International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-2 Issue-5, June 2013

Assessment of the Wound-Healing Process by Accurate Single View Issue Classification and Depth Estimation for Telemedicine

K. Sundeep Kumar, Lalitha Asokan, Priyadarshini M.P, B. Eswara Reddy.

***Abstract*— With the widespread use of digital cameras, freehand wound imaging has become common practice in clinical settings. There is however still a demand for a practical tool for accurate wound healing assessment, combining dimensional measurements and tissue classification in a single user friendly system. In this research work, we propose optimal techniques for the assessment of wound healing process. The proposed system comprises cascade of four stages - Pre - Processing Stage, Segmentation, Feature Extraction and Classification. All the implementations are done in MATLAB.**

***Index Terms*— Clustering, Epidermis, Feature vectors, Intensity, Multi -Class, Tissue.**

I. INTRODUCTION

Telemedicine is the use of telecommunication and information technologies in order to provide clinical health care at a distance. It helps eliminate distance barriers and can improve access to medical services that would often not be consistently available in distant rural communities. It is also used to save lives in critical care and situations. Although there were distant precursors to telemedicine, it is essentially a product of 20th century telecommunication and information technologies. These technologies permit communications between patient and medical staff with both convenience and fidelity, as well as the transmission of medical, imaging and health informatics data from one site to another [1].

Telemedicine can be broken into three main categories: store-and-forward, remote monitoring and (real-time) interactive services.

Store-and-forward telemedicine involves acquiring medical data (like medical images, biosignals etc.) and then transmitting this data to a doctor or medical specialist at a convenient time for assessment offline. It does not require the presence of both parties at the same time. Dermatology (teledermatology), radiology, and pathology are common specialties that are conducive to asynchronous telemedicine. A properly structured medical record preferably in electronic form should be a component of this transfer. A key difference between traditional in-person patient meetings and telemedicine encounters is the omission of an actual physical examination and history. The 'store-and-forward' process requires the clinician to rely on history report and audio/video information in lieu of a physical examination.

Remote monitoring, also known as self-monitoring or testing, enables medical professionals to monitor a patient remotely using various technological devices. This method is primarily used for managing chronic diseases or specific conditions, such as heart disease, diabetes mellitus, or asthma. These services can provide comparable health outcomes to traditional in-person patient encounters, supply greater satisfaction to patients, and may be cost-effective.

Interactive telemedicine services provide real-time interactions between patient and provider, to include phone conversations, online communication and home visits. Many activities such as history review, physical examination, psychiatric evaluations and ophthalmology assessments can be conducted comparably to those done in traditional face-to-face visits. In addition, "clinician-interactive" telemedicine services may be less costly than in-person clinical visit [1].

- *Clinical Practise*

Monitoring the wound healing process is a tedious task for clinicians and nurses as it is necessary to periodically assess the wound. All types of wounds are concerned: not only chronic wounds but also ulcers, burns, traumatic or surgical wounds, and dermatological lesions. Moreover, wound care is expensive: according to a report published by the NIGMS in 2008 in the USA, chronic wounds cost the nation $20 billion to $25 billion and acute or traumatic wounds add another $7–$10 billion to the bill annually, as the healing process can last several months;with the ageing of the population this cost will necessarily increase by 25% over the next 10 years. As health care costs need to be drastically reduced, there is a growing demand for patients to be cared for at home; wound monitoring could be carried out from a distance, outside a hospital environment, in private homes properly equipped for telemedicine practise. Pioneer experiments in this area consisted simply in uploading images to a web site where a physician could view the data at his convenience. In more recent studies, image processing has been added but it provides only ulcer stage grading. The quantitative assessment of chronic wounds still relies on visual inspection and manual techniques to describe the shape of the wound (perimeter, surface, depth, etc.) and the biological nature of the skin tissues (percentage of each class, wound severity stage, burn degree, etc.).

Manuscript published on 30 June 2013.
***** Correspondence Author (s)
Mr. K. Sundeep Kumar*, Associate Professor, Department of CSE, CMRIT, Bangaluru, India.
Mrs Lalitha Asokan, Assistant Professor, Dept. of Information Science, CMRIT, Bengaluru, India.
Ms Priyadarshini M.P, J.R.F, VGST - DST GOK,ECE, CMRIT, Bengaluru, India.
Dr. Eswara Reddy, Professor, Department of CSE, JNTUACE, Ananthapur, India.

Wound dimensions and shape are currently measured with an ordinary ruler, or sometimes through sketches on cross-ruled sheets, serum injection or alginate moldings. Assessing the type and proportion of tissues likewise remains highly empirical as evaluation is performed visually and then recorded on a red-yellow-black scale corresponding respectively to the dominant colour of the different tissues found on a wound: granulation, slough and necrosis. Healing is a complex cascade of cellular events operating to reconstruct damaged tissues, and also an individual process that exhibits considerable inter-patient variability. As the different tissues may overlap and be difficult to distinguish, wound assessment is not straightforward. The lack of quantitative data affects the coordination of care staff and hinders clinical studies focused on healing. Digital cameras, though now widespread in clinical centers, are used only for basic patient data recording and not image processing, as wound therapeutic follow-up is mainly carried out by nurses.

