Augmented Reality-Based Chronic Wound Healing Assessment Using 3D Stereoscopic Imaging and Self-Organizing Maps

Bhuneshwari Dewangan [1*], Mahendra Kumar Sahu [1]

Abstract

Background: Chronic wounds (CW) present significant public health challenges, impacting individuals' well-being and daily activities. Traditional wound measurement methods, such as the ruler technique, are time-consuming, imprecise, and pose infection risks. Advances in wound care technology, including artificial intelligence (AI) and augmented reality (AR), have improved wound healing (WH) assessment accuracy and enhanced clinician-patient communication. Methods: This study developed a novel CW evaluation device combining AR and a stereoscopic camera system. The device captures images using two Leopard Imaging LI-OV580 stereo cameras and a pico-projector to create a 3D wound model. The system calculates the wound area by processing stereoscopic images, utilizing structured-from-motion techniques and convolutional neural networks (CNNs). Additionally, the device measures epipolar and projection errors (PE) during AR-based wound evaluation. A Self-Organizing Map (SOM) was employed to refine the 3D reconstruction of the wound. Results: The AR-PE analysis demonstrated the device's accuracy, with the lowest PE recorded at 20 cm from the wound area. The projection error increased as the measurement distance moved toward the edges of the wound. The average epipolar error (EE) was 0.46 pixels, indicating high precision in stereoscopic measurements. Conclusion: The study introduced a non-invasive CW evaluation device that improves wound assessment accuracy and clinician-patient interaction. By utilizing 3D wound modeling and AR, the system enables more effective communication and progress tracking during WH. The results suggest this technology could enhance CW management, offering a reliable alternative to traditional methods.

Keywords: Chronic wound healing (CWH), 3D stereoscopic imaging, Augmented Reality (AR), Wound segmentation, Self-organizing maps (SOM)

Significance | This study presents a novel AR-based approach for accurate, non-invasive chronic wound evaluation, enhancing clinician-patient communication and care.

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1. Introduction

Chronic wounds (CW) have a significant global public health issue, affecting individuals' well-being and daily functioning, imposing financial burdens, and even leading to mortality. The skin's protective barrier is compromised when a wound occurs, increasing the likelihood of infection. Wounds are classified as either acute or chronic based on their healing time. Acute wounds heal within four weeks, following the normal stages of healing. However, if a wound does not heal within four weeks, it is considered chronic or non-healing. Various factors can disrupt the normal wound healing (WH) process, especially in individuals with underlying health conditions such as diabetes or obesity, leading to increased healthcare costs. Managing CW requires more frequent medical

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supervision compared to acute wounds, as regular assessment is crucial to ensure healing progress. Effective wound treatment involves adherence to proper steps to expedite healing and reduce complications.

Wound measurement tools play an essential role in aiding healthcare professionals to track and create treatment plans. These tools help delineate wound edges and measure tissue areas, such as granulation tissue, necrotic regions, and epithelialized zones, providing critical insights into WH progression. The conventional method uses a ruler and cotton swab to measure wound depth, width, and length. Despite its simplicity, this method is time-consuming and often inaccurate, with risks of infection during the procedure.

In wound care, clinicians frequently use various evaluation scales. The Braden scale assesses the risk of pressure ulcers, while the Wagner scale categorizes diabetic foot ulcers by severity. These tools help healthcare providers develop treatment plans that can expedite healing, alleviate pain, and reduce infection risk. However, these scales often depend on subjective judgment and the skill of the evaluator.

Recent advances have introduced digital measuring devices and smartphone apps for wound assessment. These technologies overcome the limitations of traditional methods by eliminating direct wound contact, thus reducing infection risks . Some devices allow only wound size measurements, while others assess multiple tissue types. However, most systems still require manual input to accurately track tissue changes.

Artificial Intelligence (AI) has been extensively used to address the limitations of traditional wound measurement methods, such as the ruler technique (Mumtaj Begum, 2022). AI can help create fully automated wound evaluation tools that accurately measure various wound aspects, which are essential for treatment planning (Kim et al., 2022). However, developing an AI-supported wound evaluation tool requires a substantial, high-quality dataset (Neelima et al., 2024). Unfortunately, there is a limited number of publicly available wound datasets, and many lack the necessary annotations for key wound evaluation features. Most datasets focus solely on labeling the wound region (Surendar et al., 2024). The inclusion of three distinct tissue types in the wound bed is crucial for evaluating the wound healing (WH) process and predicting the outcome.

