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Wound image evaluation with machine learning

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ABSTRACT

A pressure ulcer is a clinical pathology of localized damage to the skin and underlying tissue caused by pressure, shear or friction. Diagnosis, care and treatment of pressure ulcers can result in extremely expensive costs for health systems. A reliable diagnosis supported by precise wound evaluation is crucial in order to succeed on the treatment decision and, in some cases, to save the patient's life. However, current clinical evaluation procedures, focused mainly on visual inspection, do not seem to be accurate enough to accomplish this important task. This paper presents a computer-vision approach based on image processing algorithms and supervised learning techniques to help detect and classify wound tissue types that play an important role in wound diagnosis. The system proposed involves the use of the k-means clustering algorithm for image segmentation and compares three different machine learning approaches—neural networks, support vector machines and random forest decision trees—to classify effectively each segmented region as the appropriate tissue type. Feature selection based on a wrapper approach with recursive feature elimination is shown to be effective in keeping the efficacy of the classifiers up and significantly reducing the number of necessary predictors. Results obtained show high performance rates from classifiers based on fitted neural networks, random forest models and support vector machines (overall accuracy on a testing set [95% CI], respectively: 81.87% [80.03%, 83.61%]; 87.37% [85.76%, 88.86%]; 88.08% [86.51%, 89.53%]), with significant differences found between the three machine learning approaches. This study seeks to provide, using standard classification algorithms, a consistent and robust methodological framework as a basis for the development of reliable computational systems to support ulcer diagnosis.

1. Introduction

The European Pressure Ulcer Advisory Panel (EPUAP) defines a pressure ulcer (PU) as an area of localized damage to the skin and underlying tissue caused by pressure, shear, friction or a combination of these factors [1–3]. Prevention, care and treatment of PU pathology represent high costs for health services [4] and have important consequences for the health of the affected population, especially for those populations at risk such as elderly people. Recent studies [5] have also shown how mortality rates associated with this pathology have increased in the last few years.

Accurate diagnosis of the wounds is critical in order to proceed with the right diagnosis and appropriate treatment, which in some cases can require surgery. This crucial evaluation is carried out by clinicians using standardized scales or indexes consisting mainly of a visual inspection of the ulcer. However, this technique has been proven to be an inaccurate way to deal with diagnosis of this sort of wound [6,7].

One of the most challenging factors to cope with when working with PU images lies in the very heterogeneous colorations they present, which are related with a patient's skin color and other several anomalies that may be observed in the images, such as erythemas and skin striation. Moreover, boundaries between different tissue regions are usually extremely irregular and vague, which increases the complexity of the tissue segmentation process. Image processing and computational intelligence techniques have been applied in several current studies to address different aspects of this particular problem of wound diagnosis. One of these aspects involves the partial problem of wound area identification, which has been tackled with different

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techniques such as contour detection with histogram segmentation, active contours modelling, region growing, clustering approaches or skin texture models [8–10]. Unlike these proposals, other approaches focus on detecting the different tissues existing in the wound, by using diverse segmentation methods—such as histogram thresholding, watersheds, mean-shift smoothing, region growing, classification or graphs—sometimes combined with machine learning (ML) strategies [11–14].

