Contrast Enhancement and Segmentation using Wavelet Analysis and Non–Linear Enhancement in Diabetic Foot Ulcer Imaging

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Abstract

Diabetic Foot Ulcers(DFUs) affect between 5% to 10% of the population. The area of a diabetic foot ulcer is measured manually or semi-automatically. There is no clear procedure for evaluating the foot ulcer region for the purpose of treatment.The problem to be solved is complex due to the various shapes of the ulcers and their position on the foot, which is not necessarily flat and can cover several areas of the foot. In this research work, a combination of Logarithmic Discrete Wavelet Transform (LDWT) within a Symmetric Logarithmic Image Processing Model (S-LIP) model is applied for the contrast enhancement of foot ulcer images and then standard Grab-Cut segmentation algorithm is applied for the Region of Interest (ROI) extraction. The experimental results reveal that the proposed contrast enhancement and segmentation model is best suitable for the diabetic foot ulcer segmentation.

Keywords

Diabetic Foot Ulcer (DFU), Segmentation, Diabetes Mellitus (DM), Contrast Enhancement, Symmetric Logarithmic Image Processing Model.

1. INTRODUCTION

In India, the morbidity rate from diabetes was 65 per 1000 inhabitants in 2018, and the number of people subject to amputation is estimated at around 1500 to 3000. In 2018, 60,367 were treated. Indian patients with an amputation rate of ~2%(Ministry of Health and Family Welfare[1]). The relative risk of suffering an amputation has been reduced in 78% of the patients to whom insulin is applied, which has a direct impact on the quality of life of diabetic patients since amputations cause disability and dependence, together to mental and emotional disorders by García et al., (2011).

In India, the measurement of the DFU tissue area is done manually or semi-automatically. There is no specific and standard software, registered so far, that automatically measures the areas of the lesion to know the status of DFU before and after treatment.The problem to be solved is complex due to the various shapes of the ulcers and their position on the foot, which is not necessarily flat and can cover several areas of the foot. (García et al.,2018).The main aim of this work is to improve the accuracy of tissue segmentation and classification for assessment of the wound healing status in diabetic wound analysis and various pathologies of DFU as segmentation and classification.The wavelet-based method has been widely used in digital imaging with satisfactory results (Bhateja & Devi., 2010). However, there are few numbers of work to establish a combination of the process of selecting the wavelet base and the degree of decomposition that must be effectively processed to improve the contrast of digital images (Cheng et al.,2010). This work proposes a method for selecting the decomposition level to be process in wavelet-based algorithm. Contrast enhancement is performed by modifying wavelet coefficients using local correlation methods in a logarithmic framework (Chen et al.,1997). Quantitative contrast measure (Singh &Bovis., 2005) and principal component analysis (Jolliffe., 2010) are used to select the best combination of decomposition levels.

The remaining part of the paper is organised as follows. Section 2 brief out few literatures related to this research. Section 3 introduces the proposed prepressing method and segmentation. Section 4 discusses the obtained results along with tabulated comparative study and section concludes the paper along with cited references.

2. RELATED WORKS

Here are some of the forms of segmentation that have been studied in the current scientific literature. The prevalence of diabetes in India accounted for 13% in 2016 among those aged 30 and over, ~27% among those over 65, and the prevalence of both men and women increased with increasing age. As the prevalence of diabetes increases, it causes various complications. Among them, diabetic foot ulcer is an important cause of amputation and mortality in diabetic patients (Boulton et al., 2004). Looking at the prevalence of diabetic foot ulcers in India, as of 2011, 3% of diabetic patients 20 years of age or older, and about 1,00,000 people are diagnosed with diabetic foot ulcers and are receiving treatment.