While AI and large datasets play a significant role, other methods such as superpixel segmentation, region growth, and trained systems do not require training but rely on the expertise of the user (Kodric et al., 2021; Casal-Guisande et al., 2020). For effective management of chronic wounds (CW), a tailored approach is needed, which includes understanding the wound's cause and implementing appropriate care strategies. Wound area reduction is a critical indicator for predicting WH (Gwilym et al., 2023).

The correlation between the rate of WH during the first four weeks and complete healing after twelve weeks in diabetic foot ulcers has been well-documented (Sofiene et al., 2024). CW care professionals must manually delineate the wound edge to measure its area, a time-consuming, error-prone process with risks of infection and inconsistency between practitioners. Recently, convolutional neural network (CNN) techniques have been employed to address these issues, offering improved accuracy, reduced time, and consistency in the wound segmentation process (Wang et al., 2020). However, due to the complex curves of the human body, 2D segmentation techniques may struggle to capture wounds accurately (Malathi et al., 2024). Consequently, research has focused on measuring wounds in 3D for improved accuracy.

Niri et al. (2021) proposed a method that combines multiview tissue classification and 3D wound modeling. First, the method uses images from multiple angles with a tissue classification algorithm to segment the wound region. Then, these segmented wound areas are used to create a 3D model using a wound restoration algorithm. Similarly, Liu et al. (2019) introduced a method that measures the 3D wound area by combining structure-from-motion, least squares contour mapping, and the CNN process. Barbosa et al. (2020) developed a 3D wound reconstruction technique using image segmentation, structure from motion, and mesh restoration, showing that accuracy improves as the number of images used to create the 3D model increases.

Augmented Reality (AR) has also been extensively utilized in rehabilitation to improve user engagement and reduce monotony. By using a compact projector instead of head-mounted displays, AR offers a more practical alternative to traditional approaches (Condino et al., 2019). Wu et al. (2018) demonstrated the utility of AR technology in preoperative care, where it enhanced communication between doctors and patients regarding complex neck fractures. Additionally, a working model for wound care has been developed that estimates morphological features and provides AR capabilities to further improve doctor-patient communication.

2. Materials and Methods

Most CW images are captured using a digital camera, smartphone, or RGB-D lens. Novel techniques must possess sufficient resilience to enable image acquisition under typical lighting conditions without requiring specific CW adjustments, specialized instruments, or unique capturing conditions. The AR CW analyzing device comprises two Leopard Imaging LI-OV580 stereo camera systems, each measuring $24\,mm \times 16\,mm \times 26\,mm$, and a pico-projector measuring $64\,mm \times 64\,mm \times 24\,mm$.

As depicted in Figure 1, the CWH device is mounted on an embossed support to guarantee the integrity of the relative position

