SEGMENTATION AND CLASSIFICATION OF CUTANEOUS ULCERS IN DIGITAL IMAGES THROUGH ARTIFICIAL NEURAL NETWORKS

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Abstract: Treatments of leg ulcers are generally expensive and those conducted through the direct manipulation for analysis of its evolution. The treatment efficiency is observed through the reduction of the size of ulcers in relation to the amount of tissues found in their beds, which are classified as granulated/slough. These results are obtained through analyses performed after consultation due to the time these analyses take. This work proposes a new non-invasive technique for the follow-up of treatments aimed at cutaneous ulcers. In this methodology, it was proposed that digital photos of cutaneous ulcers would be submitted to an artificial neural network (ANN), so that all surrounding the wound except for the wound itself could be extracted (skin/background), thus obtaining the ulcerated area. Computer vision techniques have been applied in order to classify the different types of tissues found in the ulcer bed, thus obtaining the corresponding granulation and slough percentages as well as its area. The results obtained have been compared with the results obtained by Image J software. Finally, this methodology will be a useful tool for health professionals in relation to the quickness and precision that it will provide results along the consultation.

1 INTRODUCTION

Leg ulcers are a public health problem worldwide and reach from 3% to 5% of the population older than 65 years of age and 1% of the adult population. (Mekkes et al., 2003). The treatment presents some complications due to its long-term characteristic, discomfort of curatives and uncertainness in relation to its success, once its cure depends on several factors that act as intervenient variables in the process, causing significant social and economic impact. The treatment is painful, expensive and slow due to a number of associated etiopathogenic factors, and the disease represents one of the main causes for work absenteeism.

The use of computer tools involving image processing (Computer Vision) and ANN consists of an alternative analysis method for the follow-up of leg ulcer treatments. (Albu and Ungureanu, 2005). This method does not allow the direct contact with the wound, once ulcers are analyzed through digitized images (Goldman and Salcido, 2002). Therefore, the health professional disposes of tool designed to support the treatment of ulcers.

The objective of this work is to present a proposal to aid in the quantitative analysis of each tissue found in the inner part of wounds, which are classified as granulated and slough and in the calculation of the wounded area. With these measurements, one may have a perspective in relation to the treatment evolution, since it provides a dynamic-therapeutic healing follow-up.

This work also proposes the development of methodology to classify leg ulcer tissues in order to support specialists along the treatment evolution. The employment of computer software with the proposed methodology may lead the patient to feel safer, since there is no direct contact with the wound to obtain samples for analyses. In a first phase, the proposal consists of performing the extraction of features from the leg ulcer digital image base through color samples removed from ulcer images manually and of applying them to the neural

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network test for images segmentation – Training Phase. In a second phase image processing techniques were used to classify tissues found at the inner region of the wound - Test Phase.

2 LEG ULCERS

Leg ulcers occur due to more than one cause: venous hypertension (~80%), arterial insufficiency (~10%) or the combination of both – the called “mixed ulcers”, among others. (Abbade and Lastória, 2005). Ulcers occurring at the tip end of the lower limbs are a result of venous, arterial or neurovascular diseases such as varix, thrombosis venous, arteriosclerosis, diabetes and arterial hypertension, among others. (Dean, 2006).

Each type of ulcer presents own characteristics, requires different treatments, and must be evaluated separately. (Borges, 2005 and Dean, 2006).

A deficient blood circulation decreases the intake of oxygen and nutrients and reduces the removal of metabolism-derived products such as free radicals, factors that contribute for the healing delay. The main problem of leg ulcers is the recurrence; 30% of healed ulcers recur within the first year and this rate increases to 78% after two years when inadequately treated. (Barros, 2000).

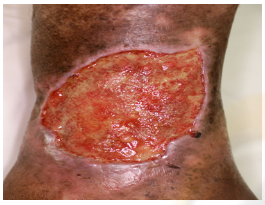


Figure 1: Venous Leg Ulcer.