- ***Types of Tissue in the wound***

The type of tissue in the wound determines the potential for healing and the type of treatment. There are three types of tissue in the wound - Granular, Slough and Necrosis [1].

Granulation tissue appears as beefy red, bumpy, shiny tissue at the base of the wound. As it heals, a full-thickness wound develops more and more granulation tissue. Such factors as tissue oxygenation, tissue hydration, and nutrition can alter the color and quality of granulation tissue.

Slough tissue can easily be confused with normal anatomical tissues such as tendons or ligaments because of their frequently yellowish coloration. This can be a costly mistake, due to the fact that slough is non-viable tissue and requires debridement. When a large amount of slough is present and obscures the wound bed, the wound is unstageable. Slough can be identified as a stringy mass that may or may not be firmly attached to surrounding tissue. Slough can range in color from white (scant bacterial colonization) to yellow or green (larger bacterial counts) to brown (hemoglobin is present). Slough may become thicker and harder to remove the longer it is present.

Necrotic tissue may appear as a moist yellow or gray area of the tissue that's separating from viable tissue. When dry, necrotic tissue appears as thick, hard, and leathery black eschar. Areas of necrotic or devitalized tissue may mask the underlying abscesses and collections of fluid. Before the wound can begin to heal, necrotic tissue, drainage, and metabolic wastes must be removed from the wound.

II. OUR APPROACH

In the proposed system, the given wound is segmented to identify the region of interest, from which features are extracted for classifying the given wound as to which type of tissue is it - Granular or Slough or Necrosis, and finally the depth of the wound is determined. The proposed flow of our approach is shown in figure 1.

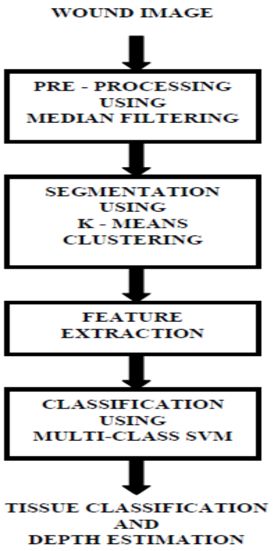

Figure 1. Proposed flow of techniques

Module 1 : Pre - Processing using Median Filtering- For the given wound image popular pre-processing technique - Median Filtering, is applied to remove the noise and hairs on the wound, so that the wound is distinct [2], [3].

Module 2 : Segmentation using *K* - Means Clustering- We make use of *K*-means clustering algorithm, which is an unsupervised method, to provide us with a primary segmentation of the image. *K*-means clustering is used because it is simple and has relatively low computational complexity. In addition, it is suitable for biomedical image segmentation as the number of clusters (*K*) is usually known for images. Wound image generally consists of regions representing the background, skin, and the wound. Hence we select *K* to be 3.

Initial cluster centers are chosen in a first pass of the data. The dataset is partitioned into *K* clusters and the data points are randomly assigned to the clusters resulting in clusters that have roughly the same number of data points. For each data point, we calculate the Euclidean distance from the data point to the mean of each cluster. If the data point is not closest to its own cluster, it will have to be shifted into the closest cluster. If the data point is already closest to its own cluster, we will not shift it. The process continues until cluster means do not shift more than a given cut-off value or the iteration limit is reached.

Module 3 : Feature Extraction - The segmentation method allows the partitioning of the image into regions but no tissue class can still be recognized. Tissue classification requires the presence of discriminating features to categorize the different regions. Region features are usually based on color, texture, and shape. However, in tissue classification, shape based features do not relevant. The features that we considered are - Mean, Standard Deviation, Smoothness and Entropy [2], [3].

Module 4 : Classifier - Once a wound image is segmented into regions, we have 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 labelled. Several classification methods have been investigated, such as decision trees, neural networks or k-nearest-neighbors.

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We opted for the support vector machines (SVMs), because of their highly generalized performance without the need for prior knowledge, limiting overlearning problems and achieving smart separation between classes.
Since our problem is a multi - class problem, we considered *"One Against All" SVM Classifier*. As in all classification problems, SVMs attempt to find a model explaining the relationship between data input and class output. They rely on a learning data set to adjust the parameters of the model. The SVM method requires good choice of the *kernel* to get an optimum separation of data. We have considered RBF kernel in the implementation. For a given set of points, the Multi - Class SVM tries to find the hyperplane that maximizes the margin separating into 'n' classes.

III. PRE - PROCESSING

Wound images often contain extraneous artifacts such as - skin texture, air bubbles and hairs on and around the wound. These artifacts might reduce the accuracy of the segmentation and increase the computational time. Inorder to mitigate the effects of these artifacts on segmentation, the wound images should be Pre - Processed with a smoothening Filter. The Median Filter is one of the most common smoothening filters. Median Filtering with a mask of appropriate size can eliminate most of the artifacts in the wound image. We used a color Median Filter with an 11 x 11 kernel to smooth the image before Segmentation [3].

IV. *K* - MEANS CLUSTERING

Unsupervised Learning refers to the problem of trying to find the hidden structure in unlabelled data. Clustering is the Task of Grouping Data based on Similarity It is the process of partitioning a set of patterns.
K - Means algorithm is an unsupervised clustering algorithm that classifies the input data points into multiple classes based on their intrinsic distance from each other. The algorithm assumes that the data features form a vector space and tries to find natural clustering in them [3], [4].

