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A Morphological Approach for Background Removal and Burn Wound Segmentation in Clinical Images

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***Abstract*—*Burn wound image analysis supports clinical observation, wound monitoring, and treatment planning. However, clinical burn wound images often contain complex background objects, shadows, illumination variation, and heterogeneous tissue structures that complicate wound extraction and segmentation. This study proposes a morphological image-processing framework for background removal and burn wound segmentation, using clinical burn wound images collected under varying environmental conditions. The proposed framework combines image preprocessing, HSV color space conversion, threshold-based segmentation, and morphological refinement to isolate wound regions from the surrounding background. The preprocessing stage improves image quality through contrast enhancement and noise reduction. HSV color conversion enhances wound visibility by separating color information from illumination intensity. Threshold segmentation generates initial wound masks, while morphological operations such as erosion, dilation, opening, and closing refine wound boundaries and reduce segmentation noise. The experimental results show that the proposed framework improves wound extraction under varying illumination conditions and complex clinical backgrounds. Morphological refinement reduces noisy regions, improves region connectivity, and preserves important wound structures during segmentation. The final segmentation results demonstrate that the proposed method suppresses irrelevant background regions while maintaining the primary wound structure.*

***Keywords*—** *burn wound segmentation, morphological image processing, background removal, HSV color conversion, threshold segmentation, medical image analysis.*

I. Introduction

Burn wounds represent a serious form of skin injury that can damage human tissue and require prolonged medical treatment[1][2]. Medical personnel perform visual examinations to evaluate wound conditions, determine tissue damage, monitor the healing process, and support clinical treatment planning[3][4]. While visual examination remains the primary clinical method, digital image processing and computer vision technologies increasingly assist clinicians in analyzing burn wound characteristics through medical images[5][6].

Clinical burn wound images often contain various background objects that interfere with wound analysis[7]. Hospital beds, medical instruments, surgical cloths, shadows, lighting variations, and surrounding skin regions frequently appear together with the wound area in a single image[8][9]. These conditions complicate wound extraction and reduce segmentation accuracy.

Burn wounds also exhibit diverse visual characteristics in clinical images. Variations in color intensity, tissue texture, necrotic tissue, blister formation, moisture conditions, and wound shape create challenges during image preprocessing and wound isolation. In addition, image acquisition conditions such as camera position, illumination level, image resolution, and patient movement introduce variability into the dataset and affect segmentation stability[9][10]. These heterogeneous characteristics make preprocessing and segmentation particularly challenging in clinical datasets.

Several previous studies applied machine learning and deep learning methods for wound segmentation and burn classification[11][12]. These approaches produced promising results in medical image analysis. However, most methods require large annotated datasets, extensive computational resources, and complex training procedures. Many healthcare facilities still require lightweight image preprocessing approaches because clinical environments do not always provide access to high-performance computing resources. Thus, there is a need for lightweight and explainable preprocessing methods that can operate under limited resources.

Morphological image processing provides an effective approach for refining object structures in medical images[13][14]. Operations such as erosion, dilation, opening, and closing help reduce noise, refine wound boundaries, improve region connectivity, and suppress irrelevant background components. These operations also preserve important tissue structures during wound extraction from complex clinical environments. This study, therefore, proposes a morphological framework to refine wound boundaries and suppress background artifacts in clinical burn wound images.

II. Literature Review

A. Burn Wound Image Analysis and Background Removal

Burn wound image analysis is essential for clinical observation, monitoring, and treatment planning. However, clinical images often contain complex backgrounds, such as hospital beds, medical instruments, clothing, shadows, and lighting variations, that interfere with wound extraction. These conditions complicate segmentation and reduce accuracy. Therefore, preprocessing and background removal play a critical role in suppressing irrelevant components and improving the clarity of wound regions before further analysis.

B. Color-Based Segmentation

Color-based segmentation is widely applied because wound

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tissue typically exhibits distinct color characteristics compared with healthy skin and background regions. Transformations such as RGB-to-HSV separate color information from illumination intensity, improving wound detection under varying lighting conditions. Threshold segmentation generates initial wound masks, but clinical images often produce noisy results due to shadows, texture variations, and background objects with similar color patterns. Consequently, refinement steps are required to achieve reliable wound isolation.