Twenty percent of diabetic patients admitted to the hospital are hospitalized for foot disease, and more than 50 percent of them experience amputation of the lower limbs (Burrell, 1992). Diabetic patients have a 15%-25% risk of developing ulcers throughout their lifetime, and 15% of patients with ulcers develop osteomyelitis and require amputation (Brown et al., 2012). To treat stubborn foot ulcers, orthopedic surgeons often perform an amputation of the lower extremities, which causes significant postoperative complications and mortality. Patients who have experienced amputation have a 50-84% probability of amputating the other leg in 2-3 years, and the 5-year survival rate of patients with amputation in both legs is less than 50% (Greant & Van, 1990). low. As such, diabetic foot ulcers have a high recurrence rate and are a major cause of hospitalization, leading to a decrease in quality of life, as well as a 10-fold increase in hospital expenses for 5 years related to foot ulcer treatment (Hicks et al., 2016) It is a cause of social and economic burdens, including loss of medical expenses.

Because diabetic foot ulcers have significant clinical implications such as increasing disease morbidity and mortality (Boulton et al., 2004), proper treatment and prevention are important, and intensive education for high-risk groups is required. Diabetic foot ulcer complications can be minimized through blood sugar control, early perception, risk factor management, etc., but after a health care professional assessed risk factors and implemented educational interventions, the score of foot care knowledge increased (Schoen et al., 2016). After providing foot care training to diabetic patients, knowledge, will, motivation for learning, and behavior were changed, and weight and blood pressure decreased after training, which played a role in preventing diabetic foot ulcers (Nemcova & Hlinkova)., 2014). Therefore, for diabetic foot ulcers, not only appropriate treatment but also changes in self-nursing behavior through foot care education are of paramount importance in improving the quality of life. In addition to professional management through medical personnel, patients should be able to perform foot management with their own identity.

In 2017, García-Zapirain and others used image processing techniques to segment ulcers from color images. To minimize algorithm execution time, ROI is automatically identified based on changes in contrast. At this point, the synthetic intensity frequency is used, based on each pixel, which is calculated using the field energy to describe the relationship between the intensity of the pixels.

The visual appearance of the observed image is modelled by a Discrete Gaussian Model Linear Combination (LCDG). In order to estimate the marginal probability of distribution of the three main tissue classes for the ROI in gray scale. Then, the probability of the appearance of the pixels of these three classification classes for the ROI of the color image is calculated using the color image that is previously in the database of manually segmented images. Finally, to preserve continuity, the labels are refined and normalized using the Generalized Gauss-Markov Random Field Model (GGMRF).In 2017, Goyal and others, used Convolutional Neural Networks for DFU classification. A convolutional neural network architecture was proposed called DFUNet, which manages to more adequately extract characteristics to identify the differences between healthy skin and lesion skin.

In addition, they introduced a database of 705 images that contain DFU and provide a golden rule of the ulcer region. In addition, they proposed a training model for a complete convolutional network (FCNs) to automatically segment it. The proposed model uses the Dice similarity coefficient of 0.794 (± 0.104) for the ulcer region, 0.851 (± 0.148) for the region surrounding the skin and 0.899 (± 0.072) for the combination of the two regions. This demonstrates the potential of FCNs in the segmentation of DFUs. The Dice coefficient is used to compare the similarity of two samples, QS = 2C / A + B where A and B are the number of species in samples A and B, respectively, and C is the number of species shared by the two samples.; QS is the similarity quotient and varies from 0 to 1.

Other segmentation techniques use the intensity or variety of color, for example, in spatial dependencies between MRI arrangements of closed elements, or image entropy by Zhang et al., (2013),both focused on the objective of obtaining the edge of the image by Yu et al., (2015). Another study is that of Wannous et al. (2008) to segment the wound area. Such research is based on a combination of unsupervised segmentation and machine learning, but despite good results in practice, it is not feasible due to its high computational requirements.

