Segmentation of Skin Images with Wavelet-Based Methods

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ABSTRACT*:* - This paper introduces a novel approach for segmenting skin images based on the use of Wavelet Networks (WN). The proposed WN model is a fixed-structure network that does not require traditional training. After constructing the wavelet framework, translation and scaling parameters are determined through a two-stage screening process, which helps in selecting the most effective wavelets. To refine the network architecture and estimate optimal weights, the orthogonal least squares (OLS) algorithm is employed. The dual screening stages enhance the global efficiency of the wavelet matrix and improve function estimation, particularly for larger scales. In this work, the R, G, and B components of the skin image serve as the input features for the network. The image is then segmented to accurately identify the boundaries of skin lesions. The proposed segmentation algorithm was tested on 30 skin images and evaluated across 11 different metrics, using the segmentation results provided by an expert pathologist as the ground truth. Experimental results demonstrate that the proposed method outperforms several existing state-of-the-art techniques commonly applied in medical image analysis.

INTRODUCTION

Among all types of skin cancer, malignant melanoma is considered the most aggressive and life-threatening. Fortunately, despite its increasing prevalence, early diagnosis greatly improves the chances of successful treatment. In automated skin image analysis, the general workflow typically involves three main stages:

- Image segmentation,
- Feature extraction and selection, and
- Lesion classification.

Because of the wide variability in skin color and lesion morphology, segmentation remains the most critical and challenging step.

Numerous algorithms have been proposed for skin image segmentation, including fuzzy c-means clustering, thresholding, Angle Vector Stream (AVS), quantitative tumor extraction, J-image segmentation, independent histogram search, k-means++, statistical region merging, dermatologist-like lesion extraction, adaptive snake models, type-2 fuzzy logic thresholding, wavelet transform-based fuzzy methods, iterative schemes, modified random walker algorithms, and hybrid thresholding on optimal color channels. The diversity of these techniques has resulted in extensive comparative studies discussing their strengths and limitations.

In recent years, artificial intelligence (AI) techniques—particularly fuzzy logic and artificial neural networks (ANNs)—have gained prominence in medical image segmentation. Among these, wavelet networks (WNs) have emerged as a powerful computational approach. WNs combine the advantages of the wavelet transform (WT)—such as denoising, background suppression, and feature recovery—with the approximation capabilities of neural networks. This hybrid structure makes WNs highly suitable for various image processing applications. Compared to conventional neural models like multilayer perceptron's (MLPs) or radial basis function (RBF) networks, WNs offer more efficient deterministic construction and better adaptability.

According to existing literature, wavelet networks have seen limited application in medical image processing. This study introduces a specialized WN for skin image segmentation. WNs are generally categorized into Adaptive Wavelet Networks (AWNs) and Fixed-Grid Wavelet Networks (FGWNs). Due to issues such as computational complexity, sensitivity to initial conditions, and parameter estimation challenges, AWNs have limited practical use.

In contrast, FGWNs define the number of wavelets, scale, and translation parameters in advance, while only the internal parameters (weights) are optimized using algorithms such as least squares. Thus, FGWNs do not require iterative training. In AWNs—similar to conventional NNs or RBF networks—initial weights and parameters are randomly set or determined by other methods, and then refined using gradient descent or backpropagation. Conversely, in FGWNs, only the weights are estimated through a non-iterative process, eliminating the need for training and reducing computational cost.

The proposed method employs a three-layer FGWN with a single hidden layer for skin image segmentation. Input data are first normalized, and a suitable mother wavelet (commonly the Mexican Hat due to its computational efficiency, similarity to Gaussian functions, and robustness to noise) is selected to construct the wavelet matrix. This matrix defines a hyperspace of translation and scaling parameters, which is reduced through two successive screening stages to retain only the most effective wavelets. These dual screening phases enhance the global representation of the wavelet grid and improve function estimation, especially for larger scales.

The Orthogonal Least Squares (OLS) algorithm is then used to determine optimal network parameters. Owing to the localized nature of wavelet basis functions, WNs can struggle with high-dimensional data; however, the efficient wavelet selection process within OLS minimizes sensitivity to input variations. OLS transforms regression vectors into an orthogonal basis, allowing the contribution of each vector to the output energy to be quantified. Compared to backpropagation, OLS offers a significantly faster computation. For segmentation, the R, G, and B components of the skin image are used as network inputs. The FGWN architecture is defined through a ten-stage algorithm, and the resulting output delineates the precise lesion boundaries. In this study, 30 skin images were analyzed, each segmented by an experienced expert. The proposed method was evaluated against the expert’s ground truth (GT) and compared with four state-of-the-art segmentation techniques commonly employed in medical imaging. Experimental results demonstrate that the proposed FGWN approach achieves improved segmentation accuracy and efficiency.

