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Hair Removal from Dermoscopy Images using Morphology and Image Inpainting

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Abstract

Hair removal from dermoscopy images is a crucial preprocessing step in computer-aided diagnosis of skin lesions. These images are often contaminated with hair artifacts, which can obscure important diagnostic features and hinder accurate analysis. Accurate and reliable diagnosis of skin lesions is essential for early detection of skin cancer and other dermatological conditions. Dermoscopy images provide valuable information for dermatologists, but the presence of hair artifacts can lead to misinterpretation and misdiagnosis. Several methods have been proposed for hair removal from dermoscopy images, including thresholding, edge detection, and machine learning-based approaches. Thresholding-based methods rely on fixed intensity thresholds to distinguish hair from skin, making them sensitive to lighting conditions and skin tone variations. As a result, they fail to remove all hair artifacts, leading to incomplete results. The proposed method combines morphology and image inpainting techniques to address the drawbacks of existing methods. In the first step, morphological operations are applied to identify and isolate hair regions based on their texture and size characteristics. This allows for a more precise and robust detection of hair artifacts compared to fixed thresholds. Next, image inpainting algorithms are employed to fill in the detected hair regions with suitable skin texture. The inpainting process relies on contextual information from the surrounding skin regions to create seamless and realistic replacements for the removed hair, preserving the vital diagnostic features at the edges of skin lesions.

Keywords: Dermoscopic images, skin lesion, hair removal, filtering, morphologic operations.

1. INTRODUCTION

Hair removal from dermoscopy images is a crucial preprocessing step in computer-aided diagnosis and analysis of skin lesions. Dermoscopy is a non-invasive imaging technique that provides a magnified view of skin lesions, aiding in the early detection of skin cancer and other dermatological conditions. However, the presence of hair on the skin can interfere with the accurate assessment of these images, making it necessary to remove the hair before analysis. The process of hair removal from dermoscopy images typically involves several steps. Firstly, image acquisition is performed using specialized dermoscopes that capture high-resolution images of the skin. Once the images are obtained, the hair removal process begins. The primary challenge in this task is distinguishing between the hair and the skin lesions, as both may have similar color and texture characteristics. To address this, various image processing techniques and algorithms are employed.

One common approach for hair removal is the use of color-based segmentation. This technique involves identifying the hair based on its color and separating it from the skin lesions. Another method involves texture analysis, where the distinctive texture patterns of hair and skin are utilized to discriminate between the two. Additionally, machine learning algorithms, such as convolutional neural networks (CNNs), can be trained to automatically detect and remove hair from dermoscopy images. Furthermore, post-processing steps may be applied to refine the results of hair removal. These steps may include morphological operations to smooth and enhance the skin region, filling in any gaps left by the removed hair, and restoring the original texture and color of the skin.

So, the accurate removal of hair from dermoscopy images is crucial for improving the reliability of automated skin lesion analysis and diagnosis. It ensures that the focus is solely on the skin features and abnormalities, allowing dermatologists and computer-aided systems to make more precise assessments of skin conditions and potentially aiding in the early detection of skin cancer.

2. LITERATURE SURVEY

In recent years, the incidence of skin cancer has been rising, contributing significantly to the rise in health care costs. [1, 2] In 2021, the United States is estimated to have 115 320 new cases and 11540 deaths attributed to skin cancer (excluding basal and squamous cell carcinoma); a similar burden exists globally. [3] Nonmelanoma skin cancer, the most common type of cancer, is increasing in parallel with melanom. Skin cancer is often curable when detected and treated early, yet dermatologists, even with the aid of dermoscopy, can misdiagnose these cancers. [4-7]

Deep learning accuracy for diagnosing dermoscopic images now exceeds that of dermatologists for both melanoma detection and exact-class diagnosis of various lesions. Handcrafted techniques can improve deep learning results. [8] Because hair artifacts can interfere with handcrafted feature recognition, hair removal has become the leading topic of artifact removal. [9] Shaving the hair from the lesion area is an alternate solution, but challenges such as the location of the lesion and the possibility of shaving irritation make this solution impractical. [10]

