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TISSUE CLASSIFICATION OF VARICOSE ULCER BASED ON FEATURES USING AN EFFICIENT CSVM CLASSIFIER

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Abstract- **Wounds occur on the body due to etiologies such as pressure, vascular insufficiencies, or chronic disease states. Varicose ulcers are chronic skin wounds that affect many people and take a long time to heal. The progress of wound healing and the effect of clinical treatments can be monitored partly by measuring the area of the wound. Most of the current wound boundary determination methods only process the image of the wound area along with a small amount of surrounding healthy skin. An efficient color correction method is applied to reduce color shifts due to uncontrolled lighting conditions. The Simple Linear Iterative Clustering (SLIC) method is used in this work for effective super-pixel segmentation. Color and texture features are extracted from these segmented regions for feature processing. A manual labeling is done for class characterization of tissues. An effective approach is presented here that uses two stage Cascaded Support Vector Machine (CSVM) to determine the wound boundary on ulcer image. Various color and texture descriptors are extracted from super- pixels that are used as input for each stage in the classifier training. Finally, wound tissues are classified according to its labeled class.**

Index Terms **– Color Correction, Super pixels, Simple Linear Iterative Clustering (SLIC), Cascaded Support Vector Machine (CSVM), Tissue Classification.**

I INTRODUCTION

Venous ulcers are wounds that are thought to occur due to improper functioning of venous valves, usually of the legs..They are the major occurrence of chronic wounds, occurring in 70% to 90% of leg ulcer cases. Venous ulcers develop mostly along the medial distal leg, and can be very painful with significant effects on quality of life. A wound region is to be determined by the refinement process.

An accurate and thorough wound assessment is an essential component of optimal wound care. A wound assessment serves two important purposes:

1) To determine wound severity in order to predict expected rate of wound healing and develop a comprehensive plan of care and
2) To act as a reliable outcome measure that can be used to assess the effectiveness of a given wound treatment.

The purpose of this work is to accurately assess the healing status of the wound. After segmenting the wound from the wound image, segmented wound is classified based on the severity of the wound which can be identified by color histogram of the wound through color image processing techniques.

II METHODS

The methods proposed here are applied in the wound images. Input images are processed in color correction and segmented into super-pixels then features are extracted and reduction is applied by PCA technique. During the training procedure, values stored in the database are classified with their corresponding optimized parameters using C-SVM classifier, finally it removes the outliers to refine the boundary efficiently.

Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels known as super-pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics.

Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. A good super-pixel segmentation algorithm should have the following three properties:

1) Good image boundary adherence 2) Computationally efficient and with modest memory requirements, and 3) Easy to use and control

III PROPOSED METHOD

A super pixel segmentation method based on SLIC algorithm has been proposed. The main contribution of this work is to develop a cascaded two stage Support Vector Machine based classifier to determine the wound boundaries and to classify the tissues.

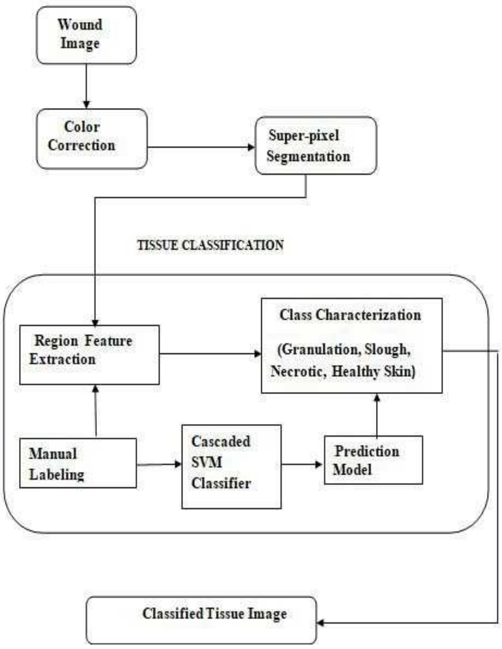


Fig.1 Wound Tissue Classification

Color correction addresses two distinct problems: firstly, obtaining a constant response from the digital camera by determining optimal settings and secondly, determining the relationship between the device-dependent RGB color data of the imaging system and some device-independent color data, so it makes possible accurate colorimetric measurements and exchange of images.

