

Chronic Wound Image Analysis by Particle Swarm Optimization Technique for Tele-Wound Network

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Abstract This paper presents an outline of methods that have been proposed for the analysis of chronic wound images. This paper indicates the details of four different ulcerous cases, provides good treatment policy, enhances quality of patient's life, improves evidence based clinical outcomes and suggests best possible issues. This paper investigates efficient filtering techniques for chronic wound image pre-processing under Tele-wound network. The aim of this work is to accurately access the healing status of chronic wound with improved image processing techniques by proper filtering. Efficient filtering techniques help to reduce the noise for wound images. The simulation results are presented by comparing different parameters. Performance parameters are peak signal to noise ratio (PSNR), mean square error (MSE), signal to noise ratio and mean absolute error. Results shows adaptive Median filtering provides better performances with respect to high PSNR and reduced MSE between original and filtered image. This work proposes the Particle Swarm Optimization (PSO) method for segmentation of wound areas via suitable color space selection. The PSO algorithm in D_b channel provided good accuracy (98.93%) for chronic wound segmentation. Here proposed Linier discriminant analysis classifier provides 98% overall tissue prediction accuracy. The aim is to develop telemedicine framework for wound diagnosis by improving good interaction between health experts, patients, and tele-medical agents who belongs to rural/urban areas that are involved in the provision of care to resolve the delayed treatment.

Keywords Chronic wound images · Wound dressing · Wound measuring devices · Particle Swarm Optimization · Image processing · Tele-wound network

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1 Introduction

Chronic wound (CW) healing, a most challenging clinical issue and accurate, efficient wound management approach is required. The proper wound management is essential with the help of new therapeutic methods and the development of technologies. Management and monitoring of CWs are becoming a big challenge in medical health care globally. Elderly people (over 60 years) are more prone to sufferings due to CWs. There are limited accessing facilities to modern technology for managing the CWs. According to clinical experience, high quality regular care especially through patients and self management is necessary for accelerating wound healing. The healing process is very slow and it may be further delayed if an ineffective treatment is used. The crisis of CWs is identified by other factors viz. poor access to health care facility and infrastructure, low literacy rates, and insufficient clinical manpower. Also inadequate education and clinical training in the basics of wound care majorly magnify the problem in India. The 5–7 million chronic wounds occur each year in North America. An occurrence of patients with a wound was 3.55 per 1000 population in UK. The popularity of wounds were surgical/trauma (48%), leg/foot (28%), and pressure ulcers (PU) (21%). Prevalence of wounds among hospital inpatients was 30.7% [1]. In United States, healing cost of a unique PU can be as much as \$50 billion and CWs affect around 6.4 million patients annually. The United Nations-2009 report showed that it affects more than 2 billion European populations and the related cost of treatment is about 8 billion Euros per year. In 2012, there was 24 million people faced CWs problem worldwide. Also it is anticipated that worldwide 380 million people will suffer from this highly branded disease by the year 2025 [2]. In fact, the annual wound care management products market was valued \$13 billion in 2008 and \$15.3 billion in 2010 and also this is projected to reach \$17 billion by 2015. The treating foot ulcers cost is estimated around \$5 billion annually [3]. Table 1 depicts the ulcer costs.

Currently clinician relies on spatial measurements techniques viz. manual approaches of ruler-based method, transparency tracing, sketches, alginate moldings, and also visual color (Black—necrotic, Yellow—slough, and Red—granulation) grading techniques have been applied for different clinical wound assessment [8]. The healing status is crucial and

Table 1 Financial costs of pressure ulcers

Incidence (over 60 years)	Financial costs	Country
PU [4]	Mean cost per home care (€ 22.31) for advanced dressings and (€16.03) for simple dressings	Europe
	Mean total cost \$15.90 for advanced dressings and \$25.31 for simples one per day	US
	Mean total cost \$13.60 for advanced dressings and \$10.78 for simples one per day	Italy
PU [5]	Average hospital treatment cost is \$129,248 for hospital-acquired ulcers (single admission), \$124,327 for community-acquired ulcers (average of 4 admissions)	US
PU [6]	\$9.1–\$11.6 billion annually	US
	Cost of treating from \$2000 to \$20,000 per ulcer	
PU [7]	Cost of treating from £1064 to £10,551	UK

