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Machine Learning for Mobile Wound Assessment

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ABSTRACT

Chronic wounds affect millions of people around the world. In particular, elderly persons in home care may develop decubitus. Here, mobile image acquisition and analysis can provide a good assistance. We develop a system for mobile wound capture using mobile devices such as smartphones. The photographs are acquired with the integrated camera of the device and then calibrated and processed to determine the size of various tissues that are present in a wound, i.e., necrotic, sloughy, and granular tissue. The random forest classifier based on various color and texture features is used for that. These features are Sobel, Hessian, membrane projections, variance, mean, median, anisotropic diffusion, and bilateral as well as Kuwahara filters. The resultant probability output is thresholded using the Otsu technique. The similarity between manual ground truth labeling and the classification is measured. The acquired results are compared to those achieved with a basic technique of color thresholding, as well as those produced by the SVM classifier. The fast random forest was found to produce better results. It is also seen to have a superior performance when the method is applied only to the wound regions having the background subtracted. Mean similarity is 0.89, 0.39, and 0.44 for necrotic, sloughy, and granular tissue, respectively. Although the training phase is time consuming, the trained classifier performs fast enough to be implemented on the mobile device. This will allow comprehensive monitoring of skin lesions and wounds.

Keywords: Chronic wound, skin lesion, photographic imaging, mobile application, segmentation, tissue classification

1. INTRODUCTION

A chronic wound is a wound that does not heal in an orderly set of stages and in a predictable amount of time the way most wounds do. Care for such conditions has been reported to cost 2% to 3% of the healthcare budgets in developed countries[1]. The burden of treating chronic wounds is growing rapidly due to increasing health care costs, an aging population, and a sharp rise in the incidence of diabetes and obesity worldwide[2]. However, quantitative assessment of wounds still depends on the analysis by physicians or other medical experts and usually requires direct contact with the wound. Such kind of invasive measurement is painful and uncomfortable for the patient. It may also cause infection of the wound. Hence, a non-invasive, economical and accurate technique for assessment and analysis of wounds which can be used at the patient's bedside is required.

A skin lesion is composed of different types of tissue: necrotic, sloughy, and granular. Usually the tissue type is identified visually by the physician. Healthy granulation tissue is pink in color and it is an indicator of healing. Unhealthy granulation is dark red in color, often bleeds on contact and may indicate presence of wound infection[1,2]. Such wounds should be treated in the light of microbiological results[3]. Excess granulation or over-granulation may also be associated with infection or non-healing wounds. Necrotic tissue is the dead tissue which is black in color. In contrast, slough is a yellow fibrinous tissue that consists of fibrin, pus, and proteinaceous material. It can be found on the surface of a previously clean wound bed and it is thought to be associated with bacterial activity[4]. Hence, identifying the type of the tissue and the amount of tissue present, one can assess the types of treatment required. The appearance of a wound has important information that can assist with the diagnosis of severity and the prognosis for healing. The analysis of the

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wound involves the detecting of the stage of healing by measuring the different tissue types, size, shape, depth and other characteristics of the wound.

In this paper, we propose a system that can automatically segment the wound into its various tissue types: necrotic, granular and sloughy, pursuing the goal of objective quantitative analysis of the healing process. Such a system shall be easily accessible and economical. Hence, we suggest a machine learning based classification scheme which is suitable to be performed on mobile devices such as smartphones and can be used without any technical or medical skills.

2. STATE OF THE ART

Precise evaluation constitutes a crucial task in diagnosing, monitoring the evolution and decisions on care interventions and pharmacological treatments to be arranged for each particular case[11]. Visual analysis and measurement of the wound vary from person to person and may not be reliable. Hence, systems are being developed to accurately and reliably analyze such wounds. Some of the recent progress in developing a system for such clinical assessment involved developing hardware equipment making use of structured light techniques. Derma System[16] has developed a laser triangulation 3D scanner to help dermatologists analyse it. The images are captured using this laser technique to provide a 3D view of the image and then tissue segmentation is performed by region growing algorithm after interactive input of the color seed by a user. This system was developed to assess the evolution of wounds over time. MAVIS[17] makes use of a reflex camera for better measurements based on structured light and focused primarily on measuring the area and volume of ulcers. MEDPHOS[18] system was developed based on photogrammetry to capture 3D wound images by matching the corresponding points of calibrated images. These techniques require advanced and expensive equipment, which may not be available to everybody or everywhere.