The RGB values of each patch color were calculated and then transformed to sRGB using the affine model and the spectrophotometric measurements of patches stored as reference values. This step is essential for stabilizing the results, because image color segmentation is highly sensitive to color shifts. It is influence on the segmentation result.

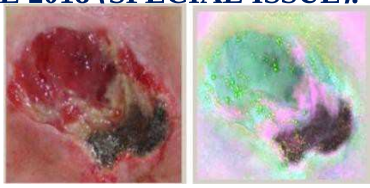


Fig 2: Color Correction

B Super-Pixel Segmentation

A super-pixel is an image patch which is better aligned with intensity edges than a rectangular patch. Super-pixels can be extracted with any segmentation algorithm; however, most of them produce highly irregular super-pixels, with widely varying sizes and shapes. A more regular space tessellation may be desired.

An image is covered with overlapping square patches of fixed size. Each pixel is covered by several patches and the task is to assign a pixel to one of them. If two neighboring pixels are assigned to the same patch, there is no penalty. If they belong to different patches, then there is a stitching penalty that is inversely proportional to the intensity difference between the pixels. A super-pixel cannot be too large, not larger than a patch size. Small super- pixels are discouraged because they contribute a higher cost to the stitching energy.

SLIC (Simple Linear Iterative Clustering) Algorithm

SLIC only computes distances from each cluster centers to pixels within 2 ×2 neighborhood region. The SLIC algorithm gives the best tradeoff on region uniformity and contrast, as well as the best efficiency.

This algorithm groups pixels into regions with similar values. Using these regions in image processing operations, such as segmentation, can reduce the complexity of these operations

In an initialization step where initial cluster centers are sampled on a regular grid spaced S pixels apart. In the assignment step, each pixel i is associated with the nearest cluster center whose search region overlaps its location. An update step adjusts the cluster centers to be the mean vector of all the pixels belonging to the cluster.

SLIC takes a desired number of approximately equally-sized super-pixels K as input. So each super-pixel will have approximately N/K pixels.

Hence, for equally sized super-pixels, there would be a super-pixel center at every grid interval S = √(N/K).K super-pixel cluster centers $C_k = [l_k, a_k, b_k, x_k, y_k]$ with k = [1, K] at regular grid intervals S are chosen. Post processing enforces connectivity by reassigning disjoint pixels to nearby super-pixels. SLIC does not explicitly enforce connectivity.

At the end of the clustering procedure, "orphaned" pixels that do not belong to the same connected component as their cluster center may remain."Orphaned pixels" are assigned with the label of the nearest cluster center using a connected components algorithm.

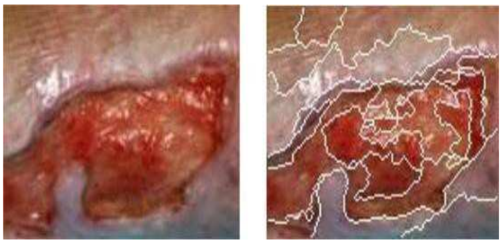


Fig 3.Super-pixel Segmentation

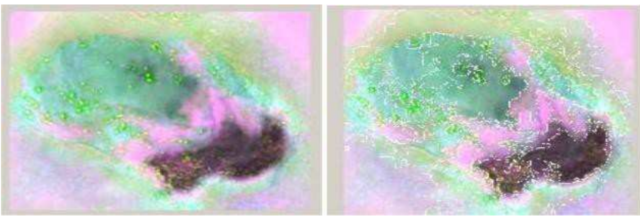


Fig 4: Super-pixel Segmentation with color Correction

C. Feature Extraction For Superpixels

The super-pixel based local color features used in wound tissue classification work include mean color, dominant color, statistics (highest peaks, variance, skewness, energy and entropy) of color histogram and sampled multi- dimensional color histogram in color spaces (RGB, normalized-RGB).The widely used local texture features have specific measures determined by the chosen descriptors:

1) Discrete Wavelet Transform (DWT)
2) Normalized texture Contrast and Anisotropy(CA)
3) Gray Level Co-occurrence Matrix (GLCM) based features.

D.Color And Feature Descriptors

Once the images have been segmented, a set of color and texture features from each one of the significant regions is extracted. Three different color models are used, RGB and normalized RGB.

Normalized-RGB is obtained from the RGB values by a simple normalization procedure. As the sum of the three normalized components is known, the third component does not hold any significant information and can be omitted, reducing the space dimensionality.