dynamic process; it changes the patient's health status. The stages of wound healing are as follows: hemostasis, inflammation, proliferation and maturation or remodeling respectively [9]. The predictive tools viz. Norton scale [10], Gosnell scale [11], Braden scale [12] and Pressure sore status tool [13] is used for visual observation and other medical information from clinicians, to monitor the likelihood of a non healing wound. The presently used conventional wound management techniques have various limitations in terms of reliability, subjectivity, reproducibility, and quantitative analysis; it can be overcome by use of computer aided wound diagnostic tool. This automated tool is provide the proper screening, robust diagnosis, and wound data management in a short time. Tele-wound network system provides effective remote treatments and the decrease the number of in-person visits required providing wound care for the patients. This photographic technique is lead to improved wound diagnosis, measurement and/or management through tele-medicine because patient's getting good treatment modality at home. A holistic approach in remote wound care helps to improve a patient's quality of life, manage symptoms and offer treatment of wounds and conditions. The aim is to provide better healthcare service to any place wherever and whenever required. This system offers reliable and efficient diagnostic aids to patients at affordable cost. It allows new technologies in sensing, medical imaging and wireless data communications with much lower cost, enabling the development of new widespread remote medicine initiatives. An optical imaging system is used for capturing wound images of a patient.

The different methodologies are required for analyzing the wound images i.e. pre-processing, segmentation, feature extraction, and classification using computer [14]. Accurate and faster wound image analysis is possible using digital image processing rather than error-prone manual observation. The wound analysis should include calculation of wound area and color distribution within the infected portion of the wound. The area of wound is measured based on total number of pixels in the region multiplied by suitable scaling factor. Exactly wound area identification is impossible by manual observation. So there is an urgent requirement of developing a computer added wound characterization and diagnostic tool for monitoring the healing process accurately and or precisely. Chakraborty et al. [15] developed smartphone based wound assessment solution that provides accurate and convenient wound measurement and documentation at the point-of-care for different ulcers. This paper is a review of typical CWs, their common attributes, the current best treatment policy, potential means for decreasing health costs and enhancing patient quality of life, suggested methods for low-tech, equipment-based telemedicine for remote treatment. Table 2 depicts the existing various segmentation techniques respectively. The

Table 2 Existing chronic wound image segmentation methodology

Literature survey	Region of interest	Segmentation techniques
Berriss et al. [16]	Wound area	Color histogram clustering
Hankan et al. [17]	Wound area	Adaptive spline based
Jones et al. [18]	Leg ulcer area	Active contour
Duckworth et al. [19]	Wound area	Iterative edge detection
Perez et al. [20]	Wound tissue	Region growing
Aslantas et al. [21]	Wound area	Differential evolution based clustering
Chakraborty et al. [22]	Wound area	K-means, Fuzzy C-means

clinical expert can take the proper diagnosis depending on percentage of tissue. Several features like morphological, texture, topological, and color descriptors can contribute to perform automatic wound classification.

The remaining of this paper is organized as follows: Sect. 2 explains the types of chronic wounds. Section 3 explains the data collection methods and Sect. 4 explain the wound image management process. Section 4 provides the experimental results.

2 Types of Wounds and Their Features

Chronic wounds can be broadly classified in four type's viz. diabetic ulcer (DU), pressure ulcer (PU), venous ulcer (VU) and ischemic or arterial ulcer (IU) respectively that shown in Fig. 1. The wound tissue can be classified as three categories viz. granulation, slough and necrosis. The clinicians are generally used RYB color coding scheme for classifying the different wound tissue [23] and digital image commonly represented as red–green–blue (RGB) color. The different ulcer types have described: (a) DU—are the most rigorous type of CWs that hamper the patient's quality of life like advance age, living alone, delayed treatment, high costs, depressed people and reduced mobility. Sheehan et al. [24] proposed multicenter trial method to monitor the fast healing rate for diabetic patients. (b) PU—is occurs in people with paralysis conditions. The most of the clinicians treat few Pus and very few good research articles are there in this dimension, none for most treatments. So treatment modalities have to be improved with safety and efficiency. The clinical features of this ulcer depend on several parameters viz. size and depth, color and necrotic tissue. Sanada et al. [25] proposed a tool for classifying the PU and monitoring the healing rate with the help of manual data entry. The some useful tools have been developed for measuring the healing progress viz. Bates-Jensen wound assessment tool (BWAT) [26], Pressure sore status tool (PSST) [27], Pressure ulcer score of healing (PUSH) [28], Sessing scale [29], Wound healing scale (WHS) [30], DESIGN tool [31], CODED scale [32], Photographic wound assessment tool (PWAT) [33] and Sussman wound [34] respectively. The subsequent steps are involved in PU such as (a) debridment, (b) topical wound care, (c) treatment of infection, (d) control of CW contamination and (e) positioning [35]. PU takes more time to heal compared to DU. (c) VU—is the most common type, mostly affected in women. The preliminary risk factors are older age, obesity, deep venous thrombosis, phlebitis and leg injuries [36]. The prevalence of this ulcer in the US is approximately 6 lakhs annually [37]. The yearly budget of treating VUs to the US health care system is expected at \$2.5–\$3.5 billion [38]. Johnson [39] measured the key factors for VUs using