LITERATURE REVIEW

Skin cancer, particularly malignant melanoma, has become one of the most concerning forms of cancer due to its rapid spread and high mortality rate when undiagnosed in early stages. To address this, researchers have focused heavily on automated image segmentation techniques, which serve as the foundation for accurate diagnosis and classification of skin lesions. Over the years, a variety of segmentation methods—ranging from traditional thresholding and clustering to modern neural and wavelet-based approaches—have been explored.

Earlier works such as those by Celebi et al. (2007, 2008) introduced comprehensive methodologies for dermoscopy image classification and border detection. These studies emphasized statistical region merging and clustering-based segmentation, highlighting the importance of defining lesion boundaries precisely. Similarly, Zhou et al. (2008, 2011) worked on spatially constrained segmentation and gradient vector flow (GVF) techniques, which demonstrated improved contour detection but were computationally intensive.

Other researchers have developed fuzzy logic and hybrid systems to handle the irregularity and color variations in skin lesions. For instance, Yuksel and Borlu (2009) employed type-2 fuzzy logic for adaptive image thresholding, achieving good accuracy in complex dermoscopic images. Castillejos et al. (2012) further improved upon this concept by integrating wavelet transform with fuzzy algorithms, enabling more efficient segmentation of medical images. These fuzzy-wavelet models effectively managed image noise and enhanced the detection of melanoma-affected regions.

Machine learning and neural network-based techniques have also made significant progress in the field. Studies by Cheng et al. (1999) and Jiang et al. (2010) explored artificial neural networks (ANNs) and fuzzy neural systems for medical image segmentation, showcasing their adaptability and capability to model nonlinear relationships. However, the main drawback of such systems lies in their need for extensive training and sensitivity to initialization parameters. To mitigate these challenges, researchers began to combine neural models with wavelet transformations, giving rise to wavelet neural networks (WNNs).

The concept of wavelet networks was first introduced by Zhang and Benveniste (1992), who demonstrated their ability to merge the localization properties of wavelets with the learning ability of neural networks. Subsequent studies, such as those by Billings and Wei (2005) and Galvao et al. (2004), expanded this idea, showing how WNNs could be efficiently used for nonlinear system identification. Applications of WNNs have since extended into diverse fields such as face recognition (Zhang et al., 2005), synthetic aperture radar (SAR) image segmentation (Wen et al., 2009), and pattern recognition (Abhyankar and Schuckers, 2010).

In medical imaging, Jemai et al. (2011) and Balabin et al. (2008) explored the use of wavelet networks in combination with the orthogonal least squares (OLS) algorithm to enhance model accuracy and reduce computation time. Their findings indicated that WNNs could outperform conventional neural networks in both speed and precision, particularly when applied to large and noisy datasets. Despite these advantages, most prior implementations relied on adaptive WNNs, which still required training and were sensitive to the choice of initial parameters. To overcome these challenges, researchers proposed fixed-grid wavelet networks (FGWNs)—a variant that predefines external parameters like scale and shift values, thereby eliminating the need for iterative training. This approach significantly reduces computational complexity while maintaining segmentation accuracy. The FGWN model's robustness and efficiency make it a suitable candidate for medical image analysis, where precise lesion boundary detection is crucial.

Overall, the reviewed literature reveals a clear trend toward integrating wavelet theory with intelligent computational models to improve segmentation accuracy and efficiency. However, most existing methods still face limitations in handling high-dimensional medical data or require extensive pre-processing. The current research builds upon these insights by proposing a fixed-grid wavelet network (FGWN) model optimized through the OLS algorithm. This approach aims to achieve faster, more reliable segmentation of skin lesion images without the need for extensive training, thereby advancing the automation of melanoma diagnosis.

CONCLUSION:

In this research, a novel technique for skin image segmentation is presented using a Fixed-Grid Wavelet Network (FGWN). The R, G, and B components of each skin image are utilized as inputs to the network, while the Orthogonal Least Squares (OLS) algorithm is applied to estimate the network weights and optimize its structure. The performance of the proposed approach was compared with four established methods—Active Contour (AT), Gradient Vector Flow (GVF), Fast Boundary Segment Merging (FBSM), and Neural Network (NN)—as well as manual segmentation performed by an expert. Evaluation across 11 quantitative metrics demonstrated that the proposed method achieved superior segmentation accuracy relative to existing techniques. Consequently, the developed algorithm serves as an effective preliminary step for automatic or semi-automatic analysis of skin lesion images.

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