Three types of features are obtained from the regions in each images (RGB and normalized RGB) can be extracted from the super-pixels in each wound image

1) Pixel based color features
2) Histogram based color features
3) Wavelet based texture features

Features extracted from both RGB and Normalized-RGB color histograms are: the variance, the skewness, the energy and the entropy.

A **color model** is an abstract mathematical model describing the way colors can be represented as tuples of numbers.

Texture Features

Texture features are useful in refining the classification results. Texture refers to visual patterns with properties of homogeneity .Texture features typically consist of contrast, uniformity, coarseness, and density. There are two basic classes of texture descriptors, namely, statistical model-based and transform-based.

Gray- Level Co-occurrence Matrix

Gray- level co-occurrence approach uses Gray-Level Co-occurrence Matrices (GLCM) whose elements are the relative frequencies of occurrence of grey level combinations among pairs of image pixels. Four statistical features of the GLCMs are computed. The features are energy, entropy, contrast, and homogeneity.

Discrete Wavelet Transform (DWT)

The wavelet transform is referred to as the Dyadic Wavelet Transform (DWT) and its specific formulation can be derived from a smoothing or scaling function. Each of these images reveals important gradient information at a given direction (horizontal, vertical and diagonal) and scale.

Gabor Features

Gabor filters are particularly appropriate for obtaining the texture representation of input images. In this work, we extract local Gabor features of images for wound tissue classification. Gabor features have sufficient discrimination abilities for dense sampling patches of given input images.

Local Bianry Pattern Features

Local binary pattern (LBP) features, were extracted from each of every segmented wound region. Local binary pattern (LBP) is a simple and efficient method for textural analysis of images. LBP labels the pixels of an image by thresholding the neighborhood of each pixel and considers the result as a binary number.LBP is a consolidating approach to the traditionally divergent structural and statistical models of textural analysis

D. Manual Labeling Of Tissues

Once a wound image is segmented into regions, next step is to classify these regions according to 4 tissue types: granulation, slough, necrosis and healthy skin. Supervised learning of tissue types may be applied for this purpose from the regions delineated by clinicians or on the segmented region directly labeled. The segmented regions of the wound image have been provided to a group of clinicians, in order to label it using the classical granulation/slough/necrosis color codes. The regions obtained feed a database for each type of tissue. A graphical interface helps to fill the regions with colors.

E. Cascaded Two Stage Svm

Cascaded Support Vector Machines is an extension of classic support vector machines that allow a fast training on large data sets. In this work, we combine cascade support vector machines with dimensionality reduction based preprocessing. The cascade principle allows fast learning based on the division of the training set into subsets and the union of cascade learning results based on support vectors in each cascade level. Cascaded SVM employs horizontal cascading; that is, it divides the training set into smaller subsets, which can be computed more efficiently. The idea to divide the problem into smaller sub-problems that is identified by the sub-problem solution are likely to be support vectors of the entire kernel SVM problem based on an adaptive clustering approach.

Two-Stage Cascade SVM

Step 1 Split the entire training image dataset into k subsets (folds) of equal size. Since it control the segmented super-pixel number by using SLIC algorithm and since the dimensions of most training images are approximately the same.

Step 2 Make the number of wound regions and non-wound regions from k-1 subsets equal. The number of wound regions is typically small compared to number of non-wound regions. This skewed distribution of the number of instances in the different categories undermines the performance of the trained classifier.

Step 3 Follow a classical 10-fold cross- validation scheme to train a binary SVM based classifiers on these 2m training patterns. Based on each subset, we further split this subset into equal size folds. Then, run the SVM (C-SVM) , where each time one fold will be the validation set and the remaining folds will be training set.

Step 4 Use the trained classifier to classify regions in the subset other than k-1 subsets for training.

Step 5 Collect the incorrectly classified instances from the results in Step 4 into the training set for the second stage.

Step 6 Repeat first stage training (Step 2 to 5) k times and let each subset be the validation set exactly once.

Step 7 Train the second stage SVM binary classifier.

F. Tissue Classification

A tissue classification for varicose ulcer wound images captured with a hand held digital camera. A tissue database has been created from labeling on computer and a tissue classifier has been designed with color and texture descriptors. The results obtained confirm that segmentation driven classification approach is suitable approach, as overlap scores on the ground truth. Direct region labeling of the segmented images, improve the classification process and reduce the time needed by clinicians. Enhanced results are obtained by taking into account spatial continuity and homogeneity, which are not considered in pixel based classification.

