Enhancement in the Identification of Slough Tissue in Chronic Wound Assessment

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Abstract—The prevalence of chronic ulcer wound is steadily increasing not only in predominantly rich nations but most markedly, in the world’s middle-income countries. In addition to the dire consequences on the health and well-being of a patient, diabetes and its complications impact harshly on the finances of individuals and their families, and the economies of nations. The current diagnosis methods utilized by the diagnosticians are expert-oriented, vision-dependant, time-consuming, have interobserver variations and cause discomfort to the patient. Therefore, in an effort to improve capacity for diagnosis, a fully-automated wound tissue characterization system has been offered that would analyze the digital images of chronic wounds to identify the tissue types namely, granulation, slough, necrosis, and epithelial. In our previous research, the three tissue types (granulation, necrosis, and epithelial) were identified with higher accuracy in 301 images. In this paper, the slough identification has been enhanced by adding reference points and contrast enhancement to evaluate which method demonstrates better experimental results. Quantitative analysis of the results proves that preprocessing the images with Adaptable Histogram Equalization technique achieved the highest accuracy of 94.0% for the slough tissue.

Index Terms—tissue characterization, colour analysis, fuzzy C-Means clustering, contrast enhancement

I. INTRODUCTION

The progression of chronic wounds is a concern worldwide as it has significant impact on the patient’s physical and mental well-being. In addition to causing pain and morbidity to the patient, high cost of diagnosis and treatment of chronic wounds have large impact on the financial prosperity of the patient’s family. Chronic wounds include, but are not limited, to diabetic foot ulcers, venous leg ulcers, and pressure ulcers. The likeliness of developing a chronic wound is increasing in Malaysia. In 2017, International Diabetes Federation reported over 3.4 million cases of diabetes in Malaysia \cite{1}. Consequently, it is crucial that a precise and an accurate diagnostic tool is required to assess the healing and/or worsening of a patient’s chronic wound.

Visually, the chronic wound tissue can be categorized as red-colored granulation (G), yellow-colored slough (S), black-colored necrosis (N), and pink-colored epithelial (Ep). Granulation is the fresh-forming tissue and have the colour appearance of shades of bright red, slough develops as a result of bacterial activity in the tissue and usually appears in colour ranges of yellow, the necrosis is produced when the tissues die by cause of deficiency in the flow of blood in that region and thus, occur blackish, and the epithelial designates the restored tissues and appear pink in colour \cite{2}. Assessment of chronic wound is done via tissue characterization techniques which analyze the quantitative percentages of tissue types are present in a wound. The tissue classification is done at each and every patient visit and this collective information is used at a later stage to monitor the wound healing progress.

The common practice done by the diagnosticians today to assess the healing of the wound are manual techniques like ruler-based, transparency tracing, and alginate casts. Additionally, dependency on the visual orientation of the expert to plot the on the red-black-yellow scale makes the assessment difficult to reproduce with high precision. Wound medical devices and applications (apps) are available for tissue characterization applications, including +WoundDesk \cite{4}, and MOWA (Mobile Wound Analyzer) \cite{5}. Largely, these systems offer better processing time relative to the traditional diagnostic techniques, but there needs to be a substantial enhancement in the accuracy and precision in the analyzed results in general. Furthermore, they often operate in certain controlled environment, such as camera at a fixed distance and/or angle from the wound, regulated lighting conditions etc.

Recent research has demonstrated the usage of supervised machine learning algorithm and unsupervised techniques for wound tissue characterization. Zahia et al. \cite{6} split the digital images of different types of wounds into patches that incorporated only one type of tissue and each patch classified using CNN. The entire wound images, containing multiple tissue types, were tested where the regions of each tissue were identified. Wannous et al. \cite{7} described robust tissue classification approaches using K-NN, Fuzzy K-NN, k-Means and SVM classifiers that provided accuracy of 80%, 81%, 68% and 88%, respectively. Although the overall accuracy of their approaches are promising, the identification of slough tissue has proved challenging due to the presence of uncontrolled lighting and a variety of colour range of such tissue. Accurate determination of slough in a wound (in the analysis stage) is
important for later stages (wound’s diagnosis and monitoring).

Herein, automated classification of slough tissue has been improved by enhancing the algorithm of our previous paper. Various techniques have been considered and the results were quantitatively compared with the ground truth provided by the doctors. The paper structure is as follows: The previous and the proposed system models have been presented and results are shown in Section II, discussion of the results is done in Section III, and a brief conclusion is done in Section IV.

II. METHODOLOGY

In our previous paper [8], a fully automated wound tissue characterization system was designed using Fuzzy C Means clustering algorithm. The process flow is shown in Fig. 2. 301 digital images of chronic wounds taken in an uncontrolled environment (of diverse wound grades, stages, and number of tissue types) as well as the ground truth were attained from Ohio State University, OSU, U.S.A., and Hospital Kuala Lumpur, HKL, Malaysia for this study. Fig. 1(a), shows the foot ulcer wound image of diabetic person. It has been presumed that the boundary of the region of interest (wound area) has already been determined, shown in Fig. 1(b), so the focus is on the tissue characterization (classification).

