IJERSS | Volume 2 | Issue 4 | APRIL 2015

Research Paper

A HYBRID APPROACH FOR PRESSURE ULCER EVALUATION BY WOUND TISSUE CLASSIFICATION

COMPUTER SCIENCE

Keywords: Neural Networks, Probability Classifier, Region Segmentation, Mean Shift smoothing, Tissue identification

M.Mahalakshmi	**Assistant Professor of CSE, Dr.Sivanthi Aditanar College of Engineering, Tiruchendur**
V.Shiny	**Assistant Professor of CSE, Dr.Sivanthi Aditanar College of Engineering, Tiruchendur**

ABSTRACT

A pressure ulcer is a lesion caused by unrelieved pressure resulting in damage of underlying skin tissue when the body stays in one position for too long without shifting the weight. The treatment of pressure ulcer is very costly for healthy services. The accurate diagnosis and the appropriate treatment are crucial because starting the treatment too late may lead to the development of more severe lesions that may be life-threatening. The computer vision approaches presently available do not provide a precise solution for the pressure ulcer problem. So this paper uses a hybrid approach based on Neural Network and Probability Classifier for automatic tissue identification in wound images. Color and texture features are extracted after Region Segmentation is done using the mean shift procedure and region growing strategy. The Neural Network is trained with these extracted features as inputs.To this end, probability committee machine is formed by training a probability classifier to combine the classifications of the k neural networks.

I. INTRODUCTION

Chronic wounds are common problems in medical and nursing practice (a,b). Although chronic wound incidence and prevalence are largely unknown, chronic wounds, particularly relatively common ones such as leg ulcers, pressure ulcers and diabetic ulcers, have a considerable socio-economic impact in countries worldwide. Between 500000–600000 persons living in the United States are suspected to be suffering from venous leg ulcers[1]. Treatment costs for this condition are substantial, with expense reaching $775 million to $1 billion annually [1]. Because many cannot afford this treatment, patient compliance remains a major problem [1], [2].A study conducted by Olin et al. set out to determine the source of out-patient expenses related to venous leg ulcers [1]. The tissue recognition in pressure ulcer is the main objective of this paper. To evaluate the wound state, pressure ulcer tissues have to be detected, segmented and finally the tissues are classified. On the other hand, manual tracing of pressure ulcer regions of significant tissues i.e., skin, healing, granulation, slough, or necrosis, is not a common task in medical practice: the most widespread clinical tools to estimate the wound state are mainly based on the simple detection of the most damaged tissue appearing in the wound, but not on the quantification of the area of each specific tissue ulcers[6]. The more accurate region segmentation and tissue classification in pressure ulcer images can be done using the computational design and computer vision approaches. The same application areas mainly concentrate on the two specific objectives of the overall problem:1)using the contour detection to identify the wound area [7], active contour modeling [8], [9], region growing [10], region segmentation or texture analysis or models [8], [11], [12] and 2) the different tissue types for detection that existing in the image by using diverse segmentation techniques such as histogram thresholding [13], meanshift smoothing, watersheds [14], region growing [15], classification [16], graphs [14], [17] that is sometimes combined with machine learning strategies [17]-[20]. For wound segmentation the active contour modeling, histogram segmentation, region growing algorithms, clustering methods or skin texture models have been proposed in the literature as possible. In [7], Kolesniket al. investigated the use of multidimensional histograms to generate a set of features which are used as input to a support vector machine classifier for segmentation of the whole wound-bed region on images of chronic wounds. This paper uses several image processing techniques and a hybrid approach based on neural networks and Probability classifiers to design an automatic procedure for effective region segmentation and identification of significant tissues in pressure ulcer color-digital images. Neural networks have shown high efficacy rates when applied to similar clinical problems such as melanoma diagnosis by digital dermoscopy [21] Our proposed methodology includes: 1) using image processing techniques such as filtering, kernel smoothing by the mean shift procedure [22] and region growing [23] to segment the images; 2) extracting significant color and texture features from these segmented regions; 3) using statistical analysis to reduce the dimensionality of the feature space; 4) training a set of K supervised neural networks—multilayer perceptrons [24]—to classify the segmented regions as belonging to one of the different tissue categories proposed by the clinicians; and 5) training a Probability classifier to form a Probability Committee Machine (PCM) [25] which combines the predictions from the K -neural networks to improve the classification performance scores of the system.