Recently, advances in mobile imaging, image processing, and communication have been presented in the context of chronic wound care[5,6,7]. Currently there are a wide range of techniques being used to determine the tissues present in the wound[4,8,9,10,11]. Some techniques rely on color segmentation. Klosenik et al.[8] analyze color thresholding by multi-dimensional histograms to generate a set of features for support vector machine (SVM) to separate the wound from the non-wound region. The JSEG algorithm[9] is used for color pre-segmentation, and extracted color and texture features are classified by the SVM classifier. Lee et al. [10] make use of the Euclidean distance from an average value computed in the wound region as the feature vector and use gradient vector flow to detect the contour around the wound regions. Contour modeling and color segmentation are generally limited by the effect of poor or varying lighting in images.

Recently, neural networks have been used widely for wound segmentation as well. Veredas et al.[11] have designed an adaptive region growing algorithm to segment wounds into different regions, where features extracted from each region were given as an input to k-neural networks; Bayesian classifier combines the features to give the classification output. Mukherjee et al.[4] have developed a computer-aided tissue classification technique using fuzzy divergence technique. The images are converted to hue-saturation-intensity (HSI) space and only the saturation component is used for wound detection. The authors conclude that the SVM classifier performs best.

However, most of these approaches do not differ the tissue type within the lesion. Furthermore, mobile image recording and analysis require faster computations. Since image segmentation using fast random forest[14] is known to be computationally expensive in training but rather fast in application, we have adopted this concept here.

3. MATERIAL AND METHODS

3.1 Overview

Image acquisition and pre-processing using a reference card for calibration has been described previously[15]. The image analysis pipeline is composed of feature extraction, training the classifier and application to test and evaluate the classifier (Fig. 1). It is implemented as a custom Java application relying on the trainable Waikato Environment for Knowledge Analysis (WEKA) toolkit[14].

Figure 1. Image processing pipeline

3.2 Feature Extraction

The images are first reduced from the original size of 4608×2592 to 512×288 pixels to reduce the computing time. In the task of wound segmentation, the major characteristics for distinguishing the tissues are their colour and texture. The various features used to train the classifier are Sobel, Hessian, membrane projections, variance, mean, median, anisotropic diffusion, bilateral filter and Kuwahara filter (Fig. 2). The result of applying the Sobel operator produces a two-dimensional map of gradient at each point and is most commonly used for edge detection. The Hessian features detect the signal changes in two directions around each pixel and is used for describing the local structures present in the neighborhood of each pixel. Membrane projections enhance the membrane-like structures in the image through directional filtering. Mean and median filters are used to remove the noise present in the image. Variance filters highlight the edges present in the image by replacing each pixel value with the neighborhood variance. Anisotropic diffusion, bilateral filter and Kuwahara filter help in noise cancellation while preserving the sharp edges in the image. These features were found to be suitable for the task of segmenting wound into its corresponding tissue types.

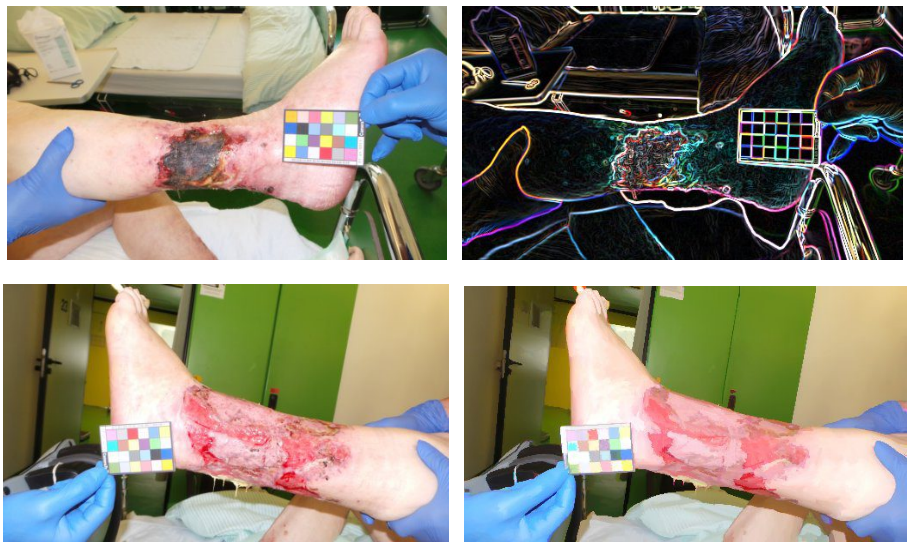

Figure 2. Original photographs (left) and example feature images (right): for Sobel filter (top) and Kuwahara filter (bottom).