3. PROPOSED PREPROCESSING AND SEGMENTATION METHOD

The research is descriptive and experimental. The experiments were carried out on the DFU dataset of 600 DFU foot images that was splitted into the 70% training, 10% validation and 20% testing. The database includes the diabetic patients who were affected with grade I-IV lesions on the Wagner scale(Frykberg et al., 2006). In the diabetic image database stereotaxic limb frame was used to obtain planimetric images of the patients' ulcers at different times of the insulin treatment. A total of 50 images were obtained, taken with a fixed camera with a resolution of 4608 × 3456. The camera is placed and fixed at constant distance for standardizes the imaging process with the existence of a positional reference of the injured limb with a DFU and allows all images to be taken at the same distance.

3.1 PREPROCESSING

The color images were converted to gray scale and these were pre-processed with the Transformed Discrete Logarithmic Wavelet algorithm, within aSymmetric Logarithmic Image Processing Model (S-LIP) (TWDL) model. (Valdés et al., 2018) This transform was applied to the images and allowed to obtain information on the local contrast. (Martins et al., 2008). In general, wavelet-based algorithms have three stages. First, the image decomposes into horizontal, vertical and diagonal approximation and detail coefficients. In the second step, the coefficients are modified, and as a final step, the Inverse of the Discrete Transform Wavelet (ITWDL) is applied to obtain the improved image.

Generally, the wavelet-based algorithms have three main stages. First, the image is decomposed in horizontal, vertical and diagonal detail coefficients and the approximation coefficients. At this stage is important to select the wavelet base and levels of decomposition to be process. Different approaches for wavelet base selection has been addressed by [Valdés et al., (2018)]. Cheng et al. proposed an automatic wavelet base selection to enhance contrast of natural images [Silva et al., 2015]. In this contribution we study a way to select the proper wavelet base to improve contrast in mammography images, also related with the type of anomaly; to our knowledge this task hasn’t been done yet.

Navarro et al. uses the Logarithmic Discrete Wavelet Transform (LDWT), and S-LIP model in compression, edge detection and noise suppression in images (Rueden et al., 2017).

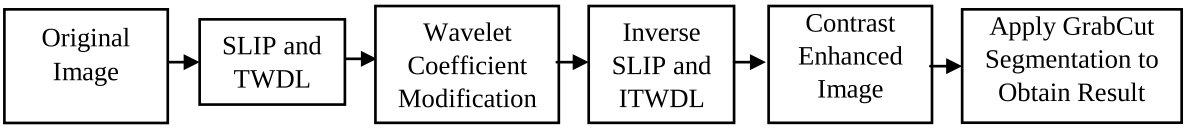

Figure 1. Proposed Contrast Enhancement and Segmentation Model

In this section we propose a methodology for wavelet selection, i.e. select the wavelet base and the combination of decomposition levels to be processed. This approach needs the wavelet decomposition of an image for a set of wavelet bases and all possible combinations of decomposition levels, i.e. the power set of {1, 2, 3, maximum level of decomposition–1}. Then, a modification of wavelets coefficients is performed in order to increase the contrast. Finally, we obtain the reconstructed image through ITWDL, and a quantitative quality measure is computed on it. The flow of the proposed contrast enhancement and segmentation model is shown in Figure 1. The experimentation presented in this research apply TWDL with S-LIP, model to an image up to the highest decomposition level using a set of wavelet bases. After that, modify the wavelet coefficients by means of the Local Correlation method. Contrast enhancement quality measures based on regions of interest are computed for all the anomalies present in the image. Having the best wavelet base, we choose the decomposition level to be processed through a Principal Components Analysis (PCA).The segmentation algorithms described in section 3.2 were applied to the pre-processed images.

3.2 SEGMENTATION

The Chan-Vese segmentation algorithm (Chan and Vese., 2001) allows to obtain the edge of objects in an image whose boundaries are not clearly defined. It is based on sets of levels that are generated iteratively to minimize energy, which is defined by weighted values corresponding to the sum of differences in intensity of the average value outside the segmented region, the sum of differences of the average value within the segmented region and a term that depends on the length of the boundary of the segmented region.