C. *Morphological Image Processing and Previous Approaches.*

Morphological image processing provides a classical yet effective technique for refining wound masks. Operations such as erosion, dilation, opening, and closing reduce noise, connect fragmented regions, and refine boundaries, while morphological gradients emphasize contours. Previous studies have explored traditional image processing, machine learning, and deep learning approaches. Traditional methods are lightweight but sensitive to image quality and parameter selection. Machine learning improves classification using features such as color and texture, but requires representative datasets. Deep learning methods, including CNNs and U-Net, achieve strong segmentation performance but require large annotated datasets and substantial computational resources. In contrast, morphological processing offers a transparent, computationally efficient, and explainable solution suitable for clinical environments with limited resources.

D. *Research Gap*

Deep learning-based techniques are the emphasis of the most recent burn wound segmentation research. These approaches provide strong segmentation performance but require large labeled datasets and high computational resources. Meanwhile, burn wound images collected in clinical environments often contain complex backgrounds, inconsistent illumination, and limited annotation quality.

This condition creates a research gap for lightweight and explainable preprocessing approaches. Morphological image processing can address this limitation by providing a simple, transparent, and computationally efficient framework for background removal. This approach can improve wound isolation before further segmentation or classification is performed.

E. *Position of This Study*

This study focuses on background removal in burn wound images using morphological image processing. The proposed framework combines image enhancement, color space conversion, threshold segmentation, and morphological refinement. This approach aims to suppress irrelevant background regions while preserving the primary wound structure.

This study does not attempt to replace deep learning-based segmentation approaches. Instead, this study provides a reliable preprocessing framework that can support future burn wound analysis systems. The proposed approach is suitable for clinical image datasets with limited sample size, complex background conditions, and varying illumination levels.

III. Methodology

The methodological framework of this study is illustrated in Figure 1, which presents the sequential stages of the proposed process. The workflow begins with wound image acquisition, followed by preprocessing to enhance image quality and normalize illumination. The HSV color conversion stage separates color information from brightness, enabling more accurate wound detection. Morphological operations are then applied to refine boundaries and reduce noise, while mask refinement produces a cleaner wound structure before the final segmentation is performed.

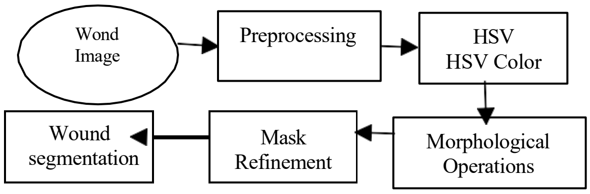

Fig. 1. Methodological Workflow for Burn Wound

A. *Equations Style Burn Wound Image Acquisition*

Burn wound images used in this study were obtained from the SkinBurn dataset and processed under various clinical image conditions. The dataset contained burn wound images with different wound characteristics, including variations in wound color, tissue texture, wound depth, moisture conditions, and surrounding skin appearance. Several images also contained complex clinical background objects such as hospital beds, medical instruments, surgical cloths, shadows, and illumination variations. These conditions created challenges during wound extraction because the wound region frequently appeared together with irrelevant background components.

The image acquisition process in the SkinBurn dataset used digital imaging under natural and controlled illumination conditions. Each image was captured from a distance and angle that allowed the wound region to appear clearly without significant perspective distortion. The dataset contained high-quality wound photos that were detailed enough for both visual inspection and computer image analysis.

All images were stored in RGB format with a standard resolution of 512 × 512 pixels to maintain a balance between image detail and computational efficiency during processing. The collected dataset represented real clinical conditions with varying image quality, lighting intensity, wound appearance, and background complexity. Therefore, the preprocessing stage became important to improve image quality and support accurate wound region extraction before segmentation was performed.

B. *Image Preprocessing*

Prior to segmentation, the preprocessing step enhances the quality of the image. This stage reduces noise, enhances wound visibility, and prepares the image for subsequent segmentation processes. The preprocessing procedure includes image resizing, noise reduction, contrast enhancement, and RGB image normalization to improve visual consistency under different clinical conditions.