II. METHODOLOGY

In this section we first define about the dataset and the magnetic resonance imaging which we use in our experiment For this purpose, in this paper an mean shift procedure for border-preserving region smoothing is used as a preliminary stage for region growing segmentation. The Region growing algorithm is used to image segmentation. After the images are segmented, a set of color and texture features is extracted from each resulting region. A Principal component Analysis (PCA) allows the reduction of dimensionality of the initial color and texture feature space. Finally, this pattern set is used to train supervised neural networks and Probability classifiers, to categorize the tissue into five different tissue types: skin, healing, granulation, slough and necrosis. Each particular stage of this general methodology will be explained in detail in the next sections.

A. Subjects

We trained and tested our methods on a datasets images are high magnification and high resolution so that fine-scale skin features such as pores and fine wrinkles are readily apparent. To minimize the margin of error, the camera lens is oriented in parallel to the plane of the wound. A total of 50 photographs were selected which were considered to be an appropriate data set for analysis because of the presence of all the tissue types significant in pressure ulcer evaluation that lead to accurate segmentation of the specific regions for effective tissue identification. 50 of these subjects were reserved for training, and 50 for testing. The training subjects were composed of 10 subjects with skin area), 10 with healing area,10 with granulation area,10 with necrosis area,and 10 slough area. The 50 testing subjects were composed of 10 skin.10 healing,10 granulation,10 necrosis, and 10 slough.

B. Magnetic resonance imaging

Magnetic resonance imaging (MRI), nuclear magnetic resonance imaging (NMRI), or magnetic resonance tomography (MRT) is a medical imaging technique used in radiology to visualize internal structures of the body in detail. MRI makes use of the property of nuclear magnetic resonance (NMR) to image nuclei of atoms inside the body. An MRI scanner is a device in which the patient lies within a large, powerful magnet where the magnetic field is used to align the magnetization of some atomic nuclei in the body, and radio frequency fields to systematically alter the alignment of this magnetization. This causes the nuclei to produce a rotating magnetic field detectable by the scanner and this information is recorded to construct an image of the scanned area of the body. Magnetic field gradients cause nuclei at different locations to rotate at different speeds. By using gradients in different directions 2D images or 3D volumes can be obtained in any arbitrary orientation.

C. Mean Shift Smoothing

Mean shift procedure is a non-parametric feature-space analysis technique, a so-called mode seeking algorithm. Application domains include clustering in computer vision and image processing [24]. In this study, we use the mean shift procedure for locating the maxima of a density function given discrete data sampled from that function. It is useful for detecting the modes of this density. This is an iterative method, and we start with an initial estimate x to region segmentation. The mean shift procedure has been fully described in [34] as a general nonparametric density estimator. It is based on kernel density estimation. Mathematically, given n points x_i,i=1,…n in the d-dimensional space R^d —in the case of images, the points are the pixels—, and assuming that each point x_i is associated with a bandwidth value $h_i > 0$, the sample point multivariate kernel density estimator with kernel K(x) ,computed at point x is given by

$$f_k(x)=1/n\sum_{i=1}^{n} 1/h_i^d \, k(||x-x_i/h_i||) \qquad …. (1)$$

based on a spherically symmetric kernel with bounded support satisfying

$$K(x)=c_{k,d}k(||x||^2) > 0 \quad ||x|| \leq 1 \qquad ….(2)$$

is an ad

aptive nonparametric estimator of the density at location x in the feature space. The function K(x) 0<x<1, is called the profile of the kernel, and the normalization constant $C_{k,d}$ e