3.3 Training

Our classification relies on supervised learning approach. Two types of classifiers were applied: the fast random forest classifier[14] and the support vector machine (SVM)[14]. The SVM constructs a set of hyperplanes in high-dimensional space to separate classes of different labels. In case the data is not linearly separable, a non-linear kernel function can be used. The kernel function maps the data into a higher dimensional space in a computationally inexpensive manner. This kernel trick makes the data separable by a hyperplane in higher dimensions. Additionally, SVM has a regularization parameter to prevent over-fitting of data. For the segmentation of wound images, the SVM classifier was implemented with radial basis function (RBF) kernel. The advantage of using the RBF kernel is in its localization and finite response for the entire range of data values.

The random forest classifier is an ensemble learning method that operates by constructing a multitude of decision trees at training time and giving the mean prediction of the individual trees as the output. In random forests, there is no need for cross-validation or a separate test set to get an unbiased estimate of the test set error. It is estimated internally, during the run. When the training set for the current tree is drawn by sampling with replacement, about one-third of the cases are left out of the sample. This out-of-bag data is used to get a running unbiased estimate of the classification error as trees are added to the forest. The fast random forest in WEKA is an improvement of the random forest algorithm that brings speed and memory use improvements.

Both classifiers were trained using the WEKA plugin in FIJI[13], which enables both, interactive training the classifier as well as using labeled data as predefined region of interest (ROI) to train the classifier. Reference labeling was drawn manually in 10 out of 120 wound images taken from the German Calciphylaxis Registry[12]. The classifier was built using five classes: necrotic, sloughy, granular, skin, and background (Fig. 3).

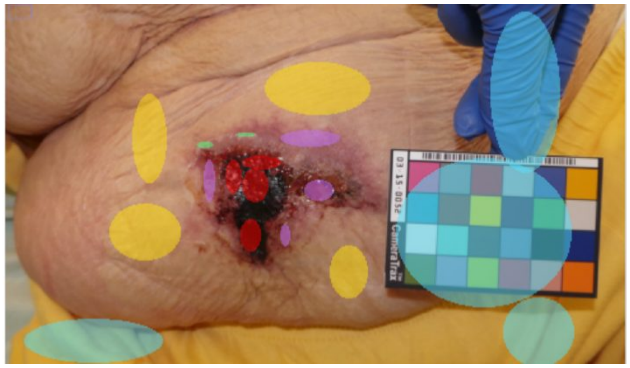

Figure 3. Interactive wound tissue labeling using trainable WEKA Segmentation plugin in FIJI.

3.4 Testing and Evaluation

The trained classifier was applied to the remaining images in the test set. To evaluate the classification results, a ground truth must be established. Therefore, all images have been marked manually according to the tissue types (Fig. 4).

Figure 4. Generation of ground truth: necrotic, sloughy and granular tissues are marked on the image (top, from left to right) and corresponding binary masks are extracted (bottom row).

The output of the classifier is a probability map for each class. This map is thresholded and converted to a binary image using the Otsu technique. This technique finds the threshold which maximizes inter-class variance and minimizes intra-class variance.

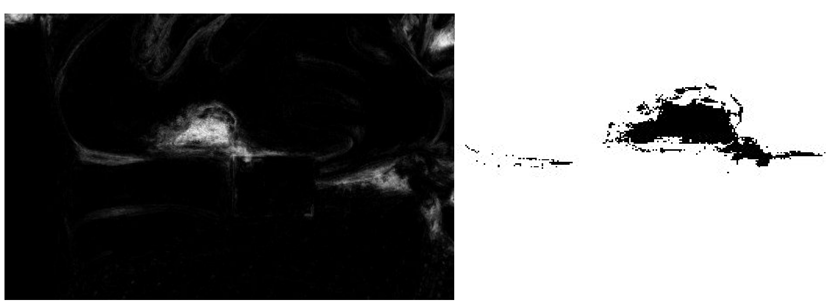

Figure 5. Probability mask of the predicted necrotic region(left); its corresponding thresholded binary map(right)

The evaluation coefficient to compare the result of this classifier with respect to the ground truth is the similarity coefficient which is defined as a ratio of number of true positives (correctly classified pixels) to the total number of masked pixels in the ground truth image.