The input RGB image is represented as:

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$$I(x,y) = [R(x,y), G(x,y), B(x,y)]$$

where (I(x,y)) represents the input image, while (R(x,y)), (G(x,y)), and (B(x,y)) represent the red, green, and blue color channels. Contrast enhancement improves wound visibility and reduces the influence of shadows and illumination variation that frequently appear in clinical burn wound images.

The preprocessing stage also normalizes illumination and color distribution to minimize the effects of uneven lighting and light reflection. After preprocessing, the RGB image is converted into the HSV color space using the following transformation:

HSV=f(R,G,B)

This transformation separates color information into hue, saturation, and value components. Hue denotes predominant color attributes, saturation denotes color intensity, and value denotes brightness information. The HSV representation improves wound isolation because burn wound regions generally exhibit dominant reddish color characteristics compared with surrounding healthy skin and background objects.

C. HSV Color Space Conversion

After preprocessing, the RGB image is converted into the HSV color space to improve wound detection under varying illumination conditions. The HSV model separates color and brightness information, making wound regions more distinguishable from healthy skin and background objects. The HSV transformation is defined as:

$$HSV = f(R,G,B)$$

where (H), (S), and (V) represent hue, saturation, and brightness intensity.

Threshold segmentation then generates an initial wound mask using predefined hue and saturation ranges:

$$M(x,y) = \begin{cases} 1, if\ H_{min} \le H(x,y) \le H_{max}\ and\ S(x,y) \ge S_{min} \\ 0, \end{cases}$$

where (M(x,y)) represents the binary mask. Pixels classified as wound regions are assigned a value of 1 (white), while non wound regions are assigned a value of 0 (black). The resulting mask highlights candidate wound regions before morphological refinement is applied.

D. Morphological operations

Morphological operations refine the segmented wound region and suppress unwanted background components. These operations improve wound mask quality by reducing noise, connecting fragmented regions, refining boundaries, and filling small holes inside the wound area.

Morphological image processing uses a structuring element to examine and modify image structures based on shape and neighborhood relationships. The proposed framework applies several morphological operations, including erosion, dilation, opening, and closing.

1. Erosion

Erosion removes small unwanted objects and reduces the size of foreground regions. This operation suppresses noise that appears around the wound boundary.

The erosion operation is expressed as:

$$A\theta B = \{z | B_z \ \ A\}$$

where (A) represents the image region and (B) represents the structuring element.

2. Dilation

Dilation enlarges foreground regions and connects separated wound areas. This operation restores important wound structures after erosion.

The dilation operation is expressed as:

$$A \oplus B = \{z | (B_z \ \cap A) \ne \emptyset\}$$

Dilation improves region connectivity and enhances wound continuity.

3. Opening

Opening combines erosion followed by dilation. This operation removes small noise while preserving the primary wound structure.

The opening operation is defined as:

$$A \circ B = (A\ \theta\ B) \oplus B$$

Opening helps eliminate small isolated regions that do not belong to the wound area.

4. Closing

Closing combines dilation followed by erosion. This operation fills small gaps and holes inside the wound region.

The closing operation is defined as:

$$A \cdot B = (A \oplus B)\ \theta\ B$$

Closing improves wound region completeness and refines the wound boundary structure.

E. Mask refinement

The mask refinement stage improves segmentation quality after morphological processing by removing remaining background artifacts, smoothing wound boundaries, and suppressing irrelevant image regions. This process preserves important wound structures, improves region connectivity, and maintains wound shape consistency, resulting in a cleaner and more accurate wound mask for subsequent medical image analysis.

F. Final Segmentation

The final segmentation stage produces the extracted wound region after preprocessing, threshold segmentation, and morphological refinement are completed. The refined binary mask is combined with the original image to isolate the wound area from surrounding background objects.

The final segmentation result is represented as:

The final result is obtained by multiplying the refined mask with the original image:

$$I_{seg}(x,y) = I_{original}(x,y) \cdot M_{final}(x,y)$$

Where is "The segmented image $I_{seg}(x,y)$is obtained by multiplying the original image $I_{original}(x,y)$with the final mask $M_{final}(x,y)$."