A good analysis of some characteristics, parameters and interpretation of clinical ulcer examinations is vital, and among these characteristics: number and size of the ulcer, edges and appearance of the lesion bottom, type of ulcer, skin-ulcer state, arterial test, venous test and evaluation of the microbiological status (culture, exams) are worth mentioning. (Kupcinskas, 2006).

Leg ulcer is a very relevant and common problem in health services worldwide and affects between 0.1% and 1% of the adult population with studies pointing to prevalence. (Mekkes et al., 2003). However, the key for the selection of effective ulcer treatments is based on the evaluation process of its etiology.

Venous-origin leg ulcers – Figure 1 – popularly known as varicose ulcers, are mainly caused by chronic venous insufficiency, term described as lower limbs syndrome, which represents the incapacity of maintaining the balance between the arterial blood flow that reaches the lower limb and the venous flow that returns to the right atrium as a result of the incompetence of the superficial and/or deep venous system with symptoms such as edema, pigmentation, pain and disabilities. (Barros, 2000) (Pitta, Castro and Burihan, 2000).

In normal people, the blood pressure decreases during the practice of physical exercises, but in patients with venous incompetence, the pressure remains high during effort. Venous ulcers are mainly characterized by the presence of edema, darkened pigmentation, varicose veins and lipodermatosclerosis (hardening and fibrosis in the dermis and subcutaneous tissue) at the lower limbs. (Phillips and Dover, 1991).

In the study conducted by Skaraborg (cited in Figueiredo, 2003), 5.6% of people with 65 years of age or older presented open or healed lower limbs ulceration and 2.4% of the adult population above 15 years of age have already had ulcers. European data show that 1.5% of the adults will have ecstasy ulcer sometime in their lives.

3 MATERIAL AND METHODS

The photographs were taken through a Sony Cyber shot P-93 camera with 3 mega pixels, 3X optical zoom and without digital zoom. The images randomly selected from our the image bank were standardized and non-standardized in relation to zoom, illumination, distance between the camera and the patient’s leg and the focus in the patient’s leg. We made the image bank because none was

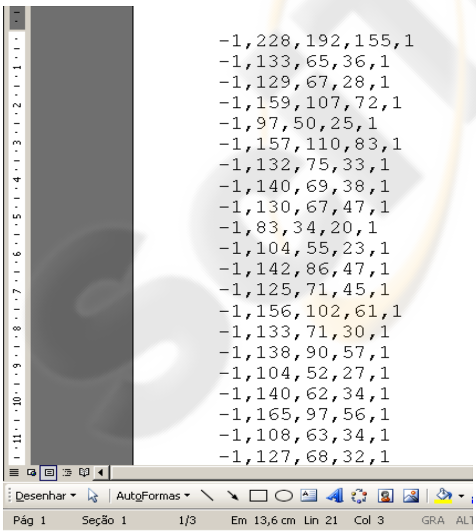
Figure 2: Example of an image with noise, skin and ulcer regions.

found publicly available library. Fifty images of thirty five patients were selected to test the validity of the proposed methodology.

The methodology proposed is divided into two phases: in the first phase, the extraction of the color characteristic and the ANN training occur (Training Phase) with ten images. (Haykin, 2001). The second phase consists of segmenting images with forty images (ANN Test), elimination of noises, improvement of the image quality and later tissue classification in the wound bed – Test Phase. (Gonzalez and Woods, 2002).

In the first phase, initially two algorithms were applied to images in order to obtain, skin, ulcer (bed) and noise (background - all that is not skin and ulcerated area) color - Figure 2-, which will serve as inputs for the ANN training to distinguish the color characteristics of the wound edge from the other colors not involved in the wound thus, forming training standards.

The color characteristics corresponding to skin and non-skin (skin/noise/background) in the RGB model are obtained through the first algorithm; this process is manually performed by the computer operator (this process should be performed by a health professional, once he will know which are the best points to be selected in order to find out what each color represents in the image). The software used for the development of this methodology was the Matlab 7.0, (Math Works, 2004) which shows the 50 images selected (one at a time) and waits for the computer operator to select the image region with the mouse with the aid of the algorithm. Each color characteristic of the selected region is stored in a text-type file to form the feature vector (skin/non-skin matrix), according to Figure 3.