Numerous hair removal algorithms have been proposed using dermoscopy images. Abbas et al. [11] summarized the current state of hair detection and restoration. The presented survey of published methods is further evaluated in our study using traditional metrics. As Lee et al. stated, [12] we may group hair removal algorithms into three categories: those using mathematical morphology methods, edge detection methods, and matched filtering methods. They used the top-hat transform and modified second-order Gaussian filter to enhance hair. The initial hair mask is then generated using an adaptive threshold and further refined using a k-nearest neighbor classifier.

Xie et al. [13] proposed an algorithm that focuses on dark hair. The method is also based on the top-hat operator and an automatic threshold; the image hair area detected is reconstructed using a partial differential equation-based inpainting technique.

Abbas et al. [14] presented a hair removal algorithm based on the first derivative of Gaussian to detect potential light and dark hairs, followed by adaptive thresholding and refinement filtering. Hair objects were inpainted using a fast-marching technique. [15]

Nguyen et al. [16] detected both dark and light hair using a universal matched filtering kernel. A binary hair mask was generated by local entropy thresholding and subsequently refined. Lee et al. [17] proposed DullRazor, consisting of three main steps. First, hair is segmented based on the morphological closing operation. Next, the detected hair segments were inpainted using a bilinear interpolation. Finally, the hair mask is smoothed.

Fiorese et al. [10] proposed the VirtualShave algorithm to find hair. VirtualShave used a top-hat filter with long structuring elements, followed by morphological postprocessing, finally inpainting the detected hair area with a PDE-based technique. Koehoorn et al. [18] used a threshold-set model, a gap-detection algorithm, morphological analysis, and further postprocessing using a skeletonizing method.

3. PROPOSED SYSTEM

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The series of operations you've outlined represents a procedure often used in research related to hair removal and inpainting in images. This procedure is typically employed in the context of cosmetic image editing or computer vision applications where the removal of hair from images is desired. This procedure can be part of a research effort aimed at developing more advanced and effective techniques for hair removal and inpainting in images. Researchers may experiment with different kernel shapes and sizes, employ various inpainting algorithms, or explore machine learning approaches to enhance the quality of hair removal results. The ultimate goal is to develop methods that can accurately and aesthetically remove hair from images while maintaining a natural appearance.

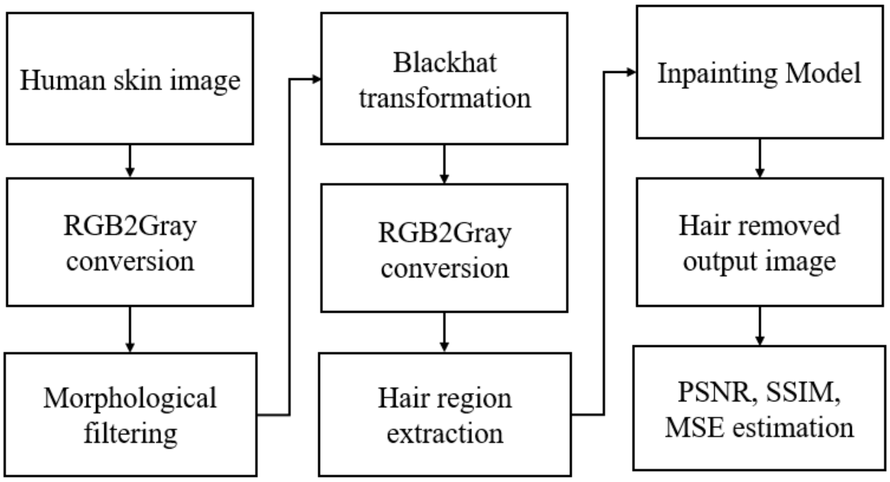

Figure 1: Block diagram of proposed system.