This expression describes how the final segmentation isolates the wound area by combining the refined mask with the original image

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IV. Results and Discussion

The proposed morphological segmentation method was applied to multiple wound images, including leg, chest, and lower limb cases. The results demonstrate the effectiveness of combining HSV color thresholding with morphological operations in isolating wound regions from complex backgrounds.

A. Original Wound Image Result

The image presents a burn injury located on the ankle and foot region with visible tissue damage and irregular wound distribution. The wound area exhibits reddish and pinkish tissue characteristics accompanied by several whitish regions that indicate differences in wound surface conditions. The burn wound also shows nonuniform texture and irregular wound boundaries, which increase the complexity of wound extraction. The clinical image contains several visual variations that influence the segmentation process. Variations in wound color intensity, tissue texture, skin appearance, and illumination conditions create challenges during wound detection and boundary identification. Some wound regions appear brighter because of light reflection on moist tissue surfaces, while other regions exhibit darker intensity caused by shadows and uneven illumination.

The image background also introduces additional complexity into the segmentation process. The wound region appears together with surrounding healthy skin and textured clinical surface materials. Several background regions exhibit intensity characteristics that are visually similar to skin regions, which may interfere with threshold segmentation and object separation. In addition, the gradual transition between wound tissue and surrounding skin makes boundary detection more difficult.

These conditions demonstrate that burn wound images collected in clinical environments contain heterogeneous visual characteristics that complicate automatic wound segmentation. Therefore, preprocessing and morphological refinement become important stages to improve wound isolation and suppress irrelevant background components before the final segmentation process is performed.

Fig. 2. Original clinical burn wound image before preprocessing

B. Preprocessing Result

The preprocessing stage improved the visual quality of burn wound images before segmentation was performed. This stage aimed to enhance wound visibility, reduce image noise, and normalize image appearance under different clinical conditions. The preprocessing framework applied image enhancement and noise reduction to improve the distinction between wound regions and surrounding background areas.

Figure 3 presents the preprocessing results for three different burn wound images collected from clinical environments. The first image shows a burn wound located on the ankle region with reddish tissue appearance and irregular wound boundaries. The preprocessing stage enhanced wound visibility and improved the contrast between the damaged tissue and surrounding healthy skin. Several small intensity variations around the wound area became less visible after noise reduction was applied.

The second image shows a large burn wound area on the chest and upper body region. The original image contained uneven illumination, varying skin color intensity, and several background components from the clinical environment. After preprocessing, the wound region appeared clearer and more distinguishable from surrounding skin areas. Contrast enhancement improved the visibility of wound boundaries and reduced the influence of lighting variation across the image.

The third image shows a burn wound located on the lower leg with complex background objects, including floor texture, cloth material, and medical equipment. These conditions created additional challenges during wound extraction because several background regions exhibited intensity characteristics similar to skin tissue. The preprocessing stage successfully improved image smoothness and reduced minor background disturbances while preserving the main wound structure.

The preprocessing results demonstrated that image enhancement and noise reduction improved wound visibility and reduced unwanted image artifacts in all tested burn wound images. The preprocessing stage also improved wound boundary clarity and produced more consistent image quality before threshold segmentation and morphological refinement were performed.

Fig. 3. Preprocessing results after image enhancement and noise reduction on burn wound images collected under different clinical conditions.

C. HSV Color Thresholding

The HSV color conversion stage transformed the preprocessed RGB images into the HSV color space to improve wound region detection under different clinical conditions. This transformation separated color information from illumination intensity and allowed the system to represent wound characteristics more consistently than direct RGB representation. The HSV model improved the visibility of burn wound regions because wound tissue generally exhibited different color characteristics compared with healthy skin and surrounding background objects.

Figure 4 presents the HSV color conversion results for three different burn wound images collected from clinical environments. Each image contained different wound characteristics, illumination conditions, and background complexity levels. The HSV transformation improved wound visibility and supported more stable threshold segmentation during the subsequent processing stage.

