation algorithm must perform well for a wide range of wound images. Initially the level set based algorithm is chosen because of the relatively fine resolution that can be achieved, the handling of slightly titled lines and corners and the precise and easy calculation of surface normal vectors. As the joining surfaces are handled implicitly, the wound contour is self-adaptive to the topological change during the evolution. This means that the implicit contour accurately follows shapes that change topology, for example when a shape splits into two, develops holes, or the reverse of these operations. This property of level set algorithm allows direct numerical computation on image grids. Because of these features, level set based algorithms have been widely used in image segmentation.

In the system, the DRLSE algorithm was applied to the image to determine the boundaries for all wound areas and measure the size of each wound by pixel. To achieve further efficiency improvement, the DRLSE algorithm was parallelized and implemented on a GPU. The problem of the level set algorithm is that iteration of global level set function is too computationally intensive to be implemented on smartphones, even with the narrow band confined implementation based on GPUs. In addition, the level set evolution completely depends on the initial curve which has to be pre-delineated either manually or by a well-designed algorithm. Finally, false edges may interfere with the evolution when the skin color is not uniform enough and when missing boundaries, as frequently occurring in medical images, results in evolution leakage (the level set evolution does not stop properly on the actual wound boundary) [1].Hence, a better method was required to solve these problems.

2.2. Region Adjacency Graph

Over-segmentation is a problem, which we solved using the region adjacency graph (RAG) based region merge algorithm. [3] A Region Adjacency Graph (RAG) is built from the watershed flooding result. The initial RAG was built from the filtered image, the modes being the vertices of the graph and the edges were defined based on four connectivity of the lattice. Then, a graph vertex image is built from the graph and the input image. Graph vertex image topology is based on a graph. Each graph vertex is mapped to a site, here the mass center of a basin. The site value is set to the mean color of the corresponding basin. Likewise, in graph edge images each graph edge is mapped to a site, here a pair of basin mass centers. The site value is actually the distance between two vertex values.

On the graph, the fusion was performed as a transitive closure operation, under the condition that the color difference between two adjacent nodes should not exceed h_r . At convergence, the color of the regions was recomputed and the transitive closure was again performed. After at most three iterations the final labeling of the image (segmentation) was obtained. Small regions (the minimum size, *m* is defined by the user) were then allocated to the nearest neighbor in the color space. Note that this post processing step can be refined by employing a look-up table which captures the relation between the smallest significant color difference and the minimum region size [5].

Here, each region in the image is a node in a graph. There is an edge between every pair of adjacent regions (regions whose pixels are adjacent). The weight of between every two nodes can be defined in a variety of ways. We will use the difference of average color between two regions as their edge weight. If more similar regions are present, then the weight will be lesser between them. Once the RAG is constructed, many similar and more sophisticated strategies can improve the initial segmentation.

2.3. Mean Shift Segmentation Algorithm

We replaced the level set algorithms with the efficient mean shift segmentation algorithm. In this paper, we present the entire process of recording and analyzing a wound image, using algorithms that are executable on a smartphone, and provide evidence of the efficiency and accuracy of these algorithms for analyzing diabetic foot ulcers.

Since the quality of the output is controlled only by the kernel bandwidth, i.e., the resolution of the analysis, the technique should be also easily integrable into complex vision systems where the control is relinquished to a closed loop process. Additional insights on the bandwidth selection can be obtained by testing the stability of the mean shift direction across the different bandwidths, in the case of the force field. The nonparametric toolbox developed in this paper is suitable for a large variety of computer vision tasks where parametric models are less adequate, for example, modeling the background in visual surveillance.

The complete solution toward autonomous image segmentation is to combine a bandwidth selection technique with top-down task related high-level information. In this case, each mean shift process is associated with a kernel best suited to the local structure of the joint domain. Several interesting theoretical issues have to be addressed, though, before the benefits of such a data driven approach can be fully exploited.

The ability of the mean shift procedure to be attracted by the modes of underlying density function can be exploited in an optimization framework. By defining the distance between the distributions of the model and candidate of the target, non-rigid objects were tracked in an image sequence under severe distortions. The distance was defined at every pixel in the region of interest of the new frame and the mean shift procedure was used to find the mode of this measure nearest to the previous location of the target.

The above-mentioned tracking algorithm can be regarded as an example of computer vision techniques which are based on in situ optimization. Under this paradigm, the solution is obtained by using the input optimization problem. The in situ optimization is a very powerful method. Each input data point was associated with a local field to produce a more dense structure from where the sought information can be reliably extracted. The mean shift procedure is not computationally expensive. While it is not clear if the segmentation algorithm described in this paper can be made so fast, given the quality of the region boundaries it provides, it can be used to support edge detection without significant overhead in time.