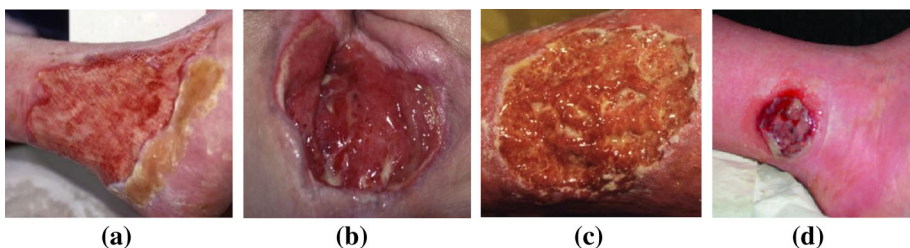


Fig. 1 Different chronic wound images **a** DU, **b** PU, **c** VU, **d** AU [42]

hierarchical multiple regression analysis, pain and mobility. This type of ulcers often takes a long time to heal. The skin colour reflectance analyzer is used to determine the levels of granulation tissue [40]. (d) IU—is usually round with a stridently demarcated boundary. It happens commonly wound with no oxygen. The causes of IUs are as follows: restrictions to blood vessels due to peripheral vascular disease, chronic vascular insufficiency, inflammatory damage of blood vessels, diabetes mellitus, renal failure, high blood pressure, arteriosclerosis, atherosclerosis, trauma, and surrounding skin may be hairless, shiny, limited joint mobility and increased age respectively. The features of different wounds have been discussed in Table 3. The various wound measurement devices viz. Measurement of Area and Volume Instrument System (MAVIS), Stereophotogrammetry (SPG), Wound measurement device (WMD), ARANZ Medical Silhouette, Advanced Wound Assessment and measurement System (AWAMS), Medical Digital Photogrammetric System (MEDPHOS), DERMA device, Verge Videometer (VeV), Stereophotogrammetry (SPG), Compression therapy device can be used to measure area and volume of skin wounds [41].

Table 3 Features of different chronic wounds

Ulcer type	Body part most affected	Types of wound	Color of wounds	Nature of pain	Risk factor	Available solution
DU	Feet, under heel, kidneys, heart and eyes	Open (deep wound)	Red, pink (granular tissue)	Painless	Yes (advanced age)	Dressings, glucose, medication super-oxidized solution therapy [43]
PU	Elbow, heels, hips, ankles, shoulders, back and back of the head	Open (deep wound)	Red, pink, purple	Painful, firm, soft	Yes	Cleanse using irrigation, bed sores, medication
VU	Legs, ankle, on malleolar area	Open (superficial wound)	Red, brown (granular tissue)	Moderate, aching, tightness, heaviness	Yes (advanced age)	Compression therapy, local wound care (including debridement), dressings, topical antibiotics for infected wounds, pharmacologic agents, surgery, adjunctive therapy [44]
IU	Tips of toes, outer ankle, calf and foot, over phalangeal heads	Open (deep, Pale wound)	Yellow, Grey, brown, black (blanched tissue)	Typically painful	Yes	Adjunctive systemic hyperbaric oxygen therapy, medication

2.1 Different Mechanism for Wounds Dressing

The chronic wounds do not heal properly due to inadequate wound care facility in rural areas. The dressings or surgical debridement is required to remove all dead tissues overlying the wound for promoting healing. The simple wound dressing classification with guidelines has been introduced [45], these different methods can be used to increase the healing viz. (a) Gauzes—it is very much effective for deep wounds treating and also eliminate dead space, (b) Films—primary method, comfortable, and transparent; wounds can be visualized without having to remove dressing, (c) Hydrogels—it is used to maintain a moist wound healing environment, it can be applied and removed with minimal pain, (d) Hydrocolloids—it helps to maintain a moist healing [46], and provides good performance over wounds with low to moderate amounts of exudates, and decrease costs, (e) Alginates—highly absorbent on wounds with moderate to heavy levels of exudates [47], (f) Foams—moderately absorbent used light to moderately draining wounds, (g) Collagens—helps to maintain wound moisture, (h) Antimicrobials—employed to reduce the wound bio-burden, (k) Bead dressing—it is used to maintain position of the wound affected portion. The wound assessing features have been discussed that is used to optimize the healing with effective wound bed preparation using appropriate dressing mechanism.