Fig. 1. (a) Original wound image (b) Wound region (Region of interest) used as the input

(a) (b)

In order to label the data points, 36 average intensity information (R, G, and B channel) was extracted from the cropped tissue regions annotated by the diagnosticians. These initial quantified clusters were further split and examined using their membership value difference (the threshold of 0.200 as the difference between highest membership value and second highest membership value) and Blob Analysis (the threshold of 800 pixels). The region with bigger blobs and higher membership difference were extracted. The regions with bigger blobs and lower membership difference were relabelled using tissue analysis, and the regions with smaller blobs were relabelled using spatial analysis. To ensure minimum mislabelling, the specularity of granulation and epithelial was taken into account to utilize the shiny and wetter characteristics of the tissues.

After testing on 301 images, the experimental results showed the accuracy 95.1%, 90.1%, and 92.5% and F-Score of 86.0%, 81.9%, and 79.9% of granulation, necrosis, and epithelial respectively. However, identification of slough proved more challenging (accuracy of 89.7% and F-Score of 77.0%). Therefore, in this paper, four different approaches have been added to our previous algorithm and the results compared. The accuracy and F-score of each tissue type has been examined using the ground truth provided by the experts but the prime focus is on the slough tissue. The experiments were done on 301 different wound images but for the purpose of illustration, experimental results and ground truth (Fig. 3) of one such wound (shown in Fig. 1(b)), have been presented in this paper.

Fig. 3. Ground truth provided by the diagnosticians: Tissue types present in the chronic wound

Fig. 2: Process Flow
This section discusses the five methods, sub-divided into two categories, used to improve the slough tissue identification: Reference Points - 36 reference points (used in our previous research), and additional slough points (Slough RP), and Contrast Enhancement Techniques - contrast stretching, adaptive histogram equalization (AHE), and Contrast-limited adaptive histogram equalization (CLAHE).

A. Reference Points

1) 36 Reference Points:
This approach was used in our previous research [8] to identify the tissue types in a chronic wound and calculate their percentages. The average intensity information was extracted from the 36 cropped regions of the wound and these reference points were used for the initial labelling of the clusters. From the 36 points, 10 belonged to granulation, 8 to slough, 9 to necrosis, and 9 to epithelial.

The approach provided accuracies of 95.1%, 89.7%, 90.1%, and 92.5% and F-Score of 86.0%, 77.0%, 81.9%, and 79.9%, for granulation, slough, necrosis, and epithelial, respectively. From this quantitative analysis, it can be stated that the identification of slough proved more challenging than the other tissue types. The wound tissue segmentation results are displayed in Fig. 4 and the quantitative results are shown in Table I.

2) Additional 10 Slough Reference Points:
It was noted in our previous results that there were cases of misclassification of the slough, where it was characterized as epithelial tissue in some instances. To improve the results of our previous paper, in addition to the yellow or green slough used previously, the colour range information of white slough, and slough with a brown tinge were taken into account [9]. To achieve this, 10 additional reference points were added to allow for the identification of the slough of all colours. This methodology displayed an improvement in the identification of the slough region as well as epithelial tissue. The overall accuracy was 95.9%, 91.1%, 90.2%, and 93.4%, and F-Score was 86.3%, 81.6%, 82.0%, and 83.7% for granulation, slough, necrosis, and epithelial, respectively. Fig. 5 shows the wound tissue segmentation results and the quantitative results are shown in Table I.

B. Pre-processing using contrast enhancement techniques

The images were pre-processed with different types of contrast enhancement methods, after which, the flow of the process followed as shown in Fig. 2. The results were compared quantitatively by calculating the accuracy and F-Score of each tissue type using the ground truth provided by the doctors. However, the main objective was to enhance the identification of slough tissue and conclude which scheme provided its highest accuracy.

1) Contrast Stretching:
The contrast of the image was increased by mapping its intensity values to newer values. This produced greater prominence in slough tissue and epithelial, hence, better slough characterization compared to the previous research results. The overall accuracy of 96.5%, 93.2%, 93.9%, and 93.7% and F-Score of 87.7%, 85.8%, 84.1%, and 86.6% were observed for granulation, slough, necrosis, and epithelial, respectively. Fig. 6 depicts the visual representation of the tissue segmentation results and the quantitative results of the proposed scheme is summarized and compared in Table I.

2) Adaptive Histogram Equalization (AHE):
AHE is a contrast enhancement technique in which, computation is done on several histograms simultaneously. Each histogram represents a distinct region of the image. Hence, AHE improved the local contrast of the wound image making the distinction between slough and epithelial more pronounced and detailed. Furthermore, it allowed observation of all the intensity ranges at the same time. Using this pre-processing method, each pixel was mapped differently, where the intensities were locally distributed rather than globally.