-1,228,192,155,1
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-1,129,67,28,1
-1,159,107,72,1
-1,97,50,25,1
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-1,132,75,33,1
-1,140,69,38,1
-1,130,67,47,1
-1,83,34,20,1
-1,104,55,23,1
-1,142,86,47,1
-1,125,71,45,1
-1,156,102,61,1
-1,133,71,30,1
-1,138,90,57,1
-1,104,52,27,1
-1,140,62,34,1
-1,165,97,56,1
-1,108,63,34,1
-1,127,68,32,1

Figure 3: Example of Skin/Non-Skin Matrix.

If one photo contains several interesting characteristic regions, this image is opened more than once for the selection of the characteristics.

The values presented in each line of Figure 3 represent the following:

- -1 is a bias used by the neural network for the activation of the neuron;
- The three next values refer to the RGB value in relation to the color selected by the user;
- 1 is the value to be used as exit desired by the neural network.

The second algorithm is used to obtain the wound color characteristics in the RGB model, which are obtained as in the first algorithm. The feature vector (wound matrix) of each selected color is saved in another text-type file. The desired exit of the wound matrix is the 1.

These two matrixes will form the "training patterns", which will be used for the training.

The first phase of the proposed methodology in divided into two stages. In the first stage, the entrance characteristics for the neural network are obtained (color characteristics) and in the second one, these characteristics are applied in the neural network for its training – Figure 4.

3.1 ANN Training

The extracted characteristics (training patterns) are applied to an ANN for its training and later classification and separation of the wound from the remaining portion of the image (Test Phase). The MLP Feedforward neural network architecture was used with the Back-propagation training algorithm (Haykin, 2001), which was the architecture most used for classification in several areas, and the cutaneous ulcer images were generated in the RGB color model. Before the Test Phase, the ANN must be trained in order to learn about the color characteristics obtained through both algorithms previously mentioned. The training characteristics are the following:

- Both features vectors are concatenated in order to form the training matrix. Bias, RGB and the desirable output are arranged in different variables, and the RGB characteristics are normalized for the [-1, 1] interval.
- The neural network is initialized using the minimum/maximum function of the training matrix.

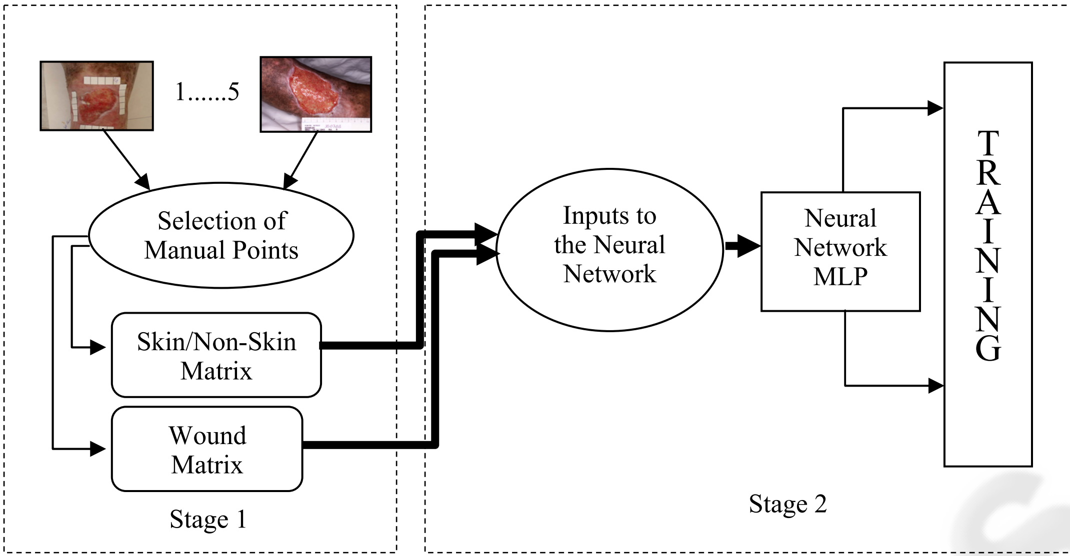

Figure 4: First phase of the proposed methodology.