3 Wound Image Sample Collection

The wound images could be taken from primary and secondary sources. The high featured smartphones viz. Xolo, Apple, Nokia, Samsung Galaxy Tab, Windows Phone, BlackBerry, iOS, Canon, Adobe, and Android would be very much useful for sensing, acquiring the variety of medical data and monitoring applications. Smartphone is used in telemedicine with inbuilt high-resolution camera, capture wound images, computing, and networking features allow direct interaction. The wound images were also acquired from webcam-laptop, personal digital assistant and simple handheld digital camera. The wound image acquisition has done in non-ideal daylight light condition in outpatient department (OPD) with no flash; because of this images with light intensity variations were obtained. The wound images can be taken from MEDLINE, Cochrane, Medetec based standard online medical database and clinics.

4 Wound Image Analysis Process

The technical issues of wound imaging and image processing are discussing briefly in this section. Correct clinical diagnose may positively enhance the wound healing rate and reduce the potential complications. TWN system is used to processing and monitoring the wound images efficiently in remote location where specialists' services are not readily available. TWN system consists of acquisition of clinical data, processing to tele-medical hub (TMH) and providing doctor's feedback. The portable smartphone can be used to capture high-resolution red-green-blue (RGB) wound images and acquire patient's demographic information and send it to the TMH [48] through wireless platform. The wound image can be processed through the pre-processing, segmentation, feature

extraction and classification stages for finding the healing status. The automated wound healing stages are shown in Fig. 2.

4.1 Wound Image Pre-processing Technique

The pre-processing technique can be implemented to improve the efficiency in terms of image quality using color correction, noise filtering, and color homogenization methods that shown in Fig. 3. Color is the main clue for the visual assessment of wound tissue, but it can be distorted by image acquisition due to improper lighting condition. Often wound images are filled with improper color casts resulting object represents untrue color. The wound image quality can be enhanced at pre-processing stage by filtering techniques. The healing process is totally depended on time i.e. may be required lengthy and several appointments with a clinician. The wound image is smoothed by an adaptive median filtering for noise reduction by providing well-defined and continuous edge information.

4.2 De-noising filters

The camera images mostly suffer from independent impulse noise that can be introduced on a wound image may be salt and pepper or random-valued impulse noise. The best filtering technique is required to remove the noises for better quality of image.

The image denoising is a significant medical imaging task that is able to remove noise while preserving edges. In this paper, different filters have been considered and a comparative study is presented below:

These important filters are as follows: (a) Mean filter, (b) Gaussian filter, (c) Median filter, and (d) adaptive Median filter respectively. The quality measure step is shown in Fig. 4. The $f(x, y)$ is represented as filtered image and $g(s, t)$ is the original corrupted image.

- (a) *Mean filter*—This filter is belongs to linear filtering scheme. This filtering is used to smoothing the images, mainly reducing the intensity variation between pixels. It is useful for removing Gaussian noise but preserving criteria is poor. The statistical model of the noise is shown in below.