3.5 Color Thresholding

A basic color thresholding was additionally implemented. The color thresholding involves classifying each pixel by determining the color thresholds for each class. The red-green-blue (RGB) image is converted to the hue-saturation-brightness (HSB) color space and thresholded. HSB is a cylindrical representation which tries to capture a more intuitive representation of colors in the image. In each cylinder, the angle around the central vertical axis corresponds to 'hue', the distance from the axis corresponds to 'saturation', and the distance along the axis corresponds to 'lightness', also known as 'value' or 'brightness'. While RGB gives an easy perception to the machine as it is an additive color model, the cylindrical representations try to provide a more perceptive representation for the user.

3.6 Background subtraction

The images in the dataset contained a diverse background along with the wound image. To compare the effect of varying background on the segmentations of tissues in the wound, the corresponding to the wound region of interest (ROI) was extracted from the background. This was done by combining the marked tissue regions: necrotic, granular and sloughy for each image into a binary mask and applying this binary mask to extract this combined region from the background. The classifier was then applied to these images with the background subtracted. This was done only with the random forest classifier

4. RESULTS

The similarity is calculated for each tissue of each image individually and the mean of the similarity in each tissue type is shown below. Our machine learning pipeline is compared with the basic color thresholding by implementing the random forest classifier and the support vector machine (SVM) classifier. Considering the corresponding to the wound ROI only, necrotic, sloughy, and granular tissues are classified with 89%, 39%, and 44%, respectively using the random forest classifier technique (Table 1). The worst results were obtained with the color thresholding technique.

Table 1. The mean and variance of similarity coefficient of necrotic, sloughy and granular tissue for each of the methods. Each signifies the percentage of the tissue that is correctly classified.

Methodology	**Necrotic**		**Sloughy**		**Granular**	
	Mean	Variance	Mean	Variance	Mean	Variance
Color thresholding (whole image)	33%	1.33%	12%	0.95%	40%	1.27%
SVM classifier (whole image)	57%	7.85%	26%	14.33%	30%	13.16%
Random forest classifier (whole image)	74%	6.20%	37%	15.56%	41%	13.41%
Random forest classifier (background removed)	**89%**	**3.89%**	**39%**	**15.60%**	**44%**	**13.59%**

The random forest classifier is seen to perform better, especially with prior ROI separation. This methodology was also able to detect the wound lesion distinguishing it from the skin and background with 84.36% accuracy.

5. DISCUSSION

From our experiments, we observed that machine learning segmentation techniques are more accurate as compared to simple color thresholding. This is because they take into account edges and local structures present in the image along with color. These techniques do not rely on a fixed color threshold but learn the threshold from the available data, hence, illumination and changes in lighting can be accounted for. It is also seen that both color and texture features play a vital role in segmentation. The features that capture edges and structures present in the image are observed to contain the information required for segmenting the tissue types. These structures can be captured and learnt best by machine learning algorithms. Still, the diverse set of images and the large differences in background might increase the false positives detected by the classifier. For example, if there is a red cloth present in the background, it might get wrongly classified as the granular tissue present in the wound. Hence, a better result in tissue segmentation is achieved by reducing the region of interest to the wound area only.

The results show that on an average 74% of necrotic tissues are labeled accurately using the random forest model on the whole image. The necrotic tissue is easier to classify compared to the sloughy and granular tissues. It can be explained considering the fact that in the given dataset, more training samples were available for necrotic tissue as compared to the other two classes. Furthermore, necrotic tissue differs more significantly in color and texture than the other types of wound tissue.

Comparing random forest with the SVM classifier using RBF kernel and the same features, SVM classifier performs slightly less accurate than the proposed random forest classifier. This can be explained by the fact that the random forest classifier accepts the data as it is without any transformation and, hence, might not lead to any loss in information. Also, the random forest classifier is faster to train as compared to the SVM and requires no external cross-validation. The random forest classifier output is also more interpretable as it gives the probability of belonging to a particular task. Therefore, the random forest classifier is preferred. We were also able to observe that detection of the complete wound region itself is possible with accuracy 84.36% when using fast random forest classification. It is worth mentioning that once trained, the random forest is quite fast and suitable for mobile implementation. Furthermore, the fast random forest implementation optimizes memory use as well as speed. Hence, such a system can be developed for direct usage on mobile devices.

Our system can be further extended into a two-step process: by first separating the wound from its background and then segmenting the tissues inside the detected wound region. Applying additional color calibration based on the reference cards within the images, can lead to further improvement. When a large dataset is available, the use of deep learning techniques devices may be considered.