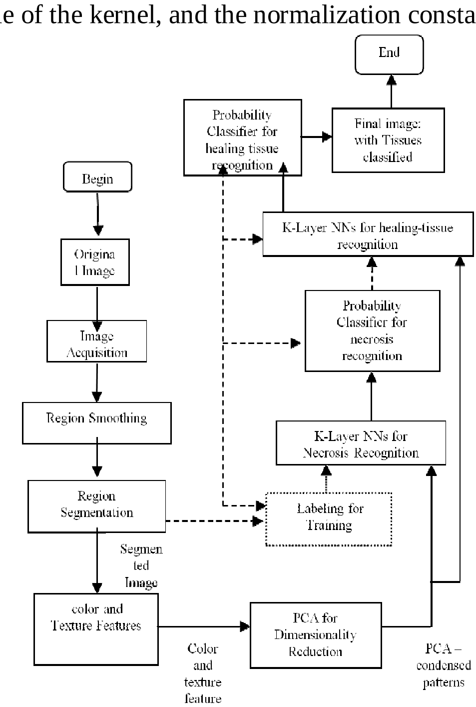

Figure 1: Overview of work flow

D. Region Segmentation

For image segmentation, after mean shift smoothing procedure, a region growing algorithm [35] (Algorithm 1) drives the image segmentation process. Segmented regions obtained this way are consistent with the separate areas of different significant tissues. The average number of regions per image in our study was approximately 250. From the 50 images analyzed in this paper, a total of 12500 regions were obtained from the mean shift and region-growing segmentation process above. From this total number of regions, a small proportion corresponds to non-significant areas such as shadows or clinical material. These undesired regions were manually ruled out. The graphical software developed dramatically reduces the time consumed during the wearisome process of labeling and separating the segmented regions in the images. The procedure for region segmentation is the following

Algorithm 1: Segmentation by region growing.

begin
Data: A mean-shift-smoothed image X^f
Result: A region segmented image X^s
1 Initialize all pixels in X^f as *nonregion-labeled*
2 **forall** nonregion-labeled *pixels* x_i^f *of* X^f **do**
3 Create a new region-label for x_i^f
4 **forall** *contiguous pixels* x_j^f *of* x_i^f *in its 8-pixel-neighborhood* **do**
5 **if** $\|x_i^f - x_j^f\| < threshold$ **then**
6 Label x_j^f with the same region-label as x_i^f
7 Mark x_j^f as a *visitable* pixel
8 **forall** *pixels marked as* visitable **do**
9 Go to line 4
end

sequence of outputs after performing mean shift smoothing, region segmentation to a sample image is given in Fig 2.

E. Feature Extraction

Based on the co-occurrence matrix, many different texture and color descriptors may be computed. To reduce the computational complexity, only some of these features were selected. The descriptions of the four most relevant descriptors that are widely used in literature and also in this work are:

$$\text{Contrast} = \sum_i \|i-j\|^k (p\ ij)^\lambda \qquad \text{.... (3)}$$

$$\text{Energy}=\sum_{i\,j}\rho_{i\,j}(\log\rho_{ij}) \qquad \text{....(4)}$$

$$\text{Entropy}=\Sigma_{\,i\,j\,\beta\,(i\,j)} \qquad \text{....(5)}$$

F.Probabilty Classifier

The Probabilty Classifier technique is based on the so-called Bayesian theorem and is particularly suited when the dimensionality of the inputs is high. Despite its simplicity, Probabilty can often outperform more sophisticated classification methods. To demonstrate the concept of Probability Classification, consider the example displayed in the illustration above. As indicated, the objects can be classified as either GREEN or RED. Our task is to classify new cases as they arrive, i.e., decide to which class label they belong, based on the currently exiting objects.

Algorithm:

Learning Phase: Given a training set S,

For each target value of c_i($c_i=c_1,\ldots,c_L$)

$P(C=c_i) \leftarrow$ estimate $p(C=c_i)$ with examples in S;

For every attribute value a_{jk} of each attribute x_j($j=1,\ldots,n$; $k=1,\ldots,N_j$)

$P(X_j=a_{jk} \mid C=c_i) \leftarrow$ estimate $p(X_j=a_{jk} \mid C=c_i)$ with examples in S;

Output: conditional probability tables; for $x_{,Nj}$ x L elements

Test Phase: Given an unknown instance $X'=(a'_1,\ldots,a'_n)$

Look up tables to assign the label *c** to X' if

$P(a'_1|c^*)\ldots P(a'_n|c^*)]P(c^*)>[P(a'_1|c)\ldots P(a'_n|c)]P©$, $c \neq c^*, c=c_{1,\ldots,}c_L$

G.Neural Network

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurones) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurones. This is true of ANNs as well.

Algorithm:

1)Initialize the weights with random numbers.
2)Initialize the vector with random numbers.
3)With the initialized values,compute the output using the procedure at explained above.
4)Adjustable of weights
a)Between hidden and output layer.
b)Between input and hidden layer.
5)Sum squared error at every iteration is calculated .
6)The above steps in adjusting the weights and vector values are repeated ,until the particular is reached.

Neural Network	Sensitivity	Specificity	Success	Accuracy
1	0.82	0.801	2	0.810389
2	0.8764	0.8345	2	0.854937
3	0.9023	0.8956	2	0.898938
4	0.914	0.905	2	0.909478

III.EXPERIMENTAL RESULTS

The Pressure ulcer disease majorly affects the of the leg area. The whole leg structure also gets degenerate due to Pressure ulcer disease. Five different types of tissues in the wound images are detected effectively.