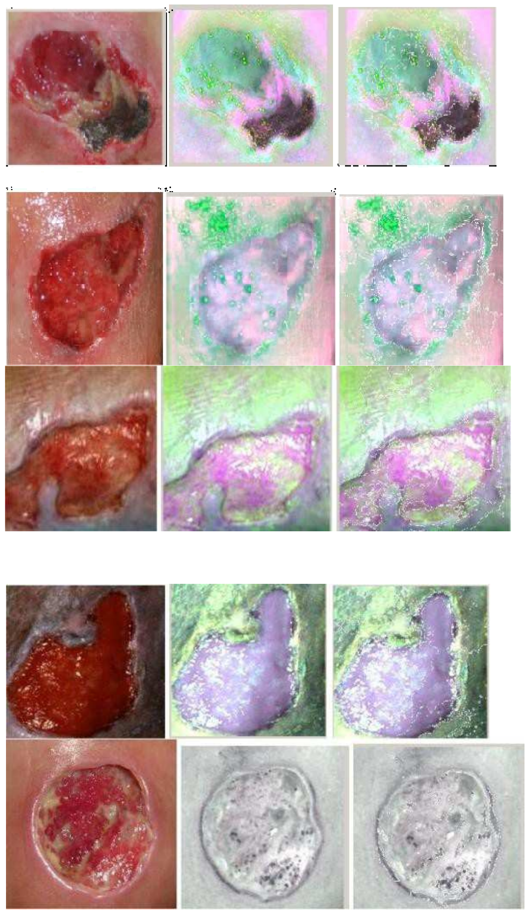
Fig 5. Manual Labeling of tissues

IV EXPERIMENTAL RESULTS

Nearly 20 samples were collected for this work. The images were taken using a high resolution camera. The input images were first segmented into super-pixels by using the SLIC algorithm. The inputs to the classifiers are color and texture descriptors of super-pixels.

Fig 6. Process of Color correction and segmenting Wound Region using MATLAB

Wound Image Analysis classifier has been implemented using MATLAB. Cascaded SVM classifier classifies the wound by considering healing status of the wound considering various colors involved in formation of wound and various stages undergoes by wound in healing process collection of wound image database from the open source wound images. Several observations from table1 can be made; firstly, best results are obtained with the learning base when features are extracted according to the directly labeled segmented regions. This can be explained by the fact that, during the training and test stages, the regions are segmented by the same method. Secondly, compared to the same ground truth, the scores are higher than that obtained by clinicians. Best scores are obtained for granulation tissue.



Wound Image Color Correction Super-pixel segmentation

Fig 7. Varicose ulcer tissue classification

Table1: Performance Evaluation

Wound Images	Granulation (Pixels)	Slough (Pixels)	Necrotic (Pixels)	Healthy Skin (Pixels)	Accuracy %
1	180	28	17	6	86.85
2	90	220	43	19	90.78
3	58	110	38	64	82.94
4	290	46	20	32	78.56

Overall Accuracy: 83.24%

V CONCLUSION AND FUTURE WORK

A super pixel segmentation method based on SLIC algorithm has been proposed in my project. The main contribution of this work is to develop a cascaded two stage Support Vector Machine based classifier to determine the wound boundaries and to classify the tissues. Nearly 20 samples were collected for this work. The images were taken using a high resolution camera. The input images were first processed by color correction then segmented into super-pixels by using the SLIC algorithm. The inputs to the classifiers are color and texture descriptors of super-pixels. In the first stage, k C-SVM based classifiers are trained by a k-fold cross-validation strategy on the entire training dataset. In the second stage, only the incorrectly classified instances when k classifiers were applied in the first stage, were used as the training set to train another C-SVM based classifier. Finally, tissues are classified using a manual labeling method.

The proposed work is mainly used to evaluate tissue classification and to confine the treatment to the refined contour boundary. This work can be further extended by performing classification of different stages of varicose ulcer and tissue classification will be relying on the accurate 3D model, to improve the classification process itself, as tissue aspect is view dependent, and also to compute real surfaces by mapping the regions on the 3D model. The final goal is to provide a complete 3D wound assessment tool for wound monitoring and clinical studies on the healing process.

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