In the first burn wound image, the wound region was located around the ankle and foot area. The original image contained reddish wound tissue with irregular boundaries and textured background surfaces. After HSV conversion, the wound region became more distinguishable from surrounding healthy skin and clinical background materials. The hue channel emphasized the reddish wound characteristics, while the saturation channel enhanced differences between damaged tissue and surrounding skin regions. The value channel reduced the influence of uneven illumination that appeared around the wound boundary. As a result, the wound contour became clearer and easier to separate during threshold segmentation.

In the second burn wound image, the burn area covered the chest, neck, and upper body region with extensive skin damage and nonuniform color intensity. The original image also contained green clinical bedding and varying illumination conditions. The HSV transformation improved the separation between the burn wound region and surrounding clinical background components. The hue representation emphasized wound tissue color differences, while the saturation channel highlighted variations between injured tissue and healthy skin. The value channel normalized brightness distribution across the image and reduced the effect of illumination variation. Consequently, the wound region appeared more homogeneous and visually stable after HSV conversion.

In the third burn wound image, the wound region appeared on the lower leg area with complex surrounding objects such as cloth material, floor texture, shadows, and medical equipment. These conditions created significant challenges during wound extraction because several background regions exhibited intensity characteristics similar to skin tissue. After HSV conversion, the wound area became more distinguishable from the surrounding environment. The hue and saturation channels enhanced the reddish wound tissue, while the value channel minimized illumination inconsistencies caused by shadows and light reflections. Although several background regions still exhibited visual similarity to skin tissue, the HSV transformation improved wound region enhancement and reduced background interference before segmentation.

Overall, the HSV color conversion stage successfully improved wound visibility and enhanced the distinction between wound regions and surrounding background objects across all tested clinical images. The HSV representation also improved illumination normalization by separating brightness intensity from color information. These improvements produced more stable wound representation and supported more accurate threshold segmentation and morphological refinement in the subsequent processing stages.

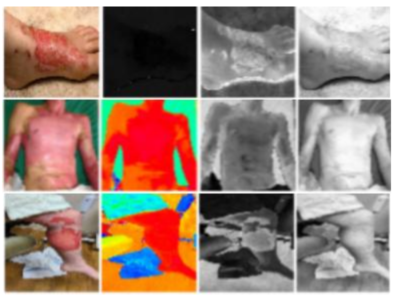

Fig. 4. HSV color space conversion results for burn wound region enhancement on three clinical burn wound images under different illumination and background conditions.

D. Threshold Segmentation Result

The threshold segmentation stage generated an initial binary mask representing the wound region based on HSV color information. This stage separated foreground wound areas from surrounding background regions by applying threshold values to the hue, saturation, and value components obtained from the HSV color space conversion. The segmentation process identified candidate wound regions that exhibited color characteristics similar to burn tissue.

Figure 5 presents the initial threshold segmentation masks generated from three different burn wound images. The threshold segmentation process successfully detected the primary wound regions in all clinical images. However, the segmentation results still contained several noisy regions and fragmented structures because clinical burn wound images exhibited complex visual characteristics and varying illumination conditions.

In the first burn wound image, the threshold segmentation stage successfully detected the reddish wound area around the ankle and foot region. The wound mask highlighted the primary wound structure and separated most of the wound tissue from surrounding skin regions. However, several small noisy regions appeared around the wound boundary and textured background surface. These artifacts occurred because some background pixels exhibited intensity values similar to the wound region.

In the second burn wound image, threshold segmentation successfully extracted the large burn wound region located on the chest and upper body area. The segmentation mask covered most of the injured skin surface and highlighted the primary wound structure. Nevertheless, several fragmented regions and small holes appeared inside the segmented area because of nonuniform illumination, variations in skin intensity, and complex wound texture. In addition, some background regions near the body boundary were incorrectly classified as foreground regions.

In the third burn wound image, the threshold segmentation stage identified the wound region located on the lower leg area despite the presence of complex background objects such as cloth material, floor texture, shadows, and medical equipment. The threshold mask successfully emphasized the wound structure, but several noisy regions also appeared around the lower image area and object boundary. These segmentation artifacts were caused by similarities between skin intensity and surrounding background components.