A few studies can be found in the specific literature on PU tissue recognition. Pioneering work by Berriss [15] addressed the design of an image processing tool based on simple histogram thresholding to separate granulation and slough tissue regions on wound images. For their part, Perez et al. [16] designed a semi-automatic tool that started with a previous calibrating and filtering stage and required user intervention to select sample regions in wound-bed and surrounding areas. With similar objectives, Galushka et al. [17] used a case-based tissue classification approach to classify square regions of interest from a grid-split structure on wound unsegmented images. In their experiments, color and texture patterns from square regions were firstly classified in three tissue types, i.e., granulation, slough and necrosis, and finally categorized into six tissue categories which include epithelial, tendon and haematoma. Lourega et al. [18] presented a hybrid approach, which they named *MeSegHi*, to image segmentation with potential application to tissue recognition tasks such as detection of carcinoma cells. On the other hand, ML strategies have been proposed by several authors as approaches to wound tissue segmentation and recognition. Pioneering work was done by Belem in his Ph.D. thesis [19], where different techniques such as logistic regression, support vector machines (SVM) and feed-forward neural networks (NN) were compared with a manual approach by clinicians with different skills. His results showed SVMs as the best performing classification engines, which gave more consistent judgements than most clinical practitioners. In a similar research area, Serrano et al. [20] designed a computer assisted diagnosis tool that used a NN to classify burn wounds by detecting tissues that determine the depth of the injury. In another ML based study, Kosmopoulos and Tzevelekou [11] presented some exploratory results from an approach which used graph-based image segmentation and SVMs for PU diagnosis. In [21] Wannous et al. used three different methods for region segmentation as well as a SVM to classify tissues in images of pressure sores and ulcers, but their approach required a preliminary manual selection of the area of interest in the wound; moreover, their results show high classification error scores, which are even greater than 50% for some critical tissues such as necrosis (see [21], table IV). More recently, Wannous's team has published [14] an innovative approach that combines 3-D wound surface measurements with tissue classification based on a SVM model to achieve enhanced wound healing assessments. Finally, in [12] we presented a mean-shift procedure along with a region-growing strategy for effective region segmentation, combined with a complex hybrid approach based on acascade of single-class classifiers for wound tissue recognition. Although we obtained high efficacy rates, our work presented some significant limitations, since the classifiers were based on an elaborate architecture consisting of NNs and Bayesian classifiers, which were combined to recognize patterns of color and texture features. Additionally, a complex set of heuristic techniques had to be applied to the classifiers' outputs to get the final classification results.

This study proposes a settled and reliable methodology to support pressure ulcer diagnosis and to serve as a starting point for more complex models. Although previous studies above have highlighted the adequacy of diverse ML approaches for classifying PU tissues from wound segmented images, most of these works lack an exhaustive analysis that addresses robust model fitting. In our study, parameter fitting is supported by *k*-fold cross-validation analysis and a rigorous statistical methodology has been followed (using statistical tests, p-values and confidence intervals) to measure the degree of significance of the differences in efficacy obtained with different ML models and parameters. Therefore, this study combines image analysis techniques with the most widely used classification methods, which are rather settled in the scientific community. Thus the efficacy of three different ML approaches for PU tissue recognition is exhaustively analyzed: SVM, feed-forward NNs and random forest (RF). Moreover, a new highly effective image processing procedure is also proposed and devised to extract a richer descriptor set than those obtained in other similar studies [11,21,13,12], since not only texture and color features are taken into account, but also morphological and topological characteristics are considered. Future development of clinical applications for PU diagnosis and treatment could benefit from both our approach and analysis results. In this vein, PU diagnosis tools based on efficient image segmentation and effective tissue recognition could be further integrated in portable devices, such as smart-phones or tablets, and give support to clinical decision-making as they could provide the clinicians with real-time diagnosis capabilities on the spot, which could contribute to the efficacy of treatments and care interventions.

This paper is structured in six sections, including the introduction given in this Section 1. In Section 2, the methodology followed in this approach is described. Experimental results achieved by different ML approaches are shown in Section 3 (for wound-bed tissue recognition) and Section 4 (for peri-ulcer tissue recognition) and discussed in Section 5. Finally, conclusions and further works are discussed in Section 6.

2. Methodology

Clinicians took color photographs of PUs of patients with home-care assistance. Sacrum and hip PUs were photographed under non-controlled illumination conditions by using a Sony Cybershot® W30 digital camera. The images were acquired with flash-light to get well-illuminated scenes, and at a distance of approximately 30–40 cm from the wound plane. Macro-photography focusing was used to ensure well-focused pictures within these short distances. A group of clinical experts selected a total of 113 photographs that were considered to be an appropriate data set for analysis because of the presence of all significant tissue types in PU evaluation.

2.1. Segmentation process

After an initial median filtering for noise reduction, a preprocessing procedure is applied to each photograph in order to previously detect and extract those spurious regions consisting of flash-light reflections, blood stains, shadows, clinical materials, clinicians' fingers, normalization markers, etc. (see Fig. 1). To that end, an appropriate set of color space transformations and standard deviation filters—which depend on the sort of invalid region needed to be detected—are applied to the images as a previous step to image segmentation.

The objective of the segmentation module is to divide the image into groups of pixels with similar characteristics, in order to conduct the subsequent classification of the obtained regions. This segmentation process is arranged in three main sequential stages (scheduled in Fig. 1), which are based on the specific 'center-surround topology' of the ulcer images, with a centered wound-bed that consists of a variable proportion of granulation, slough and necrotic tissues, which is immediately surrounded by epithelial healing tissue (that could present different conditions, such as