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A Comparative Study of Segmentation Algorithms in the Classification of Human Skin Burn Depth

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***Abstract*— A correct first assessment of a skin burn depth is essential as it determines a correct first burn treatment provided to the patients. The objective of this paper is to conduct a comparative study of the different segmentation algorithms for the classification of different burn depths. Eight different hybrid segmentation algorithms were studied on a skin burn dataset comprising skin burn images categorized into three burn classes by medical experts; superficial partial thickness burn (SPTB), deep partial thickness burn (DPTB) and full thickness burn (FTB). Different sequences of the algorithm were experimented as each algorithm was able to segment differently, leading to different segmentation in the final output. The performance of the segmentation algorithms was evaluated by calculating the number of correctly segmented images for each burn depth. The empirical results showed that the segmentation algorithm that was able to segment most of the burn depths had achieved 40.24%, 60.42% and 6.25% of correctly segmented image for SPTB, DPTB and FTB respectively. Most of the segmentation algorithms could not segment well for FTB images because of the different nature of the burn wounds as some of the FTB images contained dark brown and black colors. It can be concluded that a good segmentation algorithm is required to ensure that the representative features of each burn depth can be extracted to contribute to higher accuracy of classification of skin burn depth.**

***Keywords*— skin burn depth; burn images; classification; segmentation; image mining approach.**

I. INTRODUCTION

Human skin is made up of three layers, namely (i) the epidermis, which is the outermost layer of the skin, (ii) the dermis, laying underneath the epidermis and is divided into two sub-layers, which are the papillary layer (superficial) and the reticular layer (deep) and (iii) the subcutaneous layer, which is the inner layer comprising of fat and connective tissues [1]. Fig. 1 shows the human skin structure.

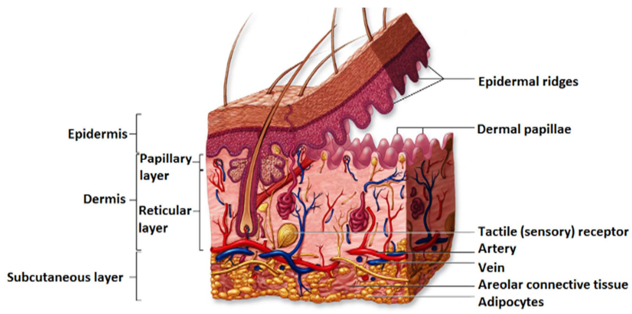

Fig. 1 Human skin structure [2]

Burns are generally classified into: (i) Superficial burn, which involves only the epidermis, (ii) Partial-thickness burn, which is further divided into (a) Superficial partial-thickness burn, which involves the entire epidermis and the upper layer of the dermis (papillary layer) and (b) Deep partial thickness burn, which affects the entire epidermis and most of the dermis and (iii) Full thickness burn, in which all the layers of the skin are destroyed, and may extend into muscle and bone [3].

The first assessment of a burn depth is always very important as a wrong assessment can result in partial-thickness appropriate and inaccurate initial management of the burn injuries. These mistakes will eventually translate into poor healing process, infections, undesirable scars and impaired body functions post burns. The severity of a burn is determined by its depth and it is diagnosed based on clinical visual examination by an experienced burn specialist.

The current state-of-the-art in the segmentation and classification of skin burn depth was using deep learned convolutional neural network (CNN) [4], [5] and fully convolutional network (FCN) [6] in identifying the burned skin from the healthy skin. However, deep learning requires a large amount of labelled data and high computational power.

In this paper, we conduct the classification of skin burn depth images using the image mining approach. Image mining is not just an extension of data mining to image domain. It is an interdisciplinary field with a combination of techniques such as computer vision, image processing, image retrieval, data mining, machine learning, database and artificial intelligence [7]. Image mining approach consist of several sub-processes, which including image acquisition, image pre-processing, image feature extraction, image classification and result interpretation. In image pre-processing stage, the image segmentation can be carried out, either automatically or manually, based on the requirement of the application [8]. In some existing research works, the image pre-processing was conducted under the umbrella term of image segmentation as shown in the work of Acha et al. [9], while some separate both processes into individual modules as shown in the work of Deshpande & Amruta [10]. There are some works that directly went through feature extraction stage from pre-processing stage, when cropped burn wound images were used, such as in the work of Suvarna, Sivakumar, Kumar, et al. [11].