The experimental results demonstrated that threshold segmentation effectively identified candidate wound regions after HSV color conversion. However, the initial threshold masks still contained noise, fragmented boundaries, isolated foreground regions, and incomplete wound structures. These limitations occurred because threshold segmentation relied primarily on pixel intensity and color similarity without considering object connectivity or structural consistency.

Overall, the threshold segmentation stage provided an effective initial wound detection mechanism, but additional refinement was required to improve segmentation quality and suppress irrelevant background components. Therefore, morphological operations were applied in the subsequent stage to reduce noise, improve region connectivity, and refine wound boundaries.

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Fig. 5. Initial threshold segmentation masks generated from HSV color information for three clinical burn wound images. Several noisy regions and fragmented structures remain because threshold segmentation is sensitive to illumination variation and color similarity between wound tissue and surrounding regions.

E. Morphological Refinement Result

The morphological refinement stage improved the quality of the initial threshold segmentation masks by reducing noise, refining wound boundaries, and improving region connectivity. This stage applied several morphological operations, including erosion, dilation, opening, and closing, to produce cleaner and more stable wound segmentation results.

Figure 6 presents the morphological refinement results obtained from the three clinical burn wound images. The refinement process successfully suppressed unwanted background regions and improved the structural consistency of the segmented wound areas. The refined masks appeared smoother and more connected compared with the initial threshold segmentation results.

The erosion operation removed small isolated foreground regions and reduced segmentation noise around the wound boundaries. Several small artifacts that appeared during threshold segmentation were successfully eliminated after erosion was applied. This process improved the separation between the primary wound structure and surrounding background components.

The dilation operation enlarged the foreground wound regions and restored important structural information that was reduced during erosion. Dilation also improved connectivity between fragmented wound areas and produced more continuous wound structures. As a result, the wound masks became more solid and visually consistent.

Opening operations combined erosion followed by dilation to remove small unwanted regions while preserving the primary wound structure. This operation effectively eliminated isolated noise that appeared in the threshold masks without significantly damaging the wound contour. Opening also improved the smoothness of segmented wound regions.

Closing operations combined dilation followed by erosion to fill small holes and gaps inside the wound region. This process improved wound completeness and refined boundary continuity. Several fragmented regions inside the wound mask became more connected after closing operations were performed.

In the first burn wound image, morphological refinement improved the wound boundary around the ankle region and reduced noisy regions surrounding the textured background surface. The wound mask became cleaner and more connected after erosion and dilation operations were applied.

In the second burn wound image, morphological refinement significantly improved segmentation stability on the large burn wound area located on the chest and upper body region. The refinement stage reduced fragmented structures and filled several small gaps inside the segmented wound region. Boundary smoothness also improved after opening and closing operations were performed.

In the third burn wound image, morphological operations reduced background interference caused by floor texture, cloth material, and medical equipment surrounding the lower leg wound area. Although several complex background components remained visually similar to skin tissue, the refinement stage improved wound isolation and reduced segmentation artifacts around the object boundary.

Overall, the morphological refinement stage successfully improved segmentation quality for all tested clinical burn wound images. The refined wound masks exhibited reduced noise, smoother boundaries, improved region connectivity, and better structural consistency compared with the initial threshold segmentation results. These improvements supported more accurate wound extraction before the final segmentation stage was performed.

Fig. 6. Morphological refinement results after erosion, dilation, opening, and closing operations.

Morphological processing reduces segmentation noise, improves wound region connectivity, and refines boundary structures generated during the initial threshold segmentation stage.

F. Final Wound Segmentation

The final segmentation stage produced the extracted burn wound regions after preprocessing, HSV color conversion, threshold segmentation, and morphological refinement were completed. This stage combined the refined binary mask with the original clinical image to isolate the wound region from surrounding background objects and preserve important tissue structures.

Figure 7 presents the final segmentation results obtained from three different clinical burn wound images. The proposed framework successfully suppressed irrelevant background regions while maintaining the primary wound structure and surrounding anatomical information. The final segmented images appeared cleaner and more focused compared with the original clinical images and the initial threshold segmentation results.