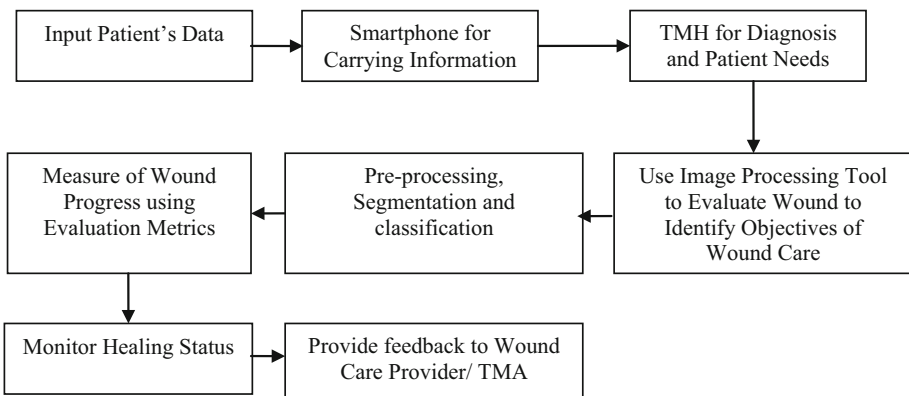


Fig. 2 Automated chronic wound healing steps under Tele-wound network

Fig. 3 Schematic diagram for wound image processing

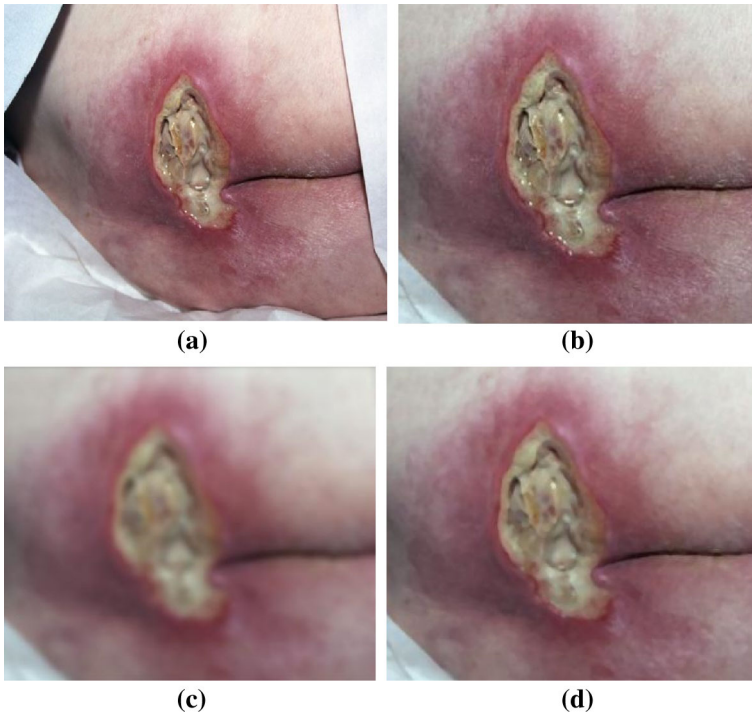
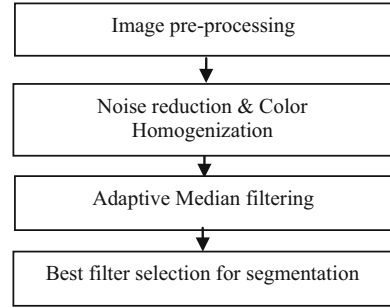


Fig. 4 **a** Original wound image, **b** image after color correction, **c** image after Anisotropic diffusion filtering and **d** image after adaptive Median filtering

$$p(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad (1)$$

$$\text{Meanfilter}(x_1 \dots x_N) = \frac{1}{N} \sum_{i=1}^N x_i \quad (2)$$

where, $x_1 \dots x_N$ is the pixel range of image.

- (b) *Gaussian filter*—This filter is responsible for corrects the spectral coefficient and amplitude spectrum coefficients within filter window.

- (c) *Median filter*—The Median filter is used in pre-processing stage for providing the image color identification. The bright white spot arises on the wound image due to reflection. Median filter (5×5) is employed to eliminate the salt-and-pepper noise in wound images. The median filter can smooth noisy regions, enhance the low-contrast wound region and better preserve the structure of the edges. The average of two middle pixel values is taken when the neighborhood under consideration contains an even number of pixels. The Median filter is represented as:

$$\text{Median filter}(x_1 \dots x_N) = \text{Median} [|\!|x_1|\!|^2 \dots |\!|x_N|\!|^2] \quad (3)$$

Hence, the median filter is much superior at preserving sharp edges than mean filter.

- (d) *Adaptive Median Filter*—Adaptive median filter performs spatial processing to find out which pixels in a wound image have been affected by random noise. This filter classifies pixels as noise by comparing every pixel in the image to its surrounding neighbor pixels. The noise pixels are replaced by median pixel value in the neighborhood. It removes impulse noise, smoothing other noise and reduces distortion along the edges.

4.3 Color Homogenization

Chronic wounds are having complex mixture of colored tissues with varied intensity. Anisotropic diffusion filtering is used for homogenization of color along with preservation of edges, only smoothing between edges. The objective of this method is to reduce image noise without eliminating significant portion of the image.

4.4 Wound Image Segmentation Technique

There are various segmentation and classification techniques have been used in wound image analysis. The aim of the segmentation technique is to distinguish all the objects in the image to region of interest/ background. The pre-processed wound image is processed to segmentation stages after proper color space selection.

4.5 Particle Swarm Optimization (PSO)

PSO segmentation algorithm is used independently as a clustering to find the best cluster centers. This is a stochastic global optimization algorithm which based on swarm intelligence [49]. PSO method has been applied to solve the thresholding problem based segmentation. PSO is an efficient scheme that provides large search space and faster convergence rate. The wound image has been partitioned into multiple objects on the basis of one or more threshold values. Threshold values have been selected from intensity profile of the image that varies from 0 to 255. All particles are initialized and number of particles selected randomly. All particles are changing their velocities and positions also find out the global best in current time that present in Eqs. (4) and (5) [50].

$$V_i^{t+1} = V_i^t + K_1 \times \text{rand}() \times (P_i - X_i^t) + K_2 \times \text{rand}() \times (G^t - X_i^t) \quad (4)$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (5)$$

where V_i^t and X_i^t represents the velocity and i th particle position in i th iteration. P_i and G^t are the $pBest$ of i th particle and $gBest$ i th iteration. K_1 and K_2 presents the speed factors. $rand()$ is the random function in the interval $[0,1]$. The PSO algorithm is summarized in Fig. 5.