Image segmentation is important in many medical imaging in determining the region of interest. With regards to skin burn images, other types of medical images also require segmentation in order to achieve an accurate classification. Past studies that had developed segmentation algorithms to segment their medical images for the purpose of classification were, for example, assessment of skin lesions [10], [12], [13], breast cancer [14], [15], lung cancer [16]–[18], diabetic foot ulcers [19], [20] and brain tumor [21]–[23].

Image segmentation, according to Sabeena and Kumar, is a process in which the input image is partitioned into non-overlapping regions, which are homogeneous region referring to each region and heterogeneous region referring to the union of any two adjacent regions. There are many different segmentation algorithms or approaches that have been applied through extensive research but the accuracy of each algorithm or approach is still difficult to assess [24]. Acha et al. explained that general-purpose segmentation algorithms are less capable to be used in separating the burnt skin from the healthy skin because of the slight difference between them. None of the existing segmentation algorithm can be used as a standard because most of these were developed specifically for its application. The main contribution of this paper is the comparative study of the application of different segmentation algorithms in the classification of skin burn depths.

There were previous related works focused on evaluating the skin burn depth in order to reduce the specialist's high experience requirement during visual examination. The research works in the literature either used a segmentation-based approach, which meant segmenting the burn wound from the skin region before feature extraction or a segmentation-free approach, which extracted features directly from the burn image.

Acha et al. [25] had proposed a segmentation approach to apply on skin burn images. The proposed segmentation approach was based on grayscale multiresolution segmentation algorithm. This was due to the need to visualize the image globally at different resolution levels. This multiresolution was founded on the mathematical stack approach [26]. This approach identified the extrema in a stack of images. The stack of images referred to each higher image was a slightly blurred version than its previous one. The moving of each extremum continuously that was caused by progressive blurring of an image would eventually blur into its background. They transformed their colour image to HSI coordinates for segmentation. A histogram of hue and saturation components for both healthy and burnt skin were needed to fix the parameter in their equations. Their result showed that the burn wound was correctly segmented in all cases.

Serrano et al. [27] studied the color image segmentation algorithm for burn wound images that were based on color and texture information. This was an improvement to the previous manual thresholding segmentation algorithm carried out by Acha et al. [28]. The same main steps as in the work of Acha et al. were taken in their latter work, which were pre-processing step, single channel conversion step, and threshold determination step. However, the latter work improved the manual thresholding conducted in the last step of the former work to automatic thresholding in achieving the segmented image. In addition, lightness and texture information were included in the single channel conversion step. The segmented image consisted of color pixels that were like the pixel value that were selected or cropped by the user. The lightness component was included in the segmentation because it was important for burns that were white, creamy or brown-colored, which were known as low saturation component. Based on the result they obtained, the algorithm did not work well if the images were not acquired by following the protocol, or had different burn depths. They reported that the segmentation worked well with most of the images, but for the incorrectly segmented images, the manual thresholding was performed.

Acha et al. [29] proposed a manual segmentation based on the Euclidean distance of CIE L*u*v* color space. This segmentation algorithm was also used in the researchers' other works [9], [28]–[30]. According to the researchers, L*u*v* and L*a*b* color representation systems are known as uniform systems. This is because the Euclidean distance between the measured color in these spaces is almost similar to human perception of color differences [29]. The researchers added that both color spaces are equally good in estimating the color difference between two color vectors, although these two-color spaces are slightly different from each other, in terms of a* and b*. They chose L*u*v* color space to be used in their work [29]. The segmentation approach proposed consisted of the following steps: (i) User selects a small region in the burn wound, and then pre-processing the selection image, (ii) Convert to single channel image, and finally (iii) Thresholding and post processing [[9] [9], [28]–[30]. The gold standard for the segmentation was the voting method by five specialists and the performance of the segmentation approach was evaluated using positive predictive value (PPV) and sensitivity (S). Their result showed that the burn wound was correctly segmented in all cases [9], [28]–[30]. The reason they need the help of user in selecting the color of the burn was because in the work of

Acha et al., the researchers had studied and noted that the healthy skin, blisters in superficial dermal burn and the full thickness burn with brown-colored appearance have strong overlapping color features among one another. Thus, it is very difficult to build a completely automatic system. Besides this reason, they also found that the healthy skin has large variability, even within the same human race [28].