The algorithm is as follows:
The clustering centers are obtained by minimizing the objective function :

$$V = \sum_{i=1}^{K} \sum_{\forall x_j \epsilon S_j} (x_j - \mu_j)^2 \qquad (1)$$

Where, there are K - clusters S_i, i = 1,2,3,..,K and μ_i is the centroid or mean point of all the points $x_i \in S_i$.

1. Initialize the centroids with K random value. Wound image generally consists of regions representing the background, skin, and the wound. Hence we select K to be 3.
2. Repeat the following steps until the cluster labels of the image do not change anymore.
3. For each data point, we calculate the Euclidean distance from the data point to the mean of each cluster -

$$C^{(i)} = arg.\min\left\|x^{(i)} - \mu_j\right\|^2 \qquad (2)$$

If the data point is not closest to its own cluster, it will have to be shifted into the closest cluster.
If the data point is already closest to its own cluster, it will not be shifted.

4. Compute the new centroid for each of the clusters -

$$\mu_i = \frac{\sum_{i=1}^{m} l\{C_{(i)} = j\} x^{(i)}}{\sum_{i=1}^{m} l\{C_{(i)} = j\}} \qquad (3)$$

Where K is a parameter of the algorithm (the number of clusters to be found), i iterates over the all the intensities, j iterates over all the centroids and $\mu_{(i)}$ are the centroid intensities.

V. FEATURE EXTRACTION

Before the segmented (clustered) data are used for the tissue classification, they will often undergo a feature extraction process. The purpose of the feature extraction process is to reduce the dimensionality of the data set that is passed to the classifier, as this increase the classifier's robustness. Here in our research we have used - texture descriptors for classification. Texture is the spatial distribution of intensities. The descriptors that we considered are - Mean, Standard Deviation, Smoothness and Entropy [4], [5].
Mean (μ) - is the measure of the average intensity. It is determined by the below expression -

$$\mu = \frac{1}{M.N} \sum_{i=1}^{M} \sum_{j=1}^{N} P_{ij} \qquad (4)$$

Standard Deviation (σ) - is the measure of average contrast. It is determined by the below expression -

$$\sigma = \sqrt{\frac{1}{M.N} \sum_{i=1}^{M} \sum_{j=1}^{N} (P_{ij} - \mu)^2} \qquad (5)$$

Smoothness (R)- Measures the relative smoothness of intensity of a region. It is determined by the below expression-

$$R = 1 - \frac{1}{1 + \sigma^2} \qquad (6)$$

Entropy (e) - is the measure of randomness. It is determined by the below expression -

$$e = -\sum_{i=1}^{M} \sum_{j=1}^{N} P_{ij} \, .\log_2(P_{ij}) \qquad (7)$$

VI. CLASSIFICATION

Image classification analyzes the numerical properties of various image features and organizes data into categories. Classification algorithms typically employ two phases of processing: *training* and *testing*. In the initial training phase, characteristic properties of typical image features are isolated and, based on these, a unique description of each classification category, *i.e. training class*, is created. In the subsequent testing phase, these feature-space partitions are used to classify image features [6], [7], [8].

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SVM, which is one of the supervised classification technique, is the maximum margin classifier defined in terms of the support vector approach.

SVM was originally defined for Binary Classification, i.e Classification of the given data into 2 classes. There are basically 2 approaches to extend SVM for Classification in k Classes ($k > 2$) : one that reduces the k classes problem to a set of binary problems; and one that involves a generalization of the binary SVM [6].

Two well known methods of Muli-Class SVM are - "One-Against - All", and "One - Against - One". In our research, we have implemented "One Against All SVM". The "One - Against - All" method builds k binary SVMs, each of them dedicated to separating each class from the others. The outputs of all SVM are then combined to generate the final classification in k - classes. The most common method for combining the k-SVM outputs is to assign the input vector to the class that provides the largest value of the decision function.

- ***"One Against All" SVM***

The "one against all" SVM constructs k SVM models where k is the number of classes. The i^{th} SVM is trained with all of examples in the i^{th} class with positive labels, and all other examples with negative labels.

Thus the given l training data (x_1,y_1) …… (x_l,y_l) , whre $x_i \in R^n$, $i = 1,2,….,l$, and $y_i \in \{1,2,….,k\}$ is the class of x_i, the i^{th} SVM solves the following problem :

$$\text{Min} \ (L(w^i,b^i,\xi^i)) : \ \frac{1}{2}(w^i)^T w^i + C\sum_{j=1}^{l}\xi^i{}_j$$

$$(w^i)^T \varphi(x_i) + b^i \geq 1 - \xi^i_j \ , \text{ if } y_i = i$$

$$(w^i)^T \varphi(x_i) + b^i \leq -1 + \xi^i_j \ , \text{ if } y_i = i$$

$$\xi^i_j \geq 0, \ j = 1,2,….l \qquad (8)$$

where, the training data x_i are mapped to a higher dimensions and space by the function φ and C is the penalty parameter. Min ($L(w^i,b^i,\xi^i)$) means that we like to maximize $2/\|w^i\|$, the margin between two groups of data.