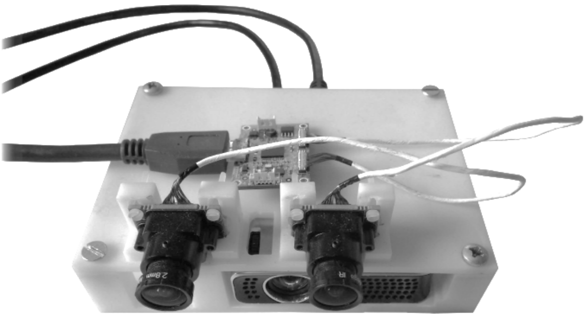

Figure 1 CWH device model

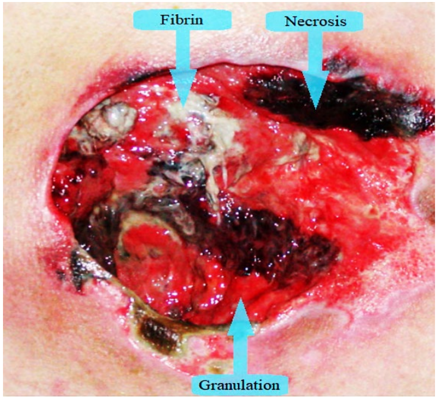

Figure 2 Kinds of tissues in CW

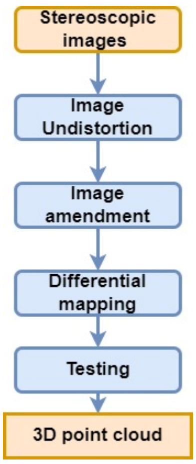

Figure 3 Process of acquiring point cloud in 3D from stereoscopic images

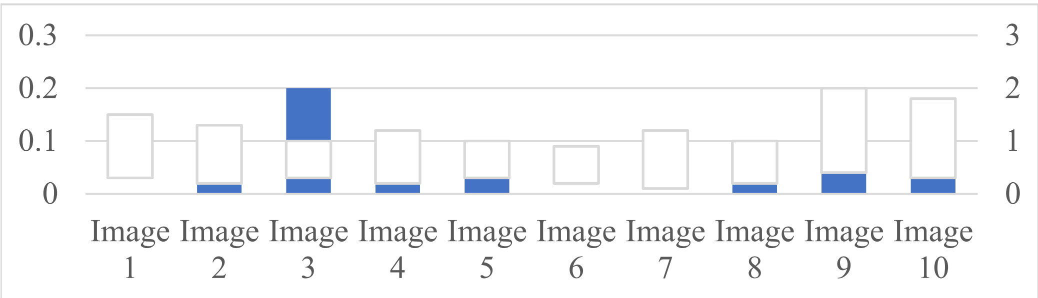

Figure 4 EE analysis of external CM of the device for CW

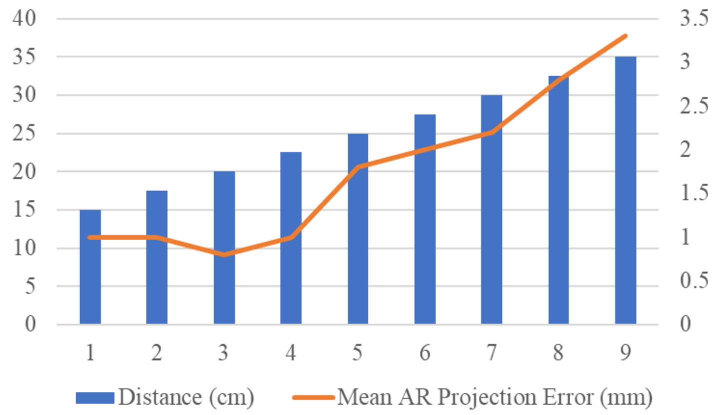

Figure 5 PE analysis of the external CM of the device for CW

of the parts. The cameras are positioned straight with an initial distance of 42 mm. The working proximity is adjusted within a range of 12 cm to 30 cm, considering the specific requirements of the clinical situation. The system necessitates the placement of a silicone patch or a temporary patch on the patient's leg as an enrollment scheme based on the clinical scenario. The pattern serves as a guide for aligning models obtained over some time and is crucial for the functioning of AR.

Tissue categorization describes various CW tissues; wound analysis establishes the size of the wound; CWS isolates the wound from its surrounding skin and background information; and healing assessment forecasts the amount of time needed for CWH. Most studies on imaging CW evaluation focus on categorizing wound tissues and CWS. As shown in Figure 2, most articles categorize CW tissues into three groups: granulation, fibrinogen, and necrosis.

A stereoscopic image set is processed using the popular 3D digital image relationship approach to produce the CW-3D area. To lessen the level of difficulty of the matching process, this technique first undistorts and rectifies the stereo image set as shown in Figure 3. While correction applies an amendment based on the epipolar topology to the pictures that narrows down the search for matching every pixel in the image to a single row, undistorted images fixes non-linear distortions generated by the lenses, enabling the representation of the camera as a hole projection system. After going through this procedure, the data points of the differential map are linked, and an extensive point cloud in 3D is created by considering the internal and external parameters received during the testing process. The internal and external characteristics of the cameras are used to geometrically calculate the clarity of the 3D reconstruction approach across the 3Ds, $\Delta X, \Delta Y\ and\ \Delta z$.