Wantanajittikul et al. [31] proposed a new segmentation algorithm to separate the skin region from the background and then in turn, separate the wound region from the healthy skin. The algorithm started with converting the entire RGB image to the Cr-space. Fuzzy C-means (FCM) clustering was used to separate the skin region from the background. After that, in order to emphasize the burn wound region, skin region from the RGB colour space was converted to the L*u*v* colour space. FCM clustering was used again to separate the wound region from the healthy skin. Finally, the segmented wound region was post-processed to eliminate noise in it by using opening and closing mathematical morphology. The performance of this segmentation algorithm was evaluated using positive predictive value (PPV) and the sensitivity (S) measures. The results showed that the algorithm worked well for the segmentation of burn images.

Badea et al. [4] proposed two main approaches for the distinguishing of burns wounds which were identifying features that were capable of differentiating between healthy skin and the burn wound as well as being dependent on the feature selection performed by intelligent classifiers, such as deep learned convolutional neural network. Their approach is to identify the rectangular patches corresponding to burns. Thus, they had a total of 200494 patches, consisting of 74763 patches for training and validation sets and 125731 patches for the test set. The classifier used to separate the healthy skin regions and burn region were convolutional deep learning networks, which take a single patch and output the skin type. The result obtained from the test set after the training process was compared with other methods, which were hue and saturation of the patches on one hand, and red-to-green ratio and textural attributes on the other hand. In addition, the color skin detection model was also compared. The result showed that there was misclassification of healthy skin as burns, in which the burns were in healing.

Sabeena and Raj Kumar [24] proposed a new automated skin lesion segmentation via image-wise supervised learning (ISL) and multiscale super pixel based. The image-wise supervised learning approach tends to initialize seeds via a probabilistic map in order to separate the burn wound from the background. The multiscale super pixel based propagated parallel with SVM classification-based model. This work employed a k-means algorithm for segmentation of the burn region from healthy skin. The proposed k-means algorithm used the centrally located object in a cluster, named as mediod to get the initial centers, instead of select k points as initial cluster centers, which might lead to different solutions due to different points used. The proposed segmentation procedure were: (i) multiple sub-samples were draw from original dataset, (ii) sub-sample were used to produce group of mediods using k-means, (iii) the solutions were compared and the refined initial points were chosen from one group that have minimal value of square-error function. This segmentation was used in the final process whereby their workflow was: input image, color conversion, database updating, feature extraction, training process, classification, and segmentation.

Despo et al. [6] introduced semantic segmentation for the classification of skin burn depth images. The proposed semantic segmentation that was performed using Fully Convolutional Network (FCN) was able to capture the image pixel level information. The input of the segmentation algorithm was an image with three dimensions and the output was a shape that represented the segmentation mask, overlaid on the burn wound region in the image. Although the segmentation algorithm was often slightly over-predicting the boundary of a burn, their results showed that the segmentation algorithm was considered successful in their first attempt in segmenting the burned skin with minimal training.

II. MATERIALS AND METHODS

A. Data Collection

The burn images used in this paper were primary data and were collected by the burn specialists from various sources such as from the hospitals and the Internet. The burn images collected are in color as color is one of the important features in differentiating the skin burn depths. Currently, there is no open-source skin burn depth image dataset available. There are three skin burn depths studied in this paper: (i) Superficial partial-thickness burn (SPTB), (ii) Deep partial-thickness burn (DPTB) and (iii) Full-thickness burn (FTB). The number of images collected for SPTB, DPTB and FTB were 82, 48 and 32 respectively with a total of 162 images. All these images were captured without applying any conditions or standardizations for the lighting and the environment. Therefore, the images that were captured contain various backgrounds in addition to body parts that contain burn wound regions.

B. Segmentation Algorithms

The collected images which were in their original state were used to perform segmentation. The purpose of the segmentation is to remove the body parts and irrelevant background image to ensure that the segmented burn wound region would be used for feature extraction and classification. This study is conducted to compare the different hybrid segmentation algorithms on our own dataset of burn wound images. The hybrid segmentation algorithms referred to the combination of different techniques in different sequences that were able to enhance the segmentation process. Table I shows the hybrid segmentation algorithms used in the comparison. The algorithm with ID 6 was proposed by the previous related work [31].

The motivation of comparing the different segmentation algorithms is to find the best algorithm that is able to segment the burn wound region from the background image. The segmented burn wound region will be used for feature extraction. The better the segmentation algorithm, the better the features for the classification of skin burn depths.