5 Simulation Results

The wounded portion can be captured using smartphone by tele-medical agents and transfer it to tele-medical hub for getting better consultation from experts. The patient's clinical information stored in database and wound image enters to image processing toolbox for pre-processing, segmentation, classification and provides percentages of wound tissues. The smartphone enabled tele-wound network systems are helping patients by preventing and treatment different types of healthcare interventions, changing user behaviors, enhancing communication between patients and TMHs. The outcomes of the four different filters are presented here. Most of them use mathematical morphology operations. 5×5 square structuring elements were used. These filters were applied on set of twenty nine randomly selected wound images from our developed wound database as well as an online wound image database. In order to access the quality of image, four different quantitative performance measures are defined as mean square error, peak signal to noise ratio, signal to noise ratio, mean absolute error.

Mean square error (MSE)—It is basically squared error between enhanced image and original CW image. Lower value of MSE indicates that there is very small change between original and filtered image. Mathematically, it is defined as:

$$MSE = \frac{1}{M \times N} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} [F(x,y) - F_{fltr}(x,y)]^2 \quad (6)$$

where $F(x,y)$ and $F_{fltr}(x,y)$ are the input and filtered output wound images.

Peak signal to noise ratio (PSNR)—It is used to estimate the ratio between maximum possible intensity value of the image and MSE. PSNR is defined as:

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Input color chronic wound image
Convert wound image to grayscale
Do (5×5) median filter (pre-processing)
Initialize each particle to contain k threshold values randomly
Repeat until number of iterations has been satisfied
For each object i:
Threshold the target image into regions using the threshold values of particle i
Evaluate the fitness of particle I using Q function
Search global best solution among all particles
Segment unlabeled pixels of the best solution
Merge small regions
Update particle position
End

```

Fig. 5 The algorithm of PSO

$$PSNR = 10 \log_{10} \left[\frac{R^2}{\frac{1}{M \times N} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} [F(x, y) - F_{fltr}(x, y)]^2} \right] \tag{7}$$

here, R is the maximum possible peak intensity value of the image.

Signal to noise ratio (SNR)—It is the ratio between enhanced image and noise in the spatial domain.

$$SNR = \left[\frac{\sum_{x=0}^{M-1} \sum_{y=0}^{N-1} [F_{fltr}(x, y)]^2}{\sum_{x=0}^{M-1} \sum_{y=0}^{N-1} [F(x, y) - F_{fltr}(x, y)]^2} \right] \tag{8}$$

Mean absolute error (MAE)—It is used to compute how close predictions are to the eventual outcomes. The MAE is given by

$$MAE = \frac{1}{n} \sum_{i=1}^n |f_i - y_i| = \frac{1}{n} \sum_{i=1}^n |e_i| \tag{9}$$

where MAE is an average of the absolute errors, $e_i = |f_i - y_i|$, f_i is the prediction and y_i is the true value, n is the number of observations.

The four important parameters have been analyzed for the quality of images. On the other hands, higher value of PSNR, SNR reports that there is very small change. From Figs. 6, 7, 8 and 9, we observe that adaptive median filter is the best choice for visualization because it provides good PSNR (64.67), SNR (59.51), MAE (0.21) and MSE (1.79). This filtering technique improves the segmentation performance with the maintaining proper homogeneity of the image. The adaptive median filtering provides better visualization after observing the all filtered image results.

The proposed PSO algorithm has been tested successfully on different wound images. Chronic wound image (560 × 433) has been considered that preprocessed by gray-scale and retinex approach for color correction. Then adaptive median filtering and anisotropic diffusion were used for noise reduction and color homogenization respectively. Here different color spaces were compared based on mean contrast between wound and non-wound regions where D_r and D_b chrominance channels of YD_bD_r color space were found to provide the highest contrast. PSO method is computationally efficient and takes less than 10 s per wound image (560 × 433) in size. PSO algorithm provides good optimization outcome than traditional methods. Then the wound regions were segmented using PSO

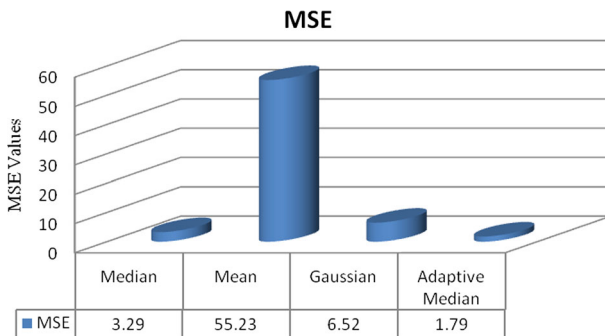


Fig. 6 Mean squire error parameter measurement with image quality

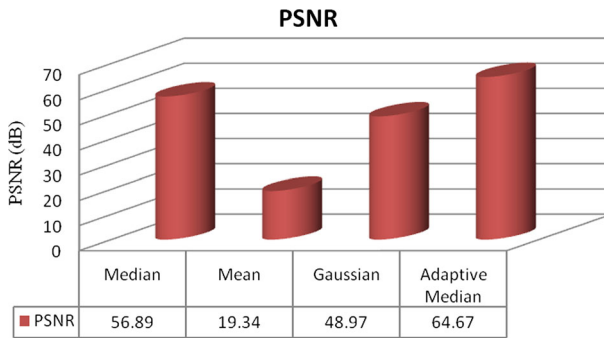


Fig. 7 Peak signal to noise ratio parameter measurement with image quality

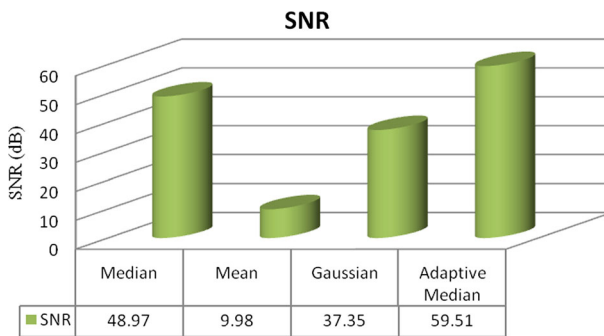


Fig. 8 Signal to noise ratio parameter measurement with image quality

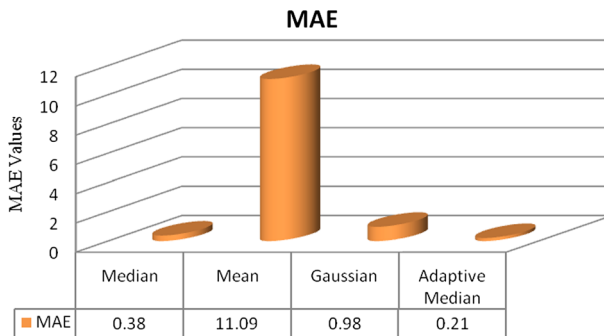


Fig. 9 Mean absolute error parameter measurement with image quality

method on D_r and D_b color channels. The PSO algorithm gives better segmented accuracy (98.93%), sensitivity (99.32%) in D_b channel i.e. compared to D_r channel where segmented accuracy (96.63%) and sensitivity (98.74%). False positive rate is defined as the ratio of incorrectly identified image over sum of incorrectly identified and correctly rejected image. It will be significantly reduced if the data used are highly sensitivity that shown in Table 4. False negative rate is defined as the ratio of incorrectly rejected wound image over summation of correctly identified and incorrectly rejected image.

Table 4 Segmentation results using PSO over D_b and D_r channels

Channels	Segmentation accuracy	False positive rate	False negative rate	Sensitivity
D_r	96.63	4.01	1.68	98.74
D_b	98.93	9.38	3.26	99.32

Also the Linear discriminant analysis (LDA) classification method is used to distinguish the wound tissues in granulation, slough, and necrotic tissue by making use of extracted features. This method uses statistical analysis of the features and robust classification techniques to reach a decision. A set of feature vectors goes to classifier, whereas outcome is estimated class value.