When data are not linear separable, there is a penalty term - $C\sum_{j=1}^{l}\xi^i{}_j$, which can reduce the number of training errors. The basic concept behind SVM is to search for a balance between the regularization terms and the training errors.

After solving (8), there are k - decisions functions : $(w^1)^T \varphi(x) + b^1$,………, $(w^k)^T \varphi(x) + b^k$, we say x is in the class which has the largest value in the decision function :

$$\text{Class of } x = \text{argmax}_{\,i=1,2…,k} \left((w^i)^T \varphi(x)\, a + b^i\right) \qquad (9)$$

VII. DEPTH ESTIMATION

- Skin Anatomy

The skin is the largest organ of the human body. Its primary roles are to protect the body from external pathogens and chemicals, and to maintain the integrity of internal systems, however it also reduces the penetration of UV radiation, regulates body temperature, enables the sense of touch and plays a role in vitamin D production.

The skin can be divided into 3 major layers: the epidermis, dermis and hypodermis (figure 2). This section focuses mainly on the epidermis for two reasons: it is the most visible region under both dermoscopy and naked-eye examination.

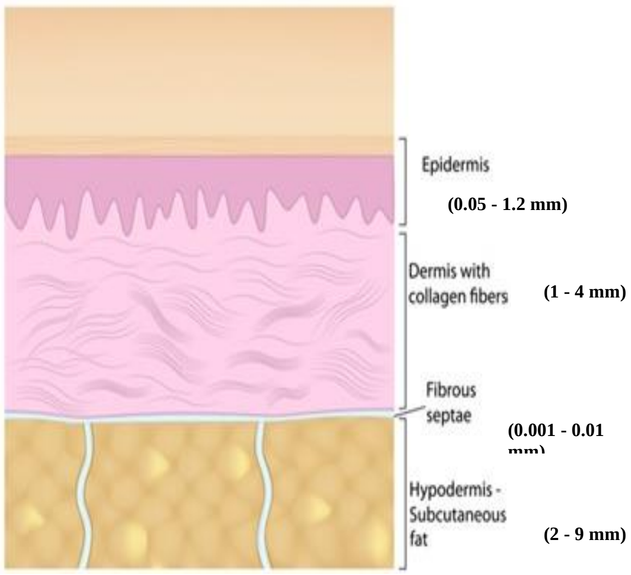

Figure 2. Cross section of a normal skin

The epidermis is the outermost layer of the skin, which consists predominantly of migrating keratinocyte cells. The epidermis is further subdivided into 4 regions, illustrated in figure 3; from the innermost outwards they are: the basal cell layer (stratum basale), the prickle cell layer (stratum spinosum), the granual cell layer (stratum granulosum) and the horny layer (stratum corneum). The epidermis is approximately 0.05mm thick, however it is considerably thicker in acral regions (palm and sole; 1.1mm) [1].

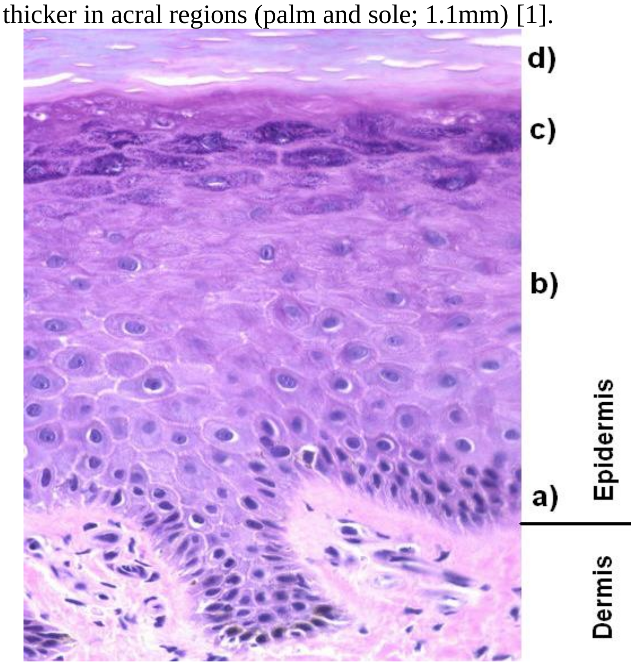

Figure 3. The layers of the epidermis. a) Stratum basale (basal cell layer), b) stratum spinosum (prickle cell layer), c) stratum granulosum (granual cell layer) d) stratum corneum (horny layer).

The dermis consists primarily of collagen and elastin. Collagen gives the skin its strength, while elastin imparts a degree of elasticity to the skin. The dermis ranges in thickness from 1mm on the eyelid to 3mm or more on the back, palms and soles.

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The connecting surface between the dermis and epidermis (known as the dermo-epidermal junction (Fibrous Septae) is not planar; rather the uppermost layer of the dermis consists of papillae which interconnect with corresponding rete ridges in the epidermis. The fibrous septae ranges in thickness from 0.001 - 0.01mm.

The hypodermis consists of loosely connected tissue and fat. It ranges in thickness from 2 - 9mm [1].