TABLE I
HYBRID SEGMENTATION ALGORITHMS

ID	Hybrid Segmentation Algorithms
1	Original RGB image → convert to HSV space → HSV skin detection → convert to gray image → morphological closing → canny edge detection → morphological dilation → morphological flood-fill → morphological clear border → morphological erosion → segmented burn wound image
2	Original RGB image → RGB skin detection → convert to LAB space → convert to gray image → morphological closing → canny edge detection → morphological dilation → morphological flood-fill → morphological clear border → morphological erosion → segmented burn wound image
3	Original RGB image → RGB skin detection → convert to LAB space → A* component → fuzzy c-means (FCM) clustering → canny edge detection → morphological dilation → morphological flood-fill → morphological clear border → morphological erosion → segmented burn wound image
4	Original RGB image → RGB skin detection → adjust image intensity → convert to LAB space → A* component → fuzzy c-means (FCM) clustering → morphological dilation → morphological flood-fill → morphological clear border → morphological erosion → segmented burn wound image
5	Original RGB image → RGB skin detection → convert to LAB space → convert to gray image → Otsu thresholding → morphological dilation → morphological flood-fill → morphological clear border → morphological erosion → segmented burn wound image
6	Original RGB image → convert to Cr space → fuzzy c-means (FCM) clustering → convert to LUV space → fuzzy c-means (FCM) clustering → morphological dilation → morphological flood-fill → morphological clear border → morphological erosion → segmented burn wound image [30]
7	Original RGB image → RGB skin detection → convert to LAB space → A* component → Otsu thresholding → morphological dilation → morphological flood-fill → morphological clear border → morphological erosion → segmented burn wound image
8	Original RGB image → RGB skin detection → convert to LAB space → A* component → fuzzy c-means (FCM) clustering → morphological dilation → morphological flood-fill → morphological clear border → morphological erosion → segmented burn wound image

The motivation of comparing the different segmentation algorithms is to find the best algorithm that can segment the burn wound region from the background image. The segmented burn wound region will be used for feature extraction. The better the segmentation algorithm, the better the features for the classification of skin burn depths.

III. RESULTS AND DISCUSSION

The overall performances of each segmentation algorithms for all the three burn depths are shown in Table II, III and IV respectively. The percentage of correctly and incorrectly segmented images are calculated by taking the total correctly or incorrectly image divided by the total images of each burn depth.

Based on Table II, Algorithm ID 8 achieved the best performance with a percentage of 51.22% in correctly segmenting the SPTB images. The second-highest percentage of correctly segmented SPTB images was achieved by Algorithm ID 7 with a value of 40.24%. The Algorithm ID 3 and 6 were like each other, with the value of 36.59% of correctly segmented SPTB images. The lowest percentage of correctly segmented SPTB images was resulted from the use of algorithms from Algorithm 1, which was 4.88%.

TABLE II
RESULTS OF DIFFERENT SEGMENTATION ALGORITHMS FOR SPTB IMAGES

ID	SPTB (Total Images = 82)		
	Total Correctly Segmented Image	*Total Incorrectly Segmented Image*	*Percentage of Correctly Segmented Image (%)*
1	4	78	4.88
2	15	67	18.29
3	30	52	36.59
4	17	65	20.73
5	23	59	28.05
6	30	52	36.59
7	33	49	40.24
8	42	40	51.22

Based on Table III the Algorithm ID 7 have achieved the best performance with a percentage of 60.42% in correctly segmenting the DPTB images. The second highest percentage of correctly segmented DPTB images was achieved by Algorithm ID 3 and 8 with a value of 41.67%. The lowest percentage of correctly segmented DPTB images was achieved by Algorithm 1, which was 6.25%.

TABLE III
RESULTS OF DIFFERENT SEGMENTATION ALGORITHMS FOR DPTB IMAGES

ID	DPTB (Total Images = 48)		
	Total Correctly Segmented Image	*Total Incorrectly Segmented Image*	*Percentage of Correctly Segmented Image (%)*
1	3	45	6.25
2	19	29	39.58
3	20	28	41.67
4	15	33	31.25
5	12	36	25
6	7	41	14.58
7	29	19	60.42
8	20	28	41.67

Based on Table IV, the Algorithm ID 2 have achieved the highest percentage of correctly segmented image with a value of 25% for FTB images. Algorithm ID 5 and 7 have yielded the same percentage of correctly segmented images, with the value of 6.25%.