Chronic wound tissue is quantified using LDA classifier where three color features are considered. The distinct non-overlapping feature distribution have been observed. Figure 10 provides the percentage wise slough tissue (93.93%), granulation tissue (3.39%) and necrotic tissue (2.66%) respectively.

$$\begin{aligned} \text{Percentage of granulation tissue} &= [\text{granulation}/(\text{granulation} + \text{necrotic} + \text{slough})] \\ &= 436/(436 + 343 + 12,077) = 3.39\% \end{aligned}$$

$$\begin{aligned} \text{Percentage of necrotic tissue} &= [\text{necrotic}/(\text{granulation} + \text{necrotic} + \text{slough})] \\ &= 343/(436 + 343 + 12,077) = 2.66\% \end{aligned}$$

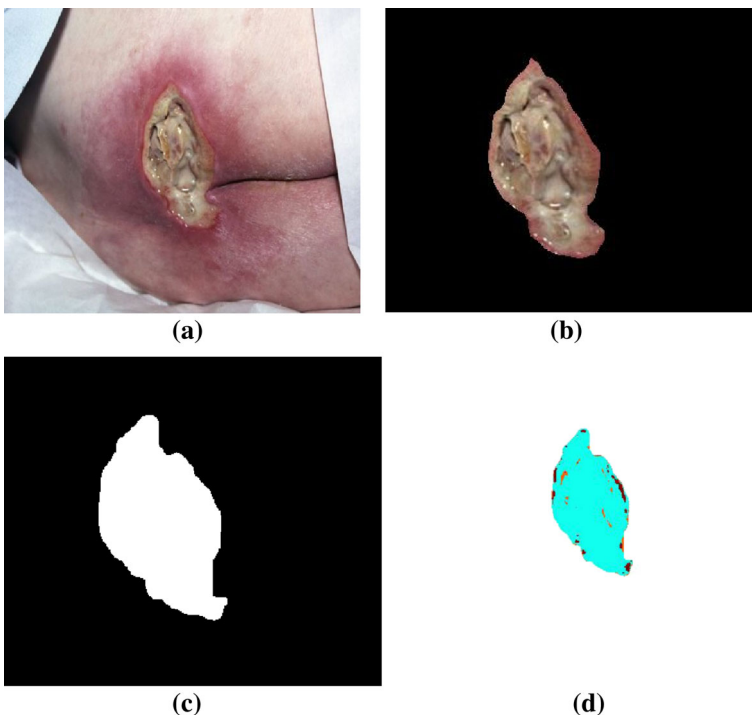
**Fig. 10** **a** Original wound image, **b** ground truth image, **c** segmented image and **d** percentage of tissue

Table 5 Confusion matrix for tissue-wise classification

239,090	428	3089
7	16,349	249
115	3473	116,483

The tissue classification accuracy can be measured as:

$$\text{Granulation} = 239090 / (239090 + 428 + 3089) = 98.55$$

$$\text{Necrotic} = 16349 / (16349 + 7 + 249) = 98.45$$

$$\text{Slough} = 116483 / (116483 + 3473 + 115) = 97.01$$

Table 6 Wound tissue-wise classification and overall accuracies

Methods	Granulation (%)	Necrotic (%)	Slough (%)	Overall accuracy (%)
LDA	98.55	98.45	97.01	98

$$\begin{aligned} \text{Percentage of slough tissue} &= [\text{slough}/(\text{granulation} + \text{necrotic} + \text{slough})] \\ &= 12,077/(436 + 343 + 12,077) = 93.93\% \end{aligned}$$

A confusion matrix is applied to describe the performance of a LDA classifier over a set of test data for which the true values are known. The three different tissue wise results are presented in Table 5 using confusion matrix. The LDA algorithm provide 98% overall classification accuracy whereas the individual tissue wise accuracy for granulation tissue is 98.55%, slough tissue is 97.01% and necrotic tissue are 98.45% that shown in Table 6. This automated wound classification system is more precise and accurate than manual measurements. The expert clinician gives better clinical outcome based on this accurate tissue-wise information.

6 Conclusion

Chronic wound treatment by large is a burden to the government and society due to its high cost and time consuming treatment. It becomes more serious with the old age patient with the lack of moving flexibility. Cost involvement is also increasing day by day for the wound treatment. Proper wound recovery management tool is needed to resolve this problem. Careful and accurate documentation is required for indentifying the patient's improvement and or deterioration timely for early diagnostic purposes. Here, we have discussed various types of chronic wounds in terms of most affected part of the body, type, color, nature of pain, risk factor and finally available solution. We have also reviewed the devices available for wound treatment along with their main features, limitations, and cost involvement. The different filtering techniques have been compared for chronic wound analysis under tele-wound network. It is observed that adaptive median filter performs well for noise removal out of others filters with respect to different performance parameter viz. peak signal to noise ratio, mean absolute error, signal to noise ratio, and mean squire error. Results shows adaptive Median filtering provides better performances with respect to high peak signal to noise ratio and reduced mean squire error between original and filtered image. The outcome obtained manifests a system has greater scope of utilization in the field of evaluation through tele-wound network. This paper represents that PSO based

segmentation algorithm and LDA classifier provides good accuracy. In 2017 year, market for med-care treatment will be growing 60 millions dollars. Chronic wound care provided through telemedicine will further support the growth of med-market but reducing the treatment cost. The accuracy and efficiency in wound diagnosis will be increase.

Compliance with Ethical Standards

Conflict of interest The author declares that there is no conflict of interests regarding the publication of this paper.

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