A panchromatic image is a 2D light intensity function, $f(x,y)$, where x and y are spatial coordinates and the value of f at (x,y) is proportional to the brightness of the scene at that point. The brightness values of different pixels have been created by using the energies recorded by the corresponding sensors. When the photon of a certain wavelength reaches the sensor from the scene, its energy is multiplied with the value of the sensitivity curve of the sensor at that wavelength and is accumulated. That is the total energy collected by the sensor is eventually used to compute the intensity value of the pixel that corresponds to the sensor. In other words, intensity value of a pixel is the energy at that scene. In our research, we have considered the intensity value, which is the energy of the pixel to determine the depth [2], [3].

By plotting the intensity values of each pixel (corresponding to the spatial coordinates x and y) in the z - axis, we are determining the depth of the scene in 3D.

VIII. RESULTS

- Data 1 :

The figure 4, shows the original image, which is corrupted with air bubbles and hairs on and around the wound. This original image was subjected to the proposed techniques.

Figure 4 : Original Image

A. Pre - Processing using Median Filter

Median Filtering was applied on the figure 4 to remove the air bubbles and hairs on and around the wound. The result of Median Filtering is shown in figure 5.

Figure 5 : Pre - Processed Image - Median Filtered

B. Segmentation using K- Means Clustering

The Pre- Processed Image (figure 5) was subjected to K - Means Clustering. The result of K - Means Clustering is shown in the figure 6. After Segmentation using K - Means Clustering, the wound is segmented from the background.

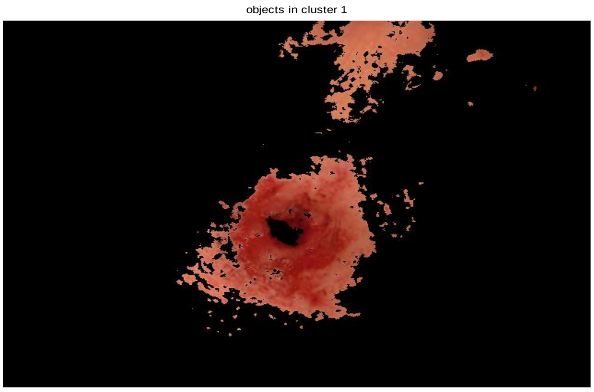

Figure 6 : Segmented Image

- Feature Extraction and *"One Against All"* SVM Classification

Transforming the input data into the set of features is called *feature extraction*. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input.

From figure 6, the Features such as - Mean, Standard Deviation, Smoothness and Entropy are extracted and are given as input to the *"One Against All" SVM* Classifier.

The *"One Against All" SVM* Classifier, classifies a data point under a certain class if and only if that class's SVM accepted it and all other classes' SVMs rejected it. While accurate for tightly clustered classes, this method leaves regions of the feature space undecided where more than one class accepts or all classes reject.

- Training Images

Image	μ	σ(x 10 $^{-3}$)	R	e
	0.0238	0.08836	7.80748 x 10 $^{-9}$	-1.1211
	0.0761	5.7912	3.35368 x 10 $^{-5}$	-2.2708

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	0.0220	0.484	2.34255 x 10 $^{-7}$	-2.7681
	0.0256	0.65536	4.29496 x 10 $^{-7}$	-0.9864
	0.0505	2.55025	6.50373 x 10 $^{-6}$	-1.8526

- Test Image

Image	μ	σ(x 10 $^{-3}$)	R	e	Result
	0.0561	2.43025	6.2001 x 10 $^{-6}$	-1.765	Slough

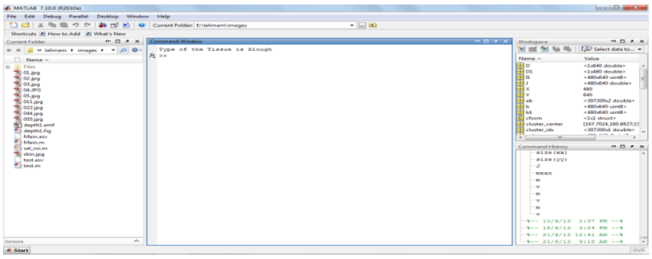

Figure 7 : Command window displaying the classification result

D.Depth Estimation

Depth of the wound is determined by projecting the 2D image (figure 6) on a 3D surface, where the z-axis corresponds to the intensity values.

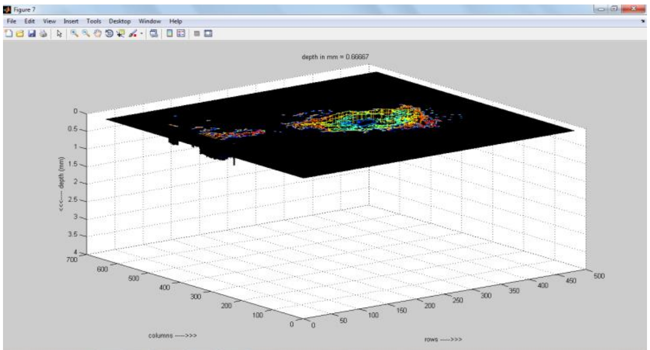

Figure 8 : 3D view the image

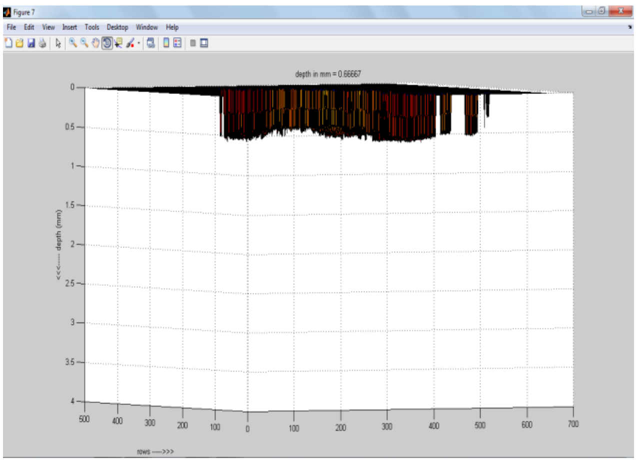

Figure 9 : Rotated - 3D view the image

- Data 2 :