Figure 1 shows the proposed system model. The detailed operation illustrated as follows:

Step 1: Convert the original image to grayscale: The research begins by acquiring an original color image containing hair. The first step is to convert this color image into grayscale. Grayscale conversion simplifies subsequent processing steps by reducing the image to a single channel of intensity values, which makes it easier to work with.

Step 2: Kernel for the morphological filtering: Morphological operations, such as dilation and erosion, rely on a kernel or structuring element to define the size and shape of the filter. In this step, researchers define the kernel that will be used for subsequent morphological operations. The choice of kernel size and shape can impact the effectiveness of hair removal.

Step 3: Perform the blackHat filtering on the grayscale image to find the hair contours: BlackHat filtering is a morphological operation that helps in highlighting dark structures or features against a lighter background. In this context, it is used to emphasize the dark hair contours against the lighter skin or background. The result of this operation is an image that highlights the hair contours, making them more prominent and distinguishable.

Step 4: Intensify the hair contours in preparation for inpainting: Once the hair contours are extracted, researchers may apply further enhancement techniques to intensify or refine these contours. This step aims to prepare the image for the inpainting process, ensuring that the hair regions are well-defined and ready for correction.

Step 5: Inpaint the original image depending on the mask: Inpainting is the final step in the process, where researchers use the extracted hair contours and any further enhancements to reconstruct or fill in the hair regions in the original image. Depending on the specific mask or guidelines used, inpainting algorithms replace the hair with content derived from the surrounding

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areas, creating a result where the hair is effectively removed, and the image appears as if the hair never existed.

4. RESULTS AND DISCUSSION

Figure 2 shows an example of an image where hair removal has been applied using an existing method. It serves as a reference point for comparing the quality of hair removal achieved by the proposed method. Figure 3 shows series of sub-figures, labeled (a) through (e), illustrates the step-by-step process of the proposed hair removal method: (a) Original Image: This is the input image with hair that you want to remove. (b) Grayscale Image: The original image has been converted to grayscale, simplifying subsequent processing. (c) Blackhat Transformed Image: This image appears to be the result of applying a blackhat morphological operation, highlighting dark features (possibly hair contours) against a lighter background. (d) Threshold Image: A thresholding operation has been performed, potentially to create a binary mask separating hair from non-hair areas. (e) Final Output Image: This is the image after applying the proposed hair removal method. Figure 4 provides a visual comparison between the existing hair removal method (Figure 2) and the proposed method (Figure 3e). It visually demonstrates the differences in the quality of hair removal achieved by the two methods.

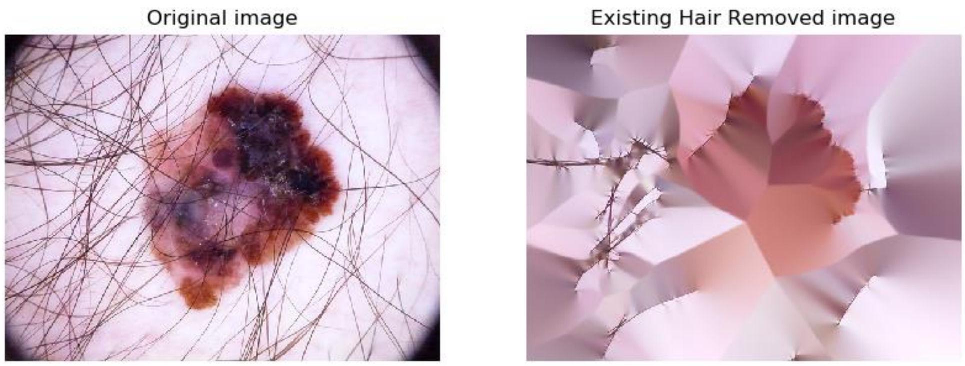
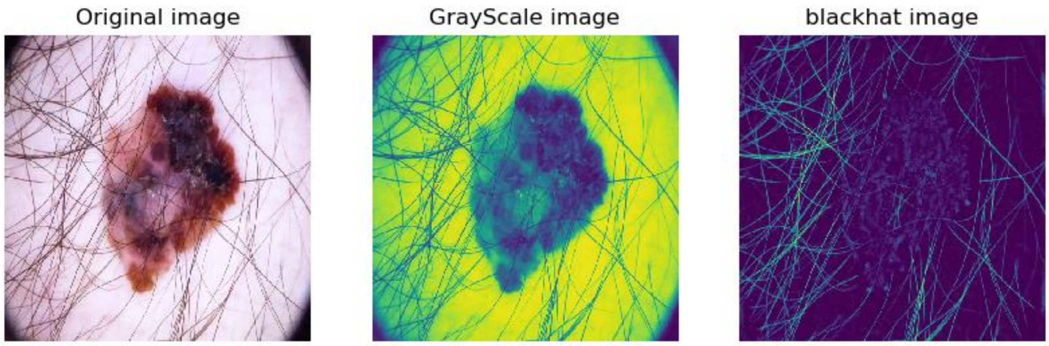