Sample Test	Wound Classification Method
1	0.854937
2	0.898938
3	0.810389
4	0.909478

Our first work is to mean shift procedure for continuity-preserving smoothing of pressure ulcer digital images, as a previous critical stage to region segmentation.Mean-shift essentially is a feature-based analysis of data points, which requires a nonparametric estimator of the gradient of the density gradient in feature space. Advantages of feature-space methods are the global representation of the original data and the excellent tolerance to noise. When a density function in feature space has peaks and valleys, it is desirable to divide data points into clusters according to the valleys of the point densities, because such boundaries in feature space are mapped back to much more natural segmentation boundaries.The mean-shift procedure consists of two steps: the estimation of the gradient of the density function, and the utilization of the results to form clusters. The gradient of the density function is estimated by a nonparametric density estimator. Then starting from each sample point, the mean-shift procedure iteratively finds a path along the gradient direction away from the valleys and towards the nearest peak.

Figure 2: Mean Shift Smoothed using Mean shift Procedure

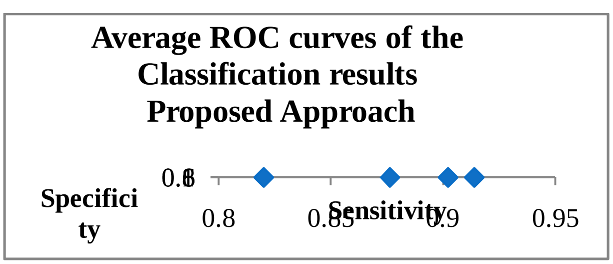

Figure 3: Error metrics which shows 1-Specificity and Sensitivity values

In our second method we have to define our Region growing segmentation algorithm has been launched on an image which is the result of the mean shift smoothing procedure. Segmented regions obtained this way are consistent with the separate areas of different significant tissues.Pressure ulcer images have been segmented using this approach. To minimize the effects of the light reflections, a median filter is applied to the images before the segmentation process is started. In order to reduce the number of regions resulting from this segmentation process and therefore limit the complexity of the subsequent classification problem, the original image resolution of 1632*1224 pixels is reduced to 204 *153 pixels.

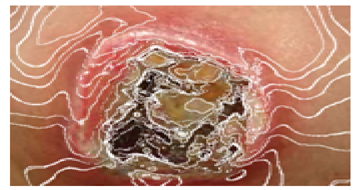

Figure 4: Region Segmentation using Region Growing Algorithm

Finally the Classification stage the classifier is used to classify the wound tissues. The purpose of classifier is to recognize the given tissue is skin,healing,granulation,slough or necrosis. The features of the five different types of tissues are extracted and these features are fed as a input to the classifier and the classifier is trained by giving some images . After this test the classifier by giving the test samples to the classifier now the classifier predict whether the given test sample is skin,healing,granulation,slough or necrosis. The classifier used in this project is Neural Network and Probability Classifier which classifies the wound tissue clustered region as skin, healing, granulation, slough or necrosis .

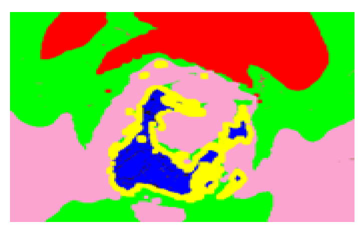

Figure 5: Tissue Classification using probability Classifier and Neural Network

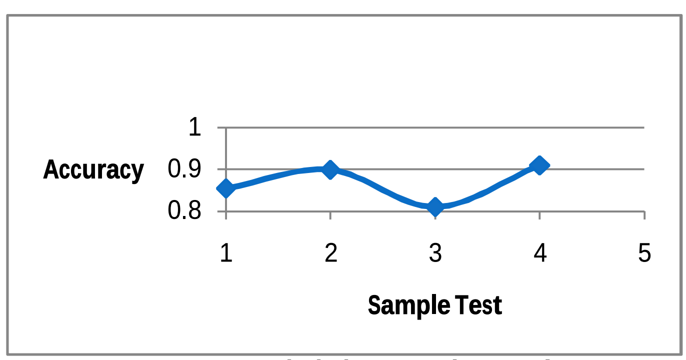

Figure 6: Error Metrics which shows Sample test and Accuracy

Evaluation Metrics

To assess the accuracy of our methods, we report some standard error metrics. Here we define accuracy, sensitivity and specificity.

$$\textbf{Sensitivity} = \frac{TP}{TP+FN} \qquad (6)$$

$$\textbf{Specificity} = \frac{TN}{FP+TN} \qquad (7)$$

where TP is true positive, FP is false positive, TN is true negative and FN is false negative.