3. WOUND IMAGE ANALYSING OVERVIEW

The wound assessment system consists of several functional modules such as wound image capture, wound image storage, wound image preprocessing, wound boundary determination, wound segmentation and wound trend analysis based of wound images for a given patient. All these steps are carried out by a single smartphone. The overall diagram of the wound assessment system is shown in Figure 1.

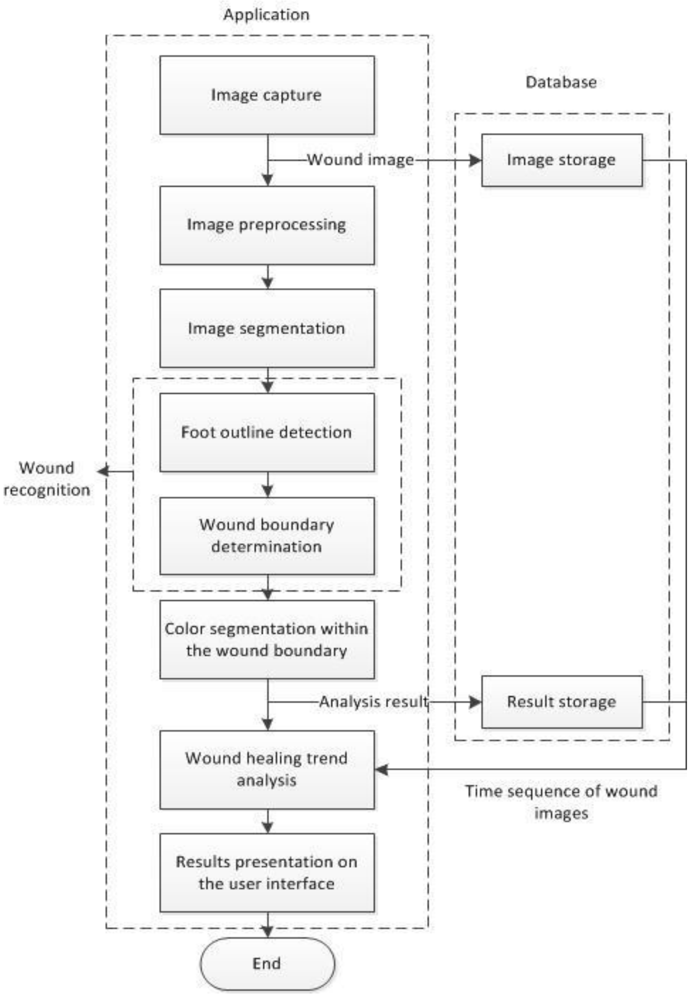

Fig-1: System Architecture [1]

In these technique, an excellent CPU + GPU performance and high resolution camera phone is used to chosen. The foot image is captured through the Smartphone and the JPEG file path of this image is added into wound image database. Compressed image file cannot be processed directly with our main image processing algorithm. So according to standard, image changed into 24bit bitmap file based on RGB color model is done for decompression.

In Image Preprocessing, the high resolution bitmap image is down-sample to speed up the subsequent image analysis and to eliminate excessive details that may complicate wound image segmentation. The First Image segmentation step is to divide the original image into pixel groups with homogeneous color values.

Foot outline detection is used for determining the wound boundary. It is performed by finding the largest connected component in the segmented image under the condition that the color of this component is similar enough to a preset standard skin color. Next, Wound Boundary Determination, we carry out it as if the foot detection result is regarded as binary image at that time infected area detect by 'White' and rest part marked as 'black' these easy to locate the wound boundary within the foot region.

Healing status of the wound can be evaluated by Color Segmentation where with the goal of categorizing each pixel in the wound boundary into certain classes labeled as granulation, slough and necrosis. After the color segmentation feature vector describe the size and dimensions of both the wound and original best record which is the earliest record for these patient [1].

The wound feature vectors between the current wound record and the one that is just one standard time interval earlier are current trend is obtained [1]. The Result Image will be store in database and system will be analyzes the infected area and provide us with needed output.

4. CONCLUSION

The analysis of various wound assessment is done in this paper. As we mention earlier, we use the mean shift based boundary determination algorithm to analysis of accurate wound boundary detection result. By using this technique Patients are active participants in their own care. Patient's travel exposure is considerably reduced. Also it will reduce the patients stress. The processing algorithms are both accurate and well suited for the available hardware and computational resources that time Patient for image capture and image processing provided.

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