Figure 2. Existing hair removed image



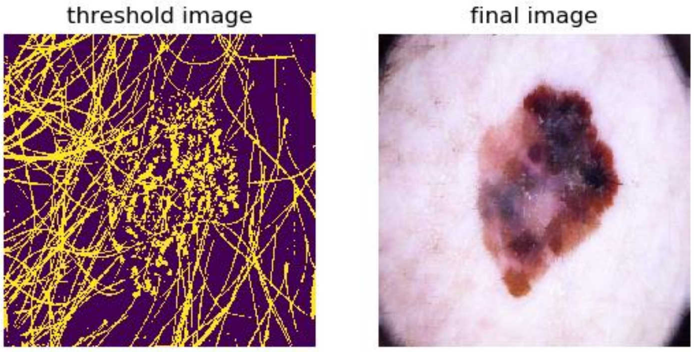


Figure 3. Process of prosed hair removal. (a) original image, (b) gray scale image, (c) blackhat transformed image, (d) threshold image, (e) final output image.

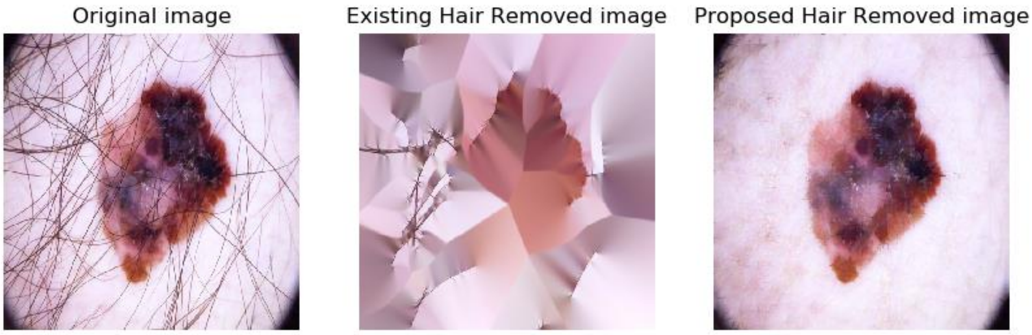


Figure 4. Comparison of existing and proposed hair removed images.

5. CONCLUSION

The outlined procedure for hair removal and inpainting in images represents a valuable approach for various applications, including cosmetic image editing and computer vision. This research work highlights the significance of preprocessing techniques like grayscale conversion, morphological filtering, and inpainting to achieve effective hair removal while maintaining the image's natural appearance. The ability to seamlessly remove hair from images is crucial in fields such as dermatology, telemedicine, and photo retouching. However, it's important to acknowledge the limitations of this procedure, such as potential loss of fine details and the need for careful parameter tuning. Future research endeavors in this area should focus on refining and automating the process, exploring advanced inpainting algorithms, and addressing challenging scenarios, such as sparse or fine hair. Overall, this research contributes to the ongoing efforts to improve image processing techniques for enhancing the quality and aesthetics of digital images.