- The neural network training was performed using the tangent-hyperbolic sigmoid activation function (so that the values corresponding to the RGB characteristics do not exceed the normalized interval). The moment gradient is used for the three occult layers of the neural network plus the output layer.
- Values corresponding to other parameters used in this algorithm and in the Neural Network will be specified in the next topics.

3.2 ANN Test (Classification of Images)

In the second phase, or Test Phase, the efficiency of the Neural Network is verified in the segmentation of the 40 images from results obtained in the training (first phase). A post-processing is required to eliminate some remaining noises to better prepare the image for the tissue classification. Figure 5 presents the second phase of the proposed methodology. The techniques employed are the erosion and dilation morphologic operations. (Gonzalez and Woods, 2002). Finally, the tissues are classified based on the counting of pixels, where similar colors are associated to the type of tissue. Besides the granulation and slough tissue classification, the percentage of these two types of tissues and the ulcer area in the image were calculated.

The algorithm used (ANN Test) presents the following steps:

1) Segmentation of Images;
2) Post-Processing: Images are processed through dilation and erosion and image superposition in order to eliminate noises and to show the wound region only;
3) Counting of pixels corresponding to the granulation and slough tissue and calculation of the percentage corresponding to each type of tissue in the image;
4) Generation of an image with markings in which pixels corresponding to granulation and slough are counted: white pixels are granulation tissue and the others are the slough tissue;
5) Calculation of the leg ulcer wounded area in cm2.

The segmentation is performed by the Neural Network using parameters from the Training Set and commands based on Neural Networks toolbox from the Matlab 7.0 software (Math Works, 2004); and the resulting image that distinguishes the wound from the rest of the image is obtained – pre-processed image.

3.2.1 Post-Processing

The pre-processed image is then submitted to a post-processing in order to eliminate noises and to show the wound region only. To do so, erosion and dilation morphologic operators were used.
In order to use erosion and dilation operators in the Matlab software, the figure has to be converted into gray scale, which is the only way that the figure allows the use of such morphologic operators (Gonzalez and Woods, 2002).

In order to use these morphologic operators, a structuring element should be created to serve a

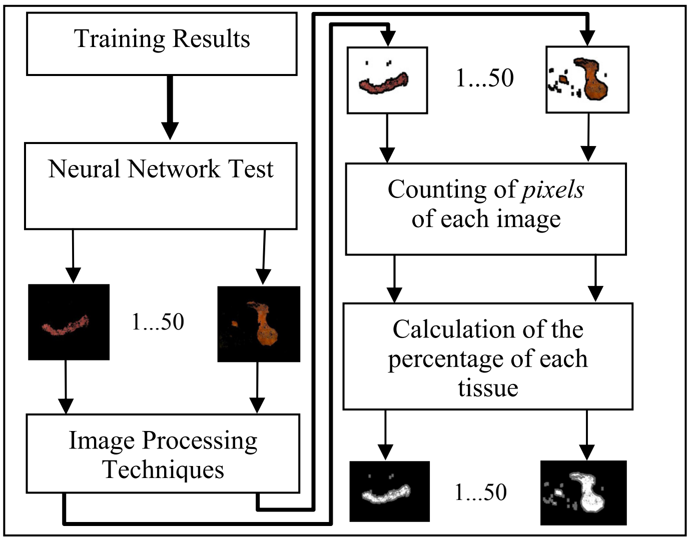

Figure 5: Second phase of the proposed methodology.