TABLE IV
RESULTS OF DIFFERENT SEGMENTATION ALGORITHMS FOR FTB IMAGES

ID	FTB (Total Images = 32)		
	Total Correctly Segmented Image	***Total Incorrectly Segmented Image***	***Percentage of Correctly Segmented Image (%)***
1	0	32	0
2	8	24	25
3	1	31	3.13
4	1	31	3.13
5	2	30	6.25
6	0	32	0
7	2	30	6.25
8	1	31	3.13

Fig. 2, 3 and 4 show an example of segmentation result for each of the three different burn depths in term of correctly segmented and incorrectly segmented images.

Original Image | Correctly Segmented Image | Incorrectly Segmented Image

Fig. 2 Example of correctly segmented and incorrectly segmented SPTB image

Original Image | Correctly Segmented Image | Incorrectly Segmented Image

Fig. 3 Example of correctly segmented and incorrectly segmented DPTB image

Original Image | Correctly Segmented Image | Incorrectly Segmented Image

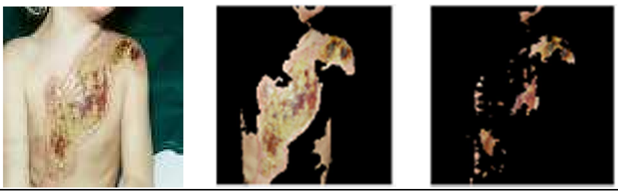

Fig. 4 Example of correctly segmented and incorrectly segmented FTB image

On closer inspection, all the segmentation algorithms performed poorly for FTB images. This is due to the reason that the contour of the most severe body part, which is in darker brown or almost black in color is difficult to be detected by the segmentation algorithm. Fig. 5 shows a few examples of FTB images that were incorrectly segmented due to the contour of the severe part that were difficult to be detected.

Fig. 5 Example of FTB images that are incorrectly segmented

Besides that, our collection of images was captured by the burn specialist without applying any standardization or protocol. Hence, the background image, in which the burn wound was captured contained variation such as the doctors' hand, patient's hair, room's door, different colors of hospital bed sheet and so on. This variation had caused difficulty for the segmentation algorithm to correctly segment the burn wound as some of the variation contain similarity to the burn wound. For example, the hospital's wall had the same color as the patient's skin color or the patient's nail color is like the burn wound color. This similarity caused the segmentation algorithm to mistakenly identify the variation as the burn wound or healthy skin regions, which led to incorrectly segmented burn wound regions.

Apart from that, the segmentation algorithms could only segment some burn images that were almost similar or related, but they could not be applied to some unsuitable images. Unsuitable images here referred to those burn images that might had been captured using different camera resolution or the burn images had different underlying intensity value or the position of the burn wound from the camera was inappropriate when the image was captured. Hence, the percentage of correctly segmented images was not that good in general.

Clear-cut burn wound and non-clear-cut burn wound might also be one of the reasons the segmentation algorithms performed poorly. Clear-cut burn wound referred to burn wound region that had a clear contour surrounding it while non-clear-cut burn wound referred to burn wound region that covered the whole-body part. Due to the difference in the nature of the burn wound region, the segmentation algorithms cannot be applied to most of the burn images in general. In addition, the hybrid segmentation algorithms using the different sequences allowed different segments to be selected in each sequence, thus, presenting different final segmented outputs.

IV. Conclusion

A comparative study of the different segmentation algorithms in the classification of skin burn depths was conducted. Different set of segmentation algorithms were experimented on our collection of skin burn images. The performance of the segmentation algorithms was evaluated by obtaining the percentage of correctly segmented image. The best segmentation algorithm was the Algorithm ID 7, by observing its performance for three burn depths. The performance of the segmentation algorithms has a huge impact on the performance in the classification of skin burn depths, as the feature extraction and classification are largely dependent on the segmented burn wound region. If the segmented burn wound region is correctly segmented in terms of the algorithm able to detect the boundary of a burn wound region adequately, then this will help in contributing to the features extracted as well as in the classification result. In future work, the segmentation algorithms need to be improved by considering all the issues surrounding the nature of the skin burn wound images, so that the percentage of correctly segmented images can be improved especially for FTB images. Besides that, a segmentation algorithm that can detect a darker color in FTB image to enable a correct segmentation of more severe FTB image will also be studied as future work.

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