The figure 10, shows the original image, which is corrupted with air bubbles and hairs on and around the wound. This original image was subjected to the proposed techniques.

Figure 10 : Original Image

A. Pre - Processing using Median Filter

Median Filtering was applied on the figure 10 to remove the air bubbles and hairs on and around the wound. The result of Median Filtering is shown in figure 11.

Figure 11 : Pre - Processed Image - Median Filtered

B. Segmentation using K- Means Clustering

The Pre- Processed Image (figure 11) was subjected to *K* - Means Clustering. The result of *K* - Means Clustering is shown in the figure 12. After Segmentation using *K* - Means Clustering, the wound is segmented from the background.

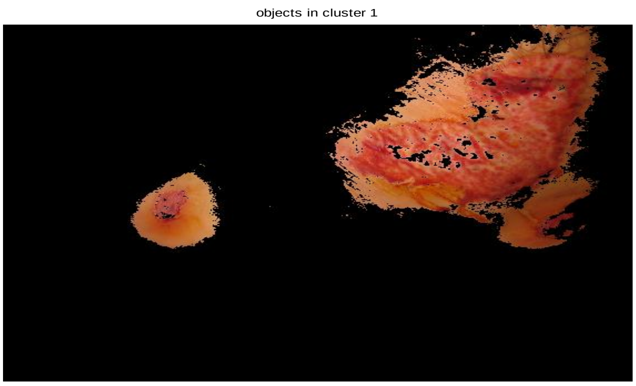

Figure 12 : Segmented Image

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C. Feature Extraction and "One Against All" SVM Classification

Transforming the input data into the set of features is called *feature extraction*. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input.

From figure 12, the Features such as - Mean, Standard Deviation, Smoothness and Entropy are extracted and are given as input to the *"One Against All" SVM* Classifier.

The *"One Against All" SVM* Classifier, classifies a data point under a certain class if and only if that class's SVM accepted it and all other classes' SVMs rejected it. While accurate for tightly clustered classes, this method leaves regions of the feature space undecided where more than one class accepts or all classes reject.

A. Training Images

Image	µ	σ(x 10^{-3})	R	e
	0.0238	0.08836	7.80748 x 10^{-9}	-1.1211
	0.0761	5.7912	3.35368 x 10^{-5}	-2.2708
	0.0220	0.484	2.34255 x 10^{-7}	-2.7681
	0.0256	0.65536	4.29496 x 10^{-7}	-0.9864
	0.0505	2.55025	6.50373 x 10^{-6}	-1.8526

B. Test Image

Image	µ	σ(x 10^{-3})	R	e	Result
	0.0665	5.5478	2.99368 x 10^{-5}	-2.1308	Granular

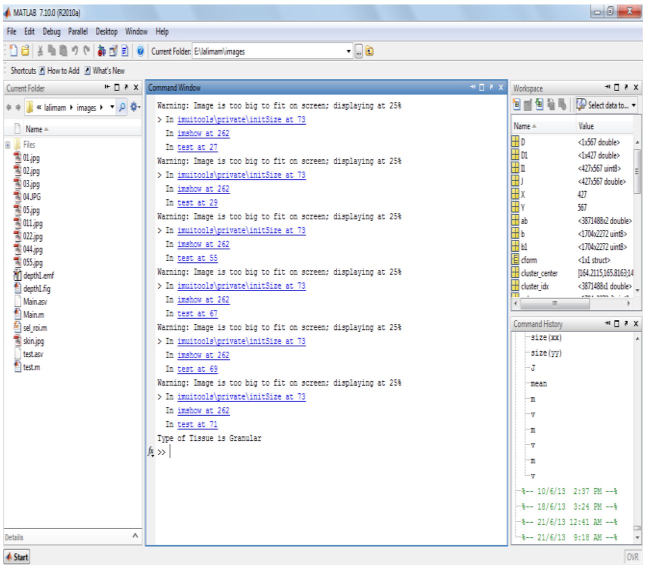

Figure 13 : Command window displaying the classification result

D. Depth Estimation

Depth of the wound is determined by projecting the 2D image (figure 12) on a 3D surface, where the z-axis corresponds to the intensity values.