$$\Delta X = \frac{2*A*\tan(\frac{H}{2})}{CH} \quad (1)$$

$$\Delta Y = \frac{2*A*\tan(\frac{V}{2})}{CV} \quad (2)$$

$$\Delta Z = \frac{A^2}{f*b} \quad (3)$$

The variables in the equation are defined as follows: A represents the average working distance, f represents the focal point of the cameras, $H, V, CH, and\ CV$ represent the camera parameters ($H - horizontal\ and\ V - Vertical\ viewing\ angle$), and b represents the baseline. Subsequently, the process proceeds with a semi-automated CWS of the 3D point cloud, carried out on the 2D picture obtained from the baseline camera (namely, the left camera) and transferred into the corresponding 3D points. The user is instructed to sketch a rough outline without precisely tracing the CW's perimeter. To streamline and expedite the process and minimize human influence, the contours are programmed to match the texture and color of the CW most accurately.

The delineated region on the 2D image identifies the associated 3D point on the CW. The SOM method generates 3D meshes representing the CW area, both with and without the tissue around it. A SOM is a neural network that utilizes machine learning to generate a 2D depiction of the input area. The model comprises nodes, which are organized in a grid of rectangles. Every node is assigned a weight, and the map undergoes a process that decreases a distance metric to adjust the weight vectors toward the input information while maintaining its structure. This work utilizes SOM to perform recovery. The input information consists of a 3D point cloud, where the map nodes relate to the edges of the resulting mesh, and the weights indicate the 3D variables. The Euclidean distance is employed as the distance measurement to adjust the mesh according to the input point cloud during the learning stage.

3.Results and Discussion

The goal image was constructed with overlapping circles that increased in radius by 0.15 cm. This goal was used to accurately measure the error in re-projecting the CW. After the goal was collected, the outer circle was physically segmented according to the suggested technique until the 3D model was generated. Later, a modification was made to the technique where the mean of the point cloud was computed and then reflected onto the target. If the object landed in the space between two circles, the mean radius of those rings was used to determine the Projection Error (PE). The PE was then calculated as the distance separating the intended center from the goal's centre.

Analysis of the external CM of the device for CW has been shown in Figure 4. The Epipolar Error (EE) is measured in units of pixels. The dark blue boxes indicate the values that reflect EE's top and bottom quartiles. Grey lines show the lowest and highest EE values. The EE was employed to evaluate the accuracy of the external measurement. In a stereo imaging system, a point in one camera viewpoint must lie on one line in another camera view. The line mentioned is the Epipolar line associated with a certain location. The EE is the separation between this line and the associated point in the picture captured by the other camera. The box diagrams in Figure 4 provide the statistical data for the EE generated by each point in every measurement image. The mean EE is 0.46 pixels.

Figure 5 depicts the PE analysis of the external CM of the device for CW. The AR-PE was evaluated via tests, and the findings obtained for distances inside the scope of operation are shown in Figure 5. The minimum PE was seen at a distance of 20 cm from the device with CM. It progressively rose as the distance moved closer to the area's borders.

4.Conclusion

This study introduces an innovative method for assessing chronic wound healing using 3D stereoscopic imaging combined with augmented reality (AR) capabilities. Traditional methods of wound assessment often lack accuracy, are time-consuming, and may cause discomfort for patients. By integrating AR technology, this device not only provides real-time visual feedback but also projects wound characteristics that improve communication between clinicians and patients. The study also utilizes self-organizing maps (SOM) to create a precise 3D model of the wound, which is critical for estimating physical metrics and tracking the wound healing process. Tests demonstrated that projection error (PE) decreases with distance from the wound, reaching a minimum at 20 cm, providing an optimal range for device use. This advancement has the potential to streamline chronic wound care by offering more accurate and consistent evaluations, ultimately leading to improved patient outcomes and more effective treatment planning.

Author contributions

BD and MKS contributed to conceptualization, fieldwork, data analysis, drafting the original manuscript, editing, funding acquisition, and manuscript review. Both BD and MKS were involved in research design, methodology validation, data analysis, visualization, and manuscript review and editing. Additionally, BD took the lead in methodology validation, investigation, funding acquisition, supervision, and final revisions. All authors have reviewed and approved the final version of the manuscript.

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Competing financial interests

The authors have no conflict of interest.

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