In the first burn wound image, the final segmentation stage successfully isolated the wound region located around the ankle and foot area. Most textured background surfaces and surrounding irrelevant regions were removed after morphological background suppression was applied. The wound boundary appeared smoother and more connected compared with the previous segmentation stages. Important wound characteristics, including irregular wound contours and reddish tissue regions, remained preserved in the final segmentation output.

In the second burn wound image, the final segmentation process successfully extracted the large burn wound region

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located on the chest and upper body area. The framework effectively suppressed the green clinical bedding and several surrounding background regions while preserving the primary wound structure and body contours. The segmentation result also maintained important wound characteristics such as tissue distribution, wound shape, and color intensity variation. Boundary continuity improved significantly after morphological refinement and background removal were performed.

In the third burn wound image, the final segmentation stage reduced interference caused by cloth material, floor texture, shadows, and surrounding clinical objects. Although the original image contained complex background structures and illumination variation, the proposed framework successfully isolated the wound region and preserved the primary leg structure. The final segmented image exhibited improved wound visibility and reduced background artifacts compared with the initial threshold segmentation result.

The experimental results demonstrated that morphological background removal effectively improved segmentation quality under different clinical conditions. The final segmentation outputs showed smoother wound boundaries, improved region connectivity, reduced noise, and better wound isolation. The proposed framework also preserved important wound structures while suppressing irrelevant background components that could interfere with further wound analysis.

Overall, the final segmentation stage demonstrated that the combination of HSV color conversion, threshold segmentation, and morphological refinement provided an effective and computationally efficient framework for burn wound extraction. The resulting segmented images can support future burn wound analysis, wound monitoring, and medical image processing applications.

Fig. 7. Final burn wound segmentation results after morphological background removal. The proposed framework preserves the primary wound structure while suppressing several irrelevant background regions under different clinical image conditions.

Discussion

The morphological segmentation approach applied to both leg and chest wound images demonstrates the capability of classical image processing to isolate wound regions effectively using HSV color thresholding and morphological filtering. The method successfully removes complex backgrounds and enhances the continuity of wound boundaries, providing a clear visual representation of affected areas. This approach is particularly useful for preliminary wound analysis where computational simplicity and interpretability are prioritized.

However, several limitations are evident across both cases. In the leg wound image, the segmentation tends to lose fine details along the edges, while in the chest wound image, over-segmentation occurs in healthy skin regions due to similar reddish tones. These issues highlight the sensitivity of HSV-based thresholding to lighting variations and skin color diversity. Moreover, morphological operations with fixed kernel sizes may either erode small wound regions or fail to remove noise completely, as seen in residual artifacts around the contours.

Another limitation lies in the method's reliance on color information alone. Texture and depth cues, which are crucial for assessing wound severity, are not captured. The segmentation results remain qualitative, lacking quantitative validation through metrics such as Dice coefficient or Intersection over Union (IoU). Furthermore, the absence of clinical correlation limits the medical interpretability of the segmented areas.

Despite these constraints, the morphological approach provides a strong foundation for developing automated wound assessment systems. Its simplicity and transparency make it suitable for integration into low-resource clinical settings or as a preprocessing step for more advanced models.

V. Conclusion

A morphological image processing framework was developed for background removal and burn wound segmentation using clinical images from the SkinBurn dataset. The workflow combined preprocessing, HSV color thresholding, morphological operations, mask refinement, and final segmentation to isolate wound regions from complex backgrounds. Preprocessing enhanced image quality under varying illumination, HSV thresholding identified candidate wound regions, and morphological operations refined boundaries while reducing noise. Mask refinement suppressed background artifacts, resulting in smoother wound structures before final segmentation. The framework effectively isolated burn-wound regions and minimized interference from surrounding objects such as cloth, floor texture, shadows, and clinical equipment. It preserved wound structures across diverse clinical conditions and provided a lightweight, computationally efficient solution suitable for medical image preprocessing and computer vision–based clinical applications. Segmentation performance remains sensitive to illumination variation, skin tone diversity, and complex backgrounds. Future work will explore adaptive thresholding, advanced morphological refinement, polygon-based segmentation, texture and depth analysis, and deep learning integration to improve robustness and accuracy in clinical wound segmentation.

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