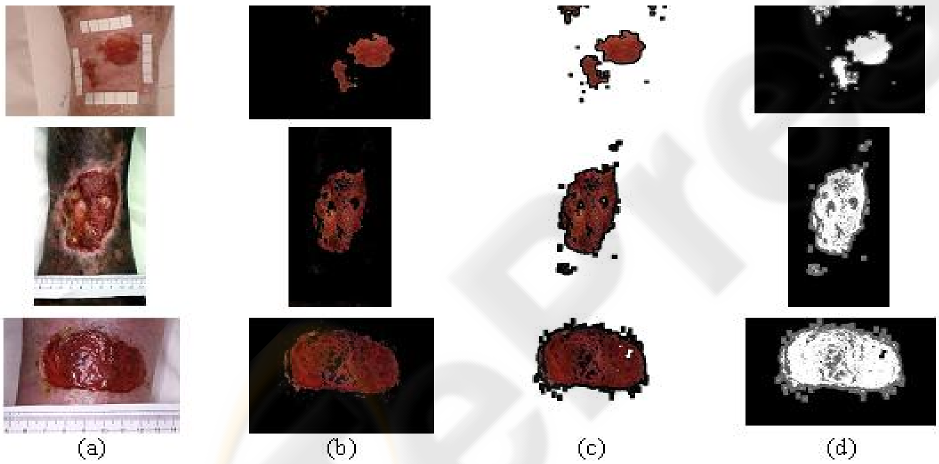

Figure 6: Leg Ulcer Segmentation Results. In (a) Original Image – (b) Pre-Processed Image – (c) Post-Processed Image – (d) Image with counted pixels.

dilation parameter. The structuring element used had a square format (Math Works, 2004). Following, the Sobel edge detector was used.

This image was superposed to the original image with the objective of obtaining an improved and less noisy new image – post-processed image in which pixels were counted and calculations were performed. Finally, an image based on the post-processed image was generated, with marking of the sites in which slough and granulation pixels were counted. Figure 6 presents images according to the algorithm execution sequence. The parameters used in the neural network of this methodology may be observed in Table 1.

Table 1: Values of the Neural Network Parameters.

Parameter	Value
Neurons in the 1st hidden layer	4
Neurons in the 2nd hidden layer	4
Neurons in the 3rd hidden layer	1
Moment Term	0.5
Maximum Number of Iterations	1000
Training Error Rate	$1x10^{-3}$

4 RESULTS AND ANALYSES

Considering the 40 test images and the segmented wound area only, the average slough and granulation percentages in relation to the total image may be verified in Table 2. The results were obtained through the proposed methodology.

Table 2: Arithmetic average of the tissue percentage– Proposed Methodology.

	Total Image	Wound Area
Slough	10.5%	26.1%
Granulation	18.4%	73.9%

The same images tested in the proposed methodology were applied to the Image J for comparison purposes, because this software is used for made analyses of images of leg ulcers at department of dermatology of FMRP (Ribeirão Preto Medical School) and it is desirable to have a tool more practical than the Image J.

The results obtained through Image J may be observed in Table 3. (Gomes, Santana and Minatel, 2005).

Table 3: Arithmetic average of the tissue percentage – Image J.

	Total Image	Wound Area
Slough	18.9%	43.3%
Granulation	30.0%	56.7%

The area of each wound in cm^2 in relation to the total image was also calculated both through the proposed methodology and through the Image J; the arithmetic averages of results may be observed in Table 4.

Table 4: Arithmetic average of the Wound Areas.

	Proposed Methodology	Image J
Average Area	13.1cm^2	14.1cm^2

The results obtained through the Image J freeware software and with our methodology seemed to be satisfactory; in the total tissue area, the average was 13.1 cm^2 through the proposed methodology and 14.1 cm^2 through Image J (Figure 7). In relation to the granulation, the average obtained was 12.4 cm^2 through the proposed methodology and 12.6 cm^2 through Image J (Figure 8). In relation to slough, the average obtained was 1.8 cm^2 through and 1.9 cm^2 through Image J (Figure 9).