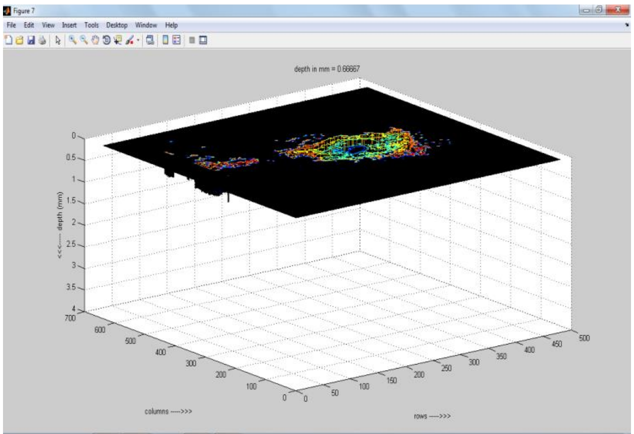

Figure 14 : 3D view the image

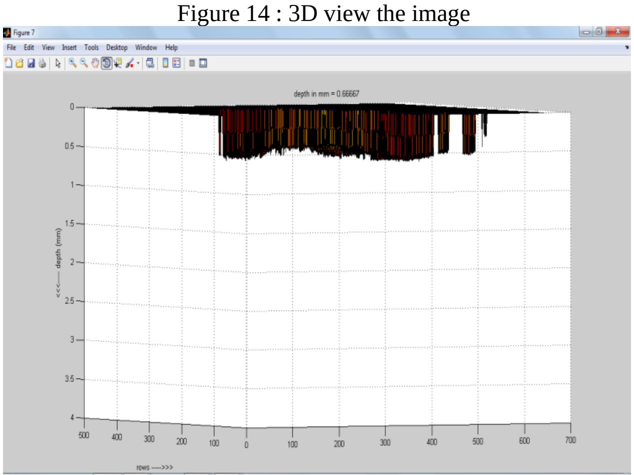

Figure 15 : Rotated - 3D view the image

- **Data 3 :**

The figure 16, shows the original image, which is corrupted with air bubbles and hairs on and around the wound. This original image was subjected to the proposed techniques.

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Figure 16 : Original Image

A. Pre - Processing using Median Filter

Median Filtering was applied on the figure 16 to remove the air bubbles and hairs on and around the wound. The result of Median Filtering is shown in figure 17.

Figure 17 : Pre - Processed Image - Median Filtered

B. Segmentation using K- Means Clustering

The Pre- Processed Image (figure 17) was subjected to *K* - Means Clustering. The result of *K* - Means Clustering is shown in the figure 18. After Segmentation using *K* - Means Clustering, the wound is segmented from the background.

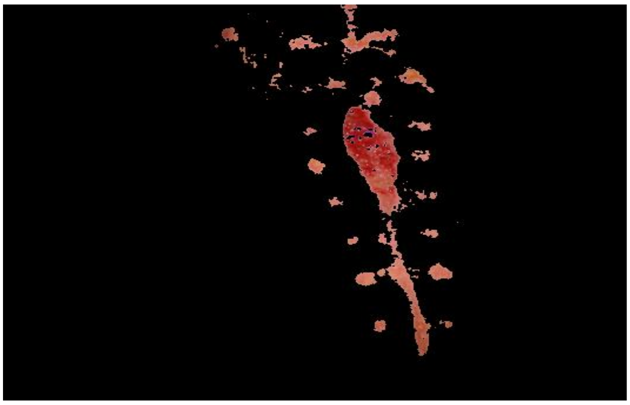

Figure 18 : Segmented Image

C. Feature Extraction and "One Against All" SVM Classification

Transforming the input data into the set of features is called *feature extraction*. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input.

From figure 18, the Features such as - Mean, Standard Deviation, Smoothness and Entropy are extracted and are given as input to the *"One Against All" SVM* Classifier.

The *"One Against All" SVM* Classifier, classifies a data point under a certain class if and only if that class's SVM accepted it and all other classes' SVMs rejected it. While accurate for tightly clustered classes, this method leaves regions of the feature space undecided where more than one class accepts or all classes reject.

- Training Images

Image	µ	$\sigma(x\ 10^{-3})$	R	e
	0.0238	0.08836	7.80748×10^{-9}	-1.1211
	0.0761	5.7912	3.35368×10^{-5}	-2.2708
	0.0220	0.484	2.34255×10^{-7}	-2.7681
	0.0256	0.65536	4.29496×10^{-7}	-0.9864
	0.0505	2.55025	6.50373×10^{-6}	-1.8526

- Test Image

Image	µ	$\sigma(x\ 10^{-3})$	R	e	Result
	0.0256	0.65536	4.29496×10^{-7}	-0.9864	Necrosis

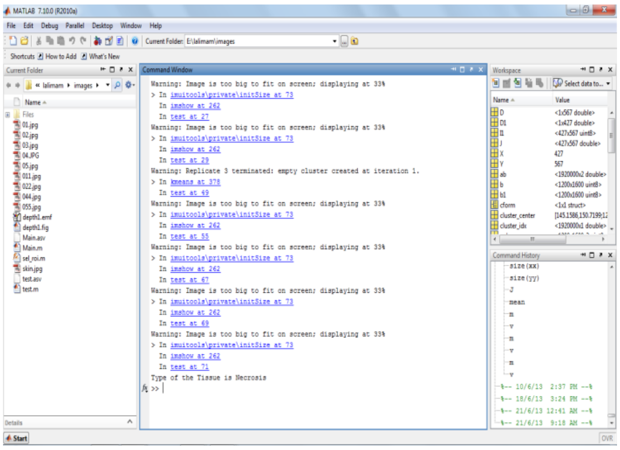

Figure 19 : Command window displaying the classification result

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D. Depth Estimation

Depth of the wound is determined by projecting the 2D image (figure 18) on a 3D surface, where the z-axis corresponds to the intensity values.