The GrabCut (Rother et al.,2004) segmentation algorithm requires the user to frame the Region Of Interest (ROI) in a rectangular region. The algorithm then obtains the ulcer segmentation. The marked region can be further modified manually.Gaussian Mixture Models (Redner and Walker., 1984) (GMM) can be used as clustering methods. These are based on the assumption that each d-dimensional group in a data set can be modelled as a multivariate (Gaussian) normal distribution. Therefore, the complete data set can be modelled as a mixture of each of these Gaussians. This algorithm (Blei and Jordan., 2006) searches for the ROI taking as a reference the midpoint of the image.

4. EXPERIMENTAL RESULTS AND DISCUSSIONS

Given the limited number of images available and the absence of a golden rule (edges of the ulcers noted by experts that allow a systematic quantitative comparison between algorithms for the automatic detection of DFU edges, allowing to know which of these is the more appropriate), a qualitative comparison of the algorithms was made, with respect to visual appreciation and the opinion of the authors. So far, there is no database of annotated images with which to make these comparisons. The methods used in this research were implemented in the Matlab programming language.All images were converted to grayscale for processing. Given the inhomogeneous illumination in the images, a pre-processing was necessary to improve their quality. TWDL was used within aSymmetricLogarithmic Image ProcessingModel (S-LIP) model.

The Chan-Vese algorithm worked better when the skin on the patient's foot was black than when the skin was white or light, as the contrast is more prominent and the algorithm is better able to detect the ulcer. This algorithm was sensitive to the presence of brightness and shadows typical of the non-uniform lighting conditions of the images.Like the Chan-Vese algorithm, GrabCut was sensitive to highlights and shadows and performed better on black skin, as there is greater contrast between wound and healthy skin. Of the proven methods for finding ROI, GrabCut had the best visual results, according to the authors.In the case of GMM, the results were better than those of Chan-Vese. The GMM method must change the reference point from which the segmentation algorithm starts, which is the center of the ulcer, since most DFUs are not concentric and segmentation may not give good results.

Taking into account these results, it was decided to apply a preprocessing to the images using TWDL in an S-LIP model and the segmentation algorithms described were executed again.The results obtained by the Chan-Vese algorithm were not adequate. The GrabCut method performed well on pre-processed images, although this method issupervised, that is, the physician must select an initial region where the DFU to be segmented. Figure 2 shows the result of segmentation with GrabCut after preprocessing with the S-LIP model, and it can be seen that an almost perfect ROI was obtained. In Figure 3 TWDL was applied and a good result is also observed.The obtained average accuracy, sensitivity and specificity results were tabulated in Table 1.

Table 1. Comparison of Different Preprocessing Methods

Segmentation Method	Proposed Preprocessing Method			Without Preprocessing		
	Accuracy	**Sensitivity**	**Specificity**	**Accuracy**	**Sensitivity**	**Specificity**
Grab-Cut	0.950	0.889	0.984	0.721	0.635	0.827
Chan-Vese	0.931	0.853	0.962	0.688	0.628	0.733
GMM	0.890	0.819	0.921	0.521	0.601	0.921

Figure 2. Result of Preprocessing with S-LIP filter and Segmenting with the GrabCut algorithm: (A) Original Image, (B) Pre-processed Image, and (C) Segmentation Result.

Figure3. Result of Preprocessing with TWDL and Segmenting with the GrabCut Algorithm: (A) Original Image, (B) Pre-processed Image, and (C) Result of Segmentation.

In preprocessing and then segmentation with GMM, good segmentations were not always obtained. The ROIs detected, in almost all cases, gave much less favourable results than in the case of the image without preprocessing, even in the ulcers of people with black skin as shown in Figure 4.

Figure 4. Images Processed with GMM, Dividedin the Following Order from Left to Right. (A) Original Image, (B) ROI, (c) Detection of Yellow Areas According to the Algorithm.