REFERENCES

[1] . Siegel RL, Miller KD, Fuchs HE, Jemal A. Cancer statistics. CA Cancer J Clin. 2021;71(1):7-33.

[2] Rogers HW, Weinstock MA, Feldman SR, Coldiron BM. Incidence estimate of nonmelanoma skin cancer (keratinocyte carcinomas) in the US population. 2012. JAMA Dermatol. 2015;151(10):1081-1086.

[3] Bray F, Ferlay J, Soerjomataram I, Siegel RL, Torre LA, Jemal A. Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. CA Cancer J Clin. 2018;68(6):394-424.

[4] Esteva A, Kuprel B, Novoa RA, et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature. 2017;542(7639):115-118.

[5] Tschandl P, Codella N, Akay BN, et al. Comparison of the accuracy of human readers versus machine-learning algorithms for pigmented skin lesion classification: an open, web-based, international, diagnostic study. Lancet Oncol. 2019;20(7):938-947.

[6] Ferris LK, Harkes JA, Gilbert B, et al. Computer-aided classification of melanocytic lesions using dermoscopic images. J Am Acad Dermatol. 2015;73(5):769-776.

[7] Haenssle HA, Fink C, Schneiderbauer R, et al. Man against machine: diagnostic performance of a deep learning convolutional neural network for dermoscopic melanoma recognition in comparison to 58 dermatologists. Ann Oncol. 2018;29(8):1836-1842.

[8] Hagerty JR, Stanley RJ, Almubarak HA, et al. Deep learning and handcrafted method fusion: higher diagnostic accuracy for melanoma dermoscopy images. IEEE J Biomed Health Inform. 2019;23(4):1385- 1391.

[9] Barata C, Celebi ME, Marques JS. A survey of feature extraction in dermoscopy image analysis of skin cancer. IEEE J Biomed Health Inform. 2018;23(3):1096-1109.

[10] Fiorese M, Peserico E, Silletti A. VirtualShave: automated hair removal from digital dermatoscopic images. Paper presented at: 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society; August 30–September 03, 2011; Boston, MA, USA.

[11] Abbas Q, Celebi M, García I. Hair removal methods: a comparative study for dermoscopy images, Biomed Signal Process Control. 2011;6(4):395-404. https://doi.org/10.1016/j.bspc.2011.01.003

[12] Lee I, Du X, Anthony B. Hair segmentation using adaptive threshold from edge and branch length measures. Comput Biol Med. 2017;89:314-324.

[13] Xie F-Y, Qin S-Y, Jiang Z-G, Meng R-S. PDE-based unsupervised repair of hair-occluded information in dermoscopy images of melanoma. Comput Med Imaging Graph. 2009;33(4):275-282.

[14] Abbas Q, Garcia IF, Emre Celebi M, Ahmad W. A feature-preserving hair removal algorithm for dermoscopy images. Skin Res Technol. 2013;19(1):e27-e36.

[15] Bornemann F, März T. Fast image inpainting based on coherence transport. J Math Imagng Vision. 2007;28(3):259-278.

[16] Nguyen NH, Lee TK, Atkins MS. Segmentation of light and dark hair in dermoscopic images: a hybrid approach using a universal kernel. Paper presented at: Medical Imaging 2010: Image Processing; March 12, 2010; San Diego, CA.

[17] Lee T, Ng V, Gallagher R, Coldman A, McLean D. Dullrazor®: a software approach to hair removal from images. Comput Biol Med. 1997;27(6):533-543.

[18] Koehoorn J, Sobiecki AC, Boda D, et al. Automated digital hair removal by threshold decomposition and morphological analysis. International Symposium on Mathematical Morphology and Its Applications to Signal and Image Processing. Springer; 2015.