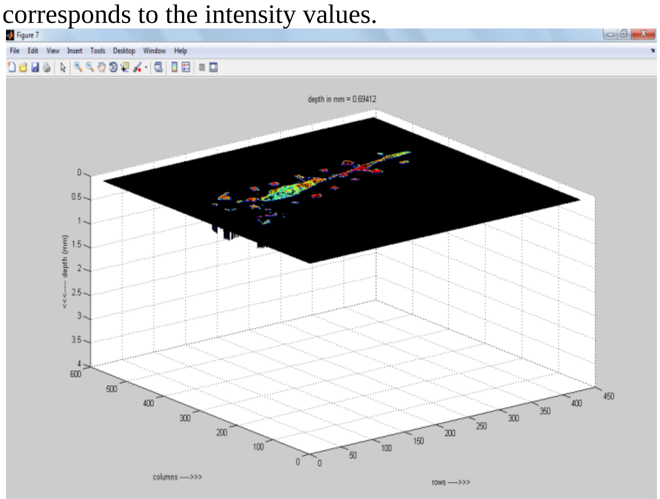

Figure 20 : 3D view the image

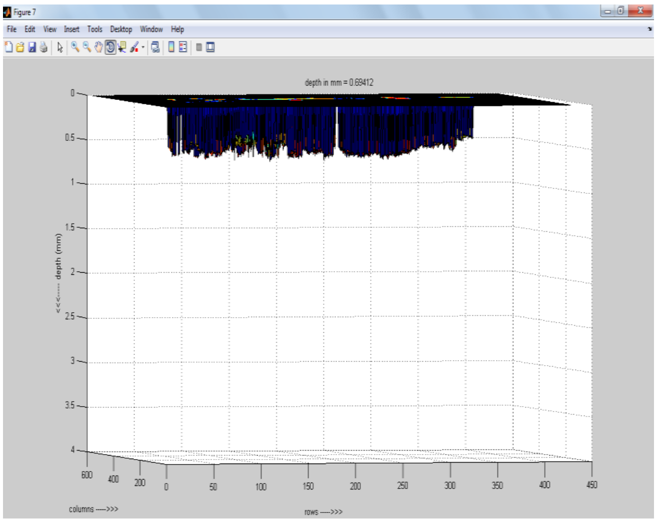

Figure 21 : Rotated - 3D view the image

IX. CONCLUSION

An optimal set of techniques for single view tissue classification and depth determination, have been discussed in this journal. Median Filtering proved to be good for the air bubbles and hairs removal on and around the wound and to enhance low contrast wound region. Using *K* - Means Clustering, the exact wound region is segmented from the skin and background. From the segmented image, features were extracted and subjected to *"One Against All"* SVM Classifier, which classifies the segmented image to type of the tissue in the wound. Finally depth of the wound was determined by projecting 2D image on a 3D surface. Future scope of this research can be extended to multi-view tissue classification and 3D modelling [9].

ACKNOWLEDGMENT

The authors would like to thank all the patients, who posed to the photographs, thus enabling to build the wound database. Also the Doctors, who acknowledged and guided us in our research,. Finally we thank our parents for their never ending blessings, love, guidance and support.

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K Sundeep Kumar received the M.Tech (IT) from Punjabi University in 2003, ME (CSE) from Anna University in 2009 and pursuing Ph. D (CSE) from JNTUA. He is with the department of Computer Science & Engineering and as an Associate Professor, CMR Institute of Technology, Bangalore. He presented more than 15 papers in International and national Conferences. His research interests include Image Processing, OOMD, Software Engineering and Data Warehousing. He is a life member in ISTE.

Lalitha Asokan received her - B.E (CSE) degree from Madras University and curremtly pursuing her MTech (CSE) Visveswaraya Technological University. Research interests are - Digital Image Processing, Data Mining,

Priyadarshini M.P. was born in Bengaluru, India. She received her - B.E (ECE) degree from University Visveswaraya College of Engineering, Bengaluru in 2009, M.Tech (DEC) from M.V.J College of Engineering, Bengaluru in 2011. Research interests are - Digital Signal Processing, Biomedical Signal and Image Processing, and Wireless Communication.

Dr. B.Eswara Reddy Graduated in B.Tech.(CSE) from Sri Krishna Devaraya University in 1995. He received Masters Degree in M.Tech.(Software Engineering), from JNT University, Hyderabad, in 1999. He received Ph.D in Computer Science & Engineering from JNT University, Hyderabad, in 2008. He served as Assistant Professor from 1996 to 2006. He is working as Professor in CSE Dept., since 2006 and currently acting as Head of CSE Dept. at JNTUACE, Anantapur. He has more than 30 Publications in various International Journals and Conferences. He is one of the author's of the text book titled Programming with Java published by Pearson/Sanguine Publishers. His research interests include Pattern Recognition& Image Analysis, Data Warehousing & Mining and Software Engineering. He is a life member of ISTE, IE, ISCA and member of CSI and IEEE.

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