The colored image was converted to L*a*b* color space and the contrast adjustment was performed on the luminositylayer.
"L*" only, after that the contrast enhancement was applied. Converting back to the RGB color space, the process flow continued as in Fig. 2. It should be noted that this preprocessing technique greatly enhanced the accuracy of each tissue type, notably the slough tissue. Furthermore, the results of other tissues were also improved noticeably, as shown in Fig. 7. The overall accuracy was measured to be 96.7%, 94.0%, 94.2%, and 95.9%, and the F-Score was 88.8%, 86.2%, 85.4%, and 87.1% of granulation, slough, necrosis, and epithelial, as summarized in Table I.

3) Contrast-Limited Adaptive Histogram Equalization (CLAHE):
CLAHE is locally adaptive contrast enhancement technique that overcomes that limitation over-amplification caused by AHE. In this work, luminosity layer "L*" channel of L*a*b* color space was selected for wound tissue segmentation, which offered the highest contrast between slough and epithelial region. This manipulation of luminosity affected the intensity of the pixels, all the while preserving the original colors. After converting the image back to the RGB color space, the process flow adhered to Fig. 2.

In the wound tissue characterization results shown in Fig. 8, all tissue types improved significantly using this preprocessing technique. The identification of slough became more precise and accurate. The overall accuracy was 96.5%, 93.6%, 94.6%, and 95.3%, and the F-Score was 87.4%, 85.9%, 84.0%, and 86.6% of granulation, slough, necrosis, and epithelial, respectively. However, from Table 1, it can be observed that there was a slight difference between the performance of AHE and CLAHE, where AHE had a higher average accuracy compared to CLAHE.

III. DISCUSSION

In this paper, the results of our previous research have been considered, utilizing five different techniques to enhance the accuracy of wound tissue identification reported earlier. Our previous results, recorded in Table I (36 RP), displayed a higher accuracy and F-Score of granulation, necrosis, and epithelial. However, the identification of slough proved more challenging. In the first tissue characterization approach, the average intensity information was extracted from the 36 cropped regions of the wound and these reference points were used for the initial labelling of the Fuzzy C-Means clusters. The clusters were later divided into small groups by using the threshold of the membership value difference (0.200) and the Blob Analysis (800 pixels). These smaller regions were analyzed further using their spatial and tissue information. This approach allowed minimization of the initial mis-labelling of the data points and produced better tissue identification results.

![Tissue characterization results using AHE](image)

**Fig. 7. Tissue characterization results using AHE**

![Tissue characterization results using CLAHE](image)

**Fig. 8. Tissue characterization results using CLAHE**

![Process Flow of the Enhanced Algorithm](image)

**Fig. 9: Process Flow of the Enhanced Algorithm**
To enhance the classification of slough tissue, the colour ranges of slough were taken into consideration. Unlike the first approach (where the yellowish slough was dealt with), the average intensity information of slough with tinges of green, brown, and white were also contemplated. From Table I (Slough RP), it can be analyzed that these additional slough reference points improved the identification of slough tissue in wound images and enhanced its accuracy and F-Score. It should be noted that the result of epithelial tissue improved with it as the ambiguity between the slough and epithelial decreased.

However, a more considerable improvement was seen when the images were pre-processed using the contrast enhancement techniques. The considered techniques include contrast stretching, AHE, and CLAHE in pre-processing stage in L*a*b* color space. Adjustment in contrast was done on L* (luminosity layer) as it suited better for the tissue identification and segmentation process.

The process flow stage after the pre-processing remained the same as the previous paper. The discrimination between the four tissue types became more prominent and therefore, the accuracy and F-Score of not only slough but other tissue types was observed. After validation with the ground truth (labelled by clinicians), the most notable enhancement in the performance of slough identification was observed when the wound image was processed using the AHE technique. The process flow of the enhanced algorithm with AHE incorporated has been shown in Fig. 9.

IV. CONCLUSION

The proposed algorithm in the previous research incorporated with the pre-processing technique discussed in this paper will support the clinicians in wound tissue identification, segmentation and its quantitative analysis. Using this model, the doctors would be able to diagnose the wound tissue composition of the patient in each visit and utilize the wound tissue information in the subsequent patient’s visit to monitor the wound healing status.

The accuracy and F-Score of the tissue types (granulation, slough, necrosis, and epithelial) in previous research were compared with the approaches described in this paper. As the identification of slough proved more difficult, the results of four different techniques that were used to enhance the results of slough tissue have been demonstrated. Experimentation was done by adding additional reference points that took into account the colour ranges of slough (green, brown, green and white), and also three contrast enhancement techniques, namely contrast stretching, AHE, and CLAHE to pre-process the images before it is fed into FCM. AHE, and CLAHE to pre-process the images before it is fed into FCM. After analyzing the tissue segmentation results of 301 images of chronic wounds (validated using the ground truth), it was observed that AHE offered the most efficient and accurate characterization.

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