6. CONCLUSION

In this paper, a system has been developed to segment the various tissues present in the wound using image processing techniques and machine learning algorithms. This system involves the extraction of color and texture features: Sobel, Hessian, membrane projections, variance, mean, median, anisotropic diffusion, and bilateral as well as Kuwahara filters; and segmenting the wound by using the fast random forest classifier. Otsu thresholding technique was used to convert the probability map to binary image and compared with the ground truth. This method was compared to two other techniques such as SVM-based segmentation and basic color thresholding. The fast random forest classifier was found to produce superior results. An added advantage of using the fast random forest technique is that it can be computed on the mobile device such as a smartphone directly. The Java implementation of this system implies that the acquisition and analysis of images can be performed directly on mobile devices. Thus, our method provides an economical and accessible option to analysis and documentation of chronic wounds and can be particularly useful in personalized healthcare.

REFERENCES

1. Robert G. Frykberg JB. Challenges in the treatment of chronic wounds. Adv Wound Care 2015;4(9):560-82
2. Sen CK, Gordillo GM, Roy S, et al. Human skin wounds: a major and snowballing threat to public health and the economy. Wound Repair Regen 2009;17(6): 763-71
3. Grey JE, Enoch S, Harding KG, ABC of wound healing: wound assessment. Brit Med J 2006;332(7536): 285-8
4. Mukherjee R, Manohar DD, Das DK, Achar A, Mitra A, Chakraborty C. Automated tissue classification framework for reproducible chronic wound assessment. BioMed research international. 2014 Jul 8;851582
5. Haak D, Doma A, Gombert A, Deserno TM. Interconnecting smartphone, image analysis server, and case report forms in clinical trials for automatic skin lesion tracking in clinical trials. Proc SPIE 2016;9789, doi: 10.1117/12.2216657
6. Bala S, Sirazitdinova E, Deserno TM. Colorimetric calibration of wound photography with off-the-shelf devices. Proc SPIE 201;10136, doi: 10.1117/12.2254721
7. Sirazitdinova E, Deserno TM. System design for 3D wound imaging using low-cost mobile devices. Proc. SPIE 2017;10138, doi: 10.1117/12.2254389

8. Kolesnik M, Fexa A. Multi-dimensional color histograms for segmentation of wounds in images. Proc. Int Conf Image Anal Recog (ICIAR) 2005;1014-22
9. Wannous H, Lucas Y, Treuillet S. Combined machine learning with multi-view modeling for robust wound tissue assessment. Procs Int Conf Comp Vis Theory Appl 2010; 92-104
10. Lee H, Lee BU, Park J, Sun W, Oh B, Yang S. Segmentation of wounds using gradient vector flow. Proc. Int Conf Intell Inf Biomed Sci (ICIIBMS) 2015;390-1
11. Veredas F, Mesa H, Morente L. Binary tissue classification on wound images with neural networks and bayesian classifiers. IEEE Trans Med Imaging 2010;29(2): 410-27
12. Deserno TM, Haak D, Brandenburg V, Deserno V, Classen C, Specht P. Integrated image data and medical record management for rare disease registries: a general framework and its instantiation to the German calciphylaxis registry. J Digit Imaging 2014;27(6): 702-13
13. Schindelin J, Arganda-Carreras I, Frise E, et al. Fiji: an open-source platform for biological-image analysis. Nature Methods 2012;9(7): 676-82, doi:10.1038/nmeth.2019.
14. Arganda-Carreras I, Kaynig V, Rueden C, et al. Trainable Weka segmentation: a machine learning tool for microscopy pixel classification. Bioinformatics 2017;33(15): 28369169, doi:10.1093/bioinformatics/btx180
15. Deserno TM, Sarandi I, Jose A, Haak D, Jonas S, Specht P, Brandenburg V. Towards quantitative assessment of calciphylaxis. Proc SPIE 2014;9035:90353C, doi: 10.1117/12.2043820
16. Callieri M, Cignoni P, Pingi P, Scopigno R, Coluccia M, Gaggio G. Derma: monitoring the evolution of skin lesions with a 3D system. Proc VMV 2003; 167-174
17. Jones CD, Plassmann P, Stevens RF, Pointer MR, McCarthy MB. Good practice guide to the use of mavis ii. Database 2006;2:4.
18. Malian A, Azizi A, Van Den Heuvel FA. Medphos: A new photogrammetric system for medical measurement. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. 2004 Jul;35(B5):311-6.