Since the previous results were not as expected, it was decided to apply the wavelet filter within the S-LIP model to the same images and test again. As seen in Figure 5, the GMM algorithm obtained better results in the detection of ROI after applying the S-LIP model together with TWDL. You can see how the ROI is detected here almost perfectly. In the case of slough detection, A must be adjusted in the algorithm, since it was only correctly detected in 13.7% of the cases.

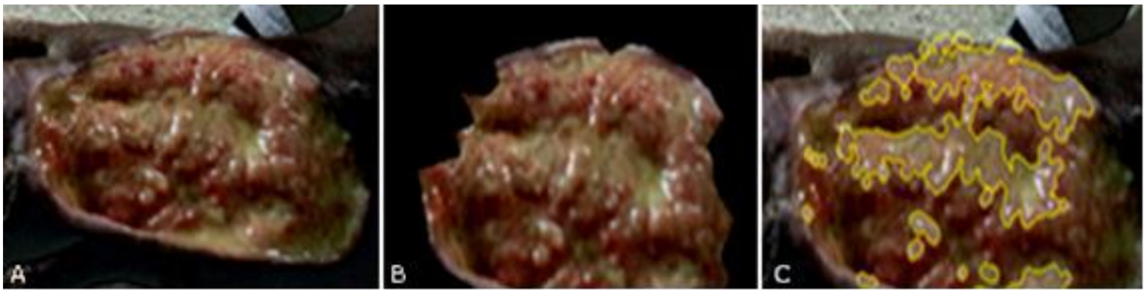

Figure5. Images Processed with GMM: (A) Original Image, (B) ROI and (C) Detection of Yellow Areas

With these results we deduced that it is necessary to apply filters to the images to be processed to find the ROI, preferably TWDL with the S-LIP model and segmentation methods so that they are obtained automatically.The Table2 shows a comparison between two of the state-of-the-art methods and all those analyzed and discussed above.

Table2. Comparison of state-of-the-art methods and studied methods

Methods	Advantages	Disadvantages	Suggestions
Goyal et al Method	ModerateAccuracy in ROI selection	Require golden rule with high volume of DFU images	There is not yet a golden rule for the images obtained
García-Zapirain Method	Moderate Accuracy in ROI selection	There is no code or manual for implementation and further testing with the images in this study	Still in the experimental phase
Proposed Method	Better Accuracy in ROI selection	They don't accurately detect ROI for the entire ulcer	More images are needed to build an annotated database and get more reliable results

5. CONCLUSION

In this paper, the problem of DFU segmentation was addressed. This task makes it possible to determine the edge of the ulcer based on algorithms and mathematical techniques, and would allow automatic measurement of the lesion area. Observation of the state of the area of the lesion allows to evaluate the healing process of the ulcers during a treatment. An automatic solution to the problem would be recommended in this case, since inaccuracy errors that specialists may comment on when making manual measurements would be avoided.As a result of the preliminary analyzes that have been carried out with the images that currently exist, it was obtained that the best method is the semi-automatic GrabCut, but this is not feasible for our study since an automatic algorithm that achievessolution to the problem. On the other hand, filter should be applied to images for best results; Based on the tests that have been done so far, S-LIP is suggested. The research presented in this contribution has limitations: the number of DFU images is relatively small and in the images obtained, the edges of the DFUs are not marked (there is no golden rule), which does not allow measuring the effectiveness of segmentation algorithms that automatically determine the edge of the ulcers. For this reason, and as a first approach to the problem of segmenting DFU, it was decided to make a qualitative evaluation based on the authors' appreciation.Although the results presented here are not definitive, it can be concluded that the GMM automatic segmentation algorithm can be included in a software to measure the ulcer area.For this reason, it is recommended to do the experimentation again when there is a greater volume of annotated images of DFU of patients, and to deepen in the improvement of the contrast of images of patients with white skin, as well as to test and compare these results with other algorithms segmentation.

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