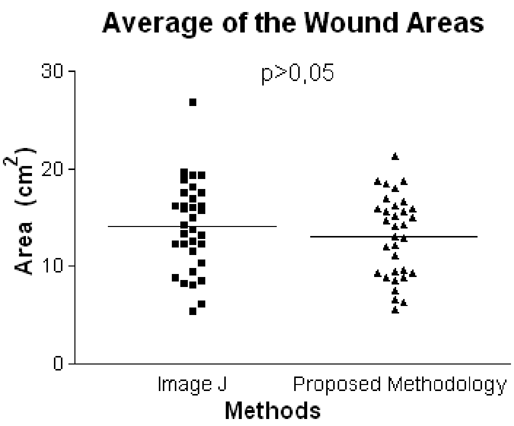

Figure 7: Results of the t Test for total area.

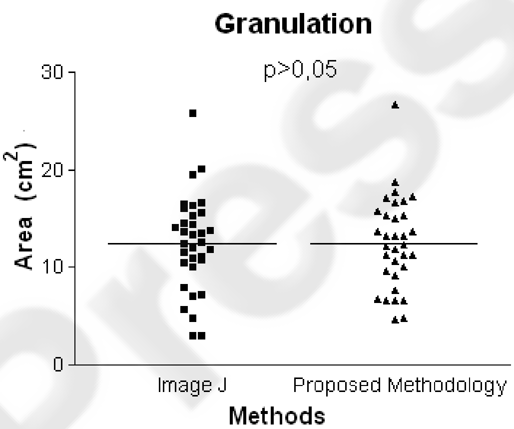

Figure 8: Results of the t Test for granulation.

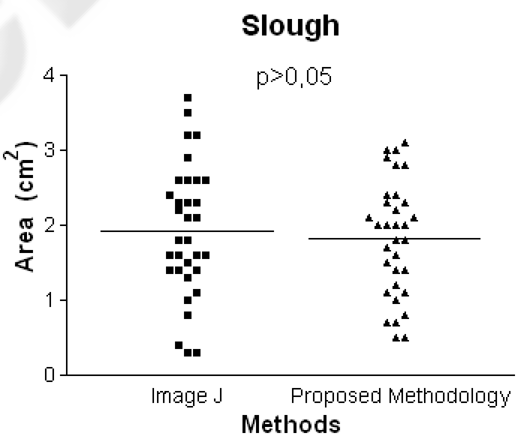

Figure 9: Results of the t Test for slough.

It is worth reminding that the area evidenced through Image J is manually performed, and takes a long time until it comes to the final results, whereas in the proposed methodology, this process is automatically performed by the neural network, which makes the processing faster and safer. This area evidenced manual affects in the difference of the results of the table 2 and 3 as well as some terrible interpretations of RNA owed the qualities of the images and of obtaining of the same ones.

The results were analyzed by a medical area specialist, who verified the concordance of results obtained.

Figure 7 shows the graphic of the t-student test applied to results obtained through both the proposed methodology and Image J for total areas. Lines in the center of the graphic show the arithmetic averages of results obtained through each methodology and one may observe that they are very close to each other.

Similarly, there are two other graphics that also corroborate the efficiency of results obtained through both Image J and the approach of this paper. Figure 8 shows the results of t-student tests for granulation area and Figure 9 for slough area.

5 CONCLUSIONS

Both the Image J and our methodology based on ANN presented satisfactory results. The t-student test at 95% was applied and the results confirmed the efficiency of both methods. This finding testifies that the variation observed between the results obtained through both methodologies is acceptable and that they can be applied in practice.

The results obtained suggest that both image analysis methods are effective in the measurement of total area, granulation and slough, being considered as adequate for the dynamic-therapeutic evaluation of leg ulcers. Artificial Neural Networks seem to be a high-level methodology for the analysis of images due to the lower interference from the operator/researcher, since it does not require manual design.

This new application will be one more tool to aid in the diagnosis at FMRP and perhaps replace the image J because of its little practicality. For better performance of this new application is desirable to use standardized images, as mentioned in item 3, because the images non-standardized not behaved so well on the standardized; but nevertheless been achieved good and acceptable results general finals.

This project encourages and contributes for the application of new technologies and hence the use of softwares in this area with the emergence of new research lines.

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