CONCLUSION AND FUTURE WORK

We proposed a method to segment the region segmentation and the classification. The results show that the five different types of tissues in the wound images are detected effectively. Normally the wound images consist of several tissues, to detect the five different types of tissues in the wound images is a risky factor. For this purpose we developed Color and texture Features that represent the suspiciousness of different tissues. This paper suggest that the five different types of tissues are also classified accurately. This paper reduces the false positive rate by detecting the different tissues as skin,healing,granulation,slough or necrosisIn the future, we will apply both of these techniques to new datasets to examine different diseases and to other segmentation methods for success and accuracy.

REFERENCES

[1] Bates-Jensen BM. Chronic wound assessment. Nurs Clin North Am 1999; 34(4):799-845.

[2] Benbow M. The chronic wound support service [editorial]. J Tissue Viability 1999; 9(2):43-4.

[3] D. Kosmopoulos and F. Tzevelekou, “Automated pressure ulcer lesiondiagnosis for telemedicine systems,” IEEE Eng. Med. Biol. vol. 26, no.5, pp. 18–22, Sep.-Oct. 2007.

[4] P. J. Stewart, “The garments we wear,” LymphLink, vol. 19, no. 2, Apr.–Jun. 2007.

[5] M. Junger and H. M. Hafner, “Interface pressure under a readymade compression stocking developed for the treatment of venous ulcers over aperiod of six weeks,” VASA, vol. 32, pp. 87–90, 2003

[6] M. H. Davis, P. Dunkley, R. M. Harden, K. Harding, J. M. Laidlaw, A.M. Morris, and R. A. B. Wood, The Wound Program. Dundee, U.K.: Centre for Medical Evaluation, University of Dundee, 1992, p. 123.

[7] J. Cuddigan, E. Ayello, and C. Sussman, Eds., Pressure Ulcers in America: Prevalence, Incidence, and Implications for the Future. Reston, VA: NPUAP, 2001.

[8] D. Beeckman, L. Schoonhoven, J. Fletcher, K. Furtado, L. Gunningberg,H. Heyman, C. Lindholm, L. Paquay, J. Verdu, and T. Defloor,“EPUAP classification system for pressure ulcers: European reliabilitystudy,” J. Adv. Nursing, vol. 60, no. 6, pp. 682–691, Dec. 2007.

[9] M. Kolesnik and A. Fexa, “Multi-dimensional color histograms for segmentation of wounds in images,” in Proc. Int. Conf. Image Anal.Recognit., 2005, pp. 1014–1022.

[10] T. D. Jones and P. Plassmann, “An active contour model for measuringthe area of leg ulcers,” IEEE Trans. Med. Imag. vol. 19, no. 12, pp.1202–1210, Dec. 2000.

[11] P. Plassmann and T. D. Jones, “Improved active contour models with application to measurement of leg ulcers,” J. Electron. Imag. vol. 12, no. 2, pp. 317–326, 2003.

[12] Z. Zhang, W. V. Stoecker, and R. H. Moss, “Border detection on digitized skin tumor images,” IEEE Trans. Med. Imag. vol. 19, no. 11, pp. 1128–1143, Nov. 2000.

[13] S. A. Karkanis, D. K. Iakovidis, D. E. Maroulis, D. A. Karras, and M. Tzivras, “Computer-aided tumor detection in endoscopic video using color wavelet features,” IEEE Trans. Inf. Technol. Biomed., vol. 7, no., pp. 141–152, Sep. 2003.

[14] O. Cula, K. Dana, F. Murphy, and B. Rao, “Skin texture modeling,” Int. J. Comput. Vis., vol. 62, no. 1–2, pp. 97–119, 2005.[12] P. Berris, “Adquisition of Skin Wound Images and Measurement of Wound Healing Rate and Status Using Colour Image Processing,” P.h.D dissertation, Univ. Reading, Reading, U.K., Sep. 2000.

[15] L. V. Lourega, D. M. Ushizima, G. D. Freitas, and M. C. D’Ornellas, “A hybrid image segmentation approach using linear and non-linear processing,” presented at the Int. Symp. Vision Brain Mach., Montevideo, Uruguay, Nov. 13–17, 2006.

[16] A. A. Perez, A. Gonzaga, and J. M. Alves, “Segmentation and analysisof leg ulcers color images,” in Proc. Int. Workshop Med. Imag. Augmented Reality, 2001, pp. 262–266.