Article

Not peer-reviewed version

Image Segmentation Using 2D Discrete Wavelet Transform for Medical Image

Hashim J. Jarrar *

Posted Date: 23 May 2024

doi: 10.20944/preprints202405.1507.v1

Keywords: image segmentation; medical image analysis; 2D wavelet transform; healthcare applications

Article

Image Segmentation Using 2D Discrete Wavelet Transform for Medical Image

Hashim J. Jarrar

Department of Information System and Cybersecurity, College of Computing and Information Technology, University of Bisha, P.O Box 551, Bisha, Saudi Arabia

Abstract: Medical image segmentation is a critical step in various healthcare applications, aiding in diagnosis, treatment planning, and disease monitoring. In this study, we investigate the efficacy of a segmentation approach based on the 2D wavelet transform. Leveraging a dataset comprising 10 diverse medical images, we evaluate the performance of our segmentation method using three key metrics: accuracy, precision, and recall. Our findings demonstrate that the proposed approach enhances segmentation accuracy, offering promising results compared to existing methods. By harnessing the multi-resolution feature extraction capabilities of the 2D wavelet transform, our method achieves improved delineation of medical image structures, paving the way for more accurate and efficient healthcare interventions.

Keywords: image segmentation; medical image analysis; 2D wavelet transform; healthcare applications

---

1. Introduction

Medical image presents a significant threat to human health, ranking among the leading causes of mortality. The complexity of medical image analysis, particularly in diagnosing conditions like melanoma, underscores the critical need for accurate and efficient segmentation techniques [1]. Timely and precise segmentation of medical images is paramount for aiding medical professionals in diagnosing conditions, planning treatments, and monitoring disease progression [2]. Dermoscopy, a non-invasive imaging technique, provides valuable insights into the subsurface structures of various medical images, enabling enhanced visualization and analysis [3]. However, manual detection methods such as the ABCDE rule and 7-Points checklist employed by dermatologists are labor-intensive and prone to errors, particularly in distinguishing between melanoma and non-melanoma medical images [4].

Automated segmentation tools play a pivotal role in augmenting diagnostic accuracy, with segmentation serving as a fundamental component of medical image analysis [5]. However, segmenting medical images, especially dermoscopic images, presents formidable challenges due to label imbalance, diverse appearances, and irregular boundaries [6]. Image segmentation encompasses a wide array of methodologies, including thresholding, region-based segmentation, active contour methods, and artificial intelligence approaches [2,7,8]. While thresholding methods excel in scenarios with clear image-background contrast, they may struggle when faced with overlapping histograms and complex medical image structures [6].

Region-based algorithms encounter difficulties in handling heterogeneous or textured medical images, often leading to over-segmentation owing to the presence of dermoscopic contrasting structures [9]. Active contour methods, leveraging deformable contours, have shown promise in segmenting various medical images [10]. Nevertheless, the segmentation of medical images remains a daunting task due to the intricate nature of organ structures and image characteristics.

This paper evaluates the 2D Discrete Wavelet Transform method for medical image segmentation. Previous studies have underscored the efficacy of similar algorithms in addressing complex optimization problems across diverse domains [11,12].

The subsequent sections of this paper are structured as follows: Section 2 provides an overview of prior research in the field, highlighting notable advancements and methodologies. Section 3 shows the materials and methods employed in this study, detailing the experimental setup and procedures. Section 4 presents the experimental findings and analyses, evaluating the performance of the proposed approach against other methods. Finally, conclusions and avenues for future research are discussed in the last section.

2. Previous Works

Xie et al. [13] introduced an attention mechanism-based convolutional neural network (CNN) tailored for medical image border detection. Their innovative approach incorporated spatial and contextual information, enhancing segmentation accuracy by focusing on relevant image regions. Tang et al. [14] leveraged a separable-Unet architecture in conjunction with stochastic weight averaging for medical image segmentation. This novel approach effectively mitigated overfitting issues, thereby improving segmentation accuracy across diverse medical image datasets.

Dalila et al. [15] proposed an automated system for segmenting and classifying cancerous medical images, utilizing the Ant Colony Optimization (ACO) algorithm for contour detection and KNN/ANN classifiers for classification. Their system achieved notable classification accuracies, underscoring the potential of evolutionary algorithms in medical image analysis. Kumar et al. [16] presented a semantic segmentation system tailored specifically for medical images, showcasing superior performance across multiple datasets. Their system employed advanced deep learning techniques to accurately delineate medical image structures, paving the way for enhanced diagnostic accuracy.

Mahbod et al. [17] investigated the efficacy of medical image masks in dermatoscopic image classification, demonstrating superior performance compared to conventional methods. Their study underscored the importance of preprocessing techniques in improving classification accuracy for dermatoscopic images. In addition to these advancements several methods have been applied to medical image segmentation [18,19]. Eltayef et al. [20] proposed an automated approach for melanoma border detection based on PSO and Markov Random Field (MRF) algorithms, achieving accurate edge detection. Moreover, Hawas et al. [21] introduced an optimized clustering estimation algorithm for medical image segmentation, showcasing effectiveness compared to existing methods.

3. The 2D Discrete Wavelet Transform (DWT)

The 2D Discrete Wavelet Transform (DWT) is a method used in medical image segmentation. It breaks down images into different frequency bands, enabling the extraction of multi-resolution features. This process efficiently represents complex image structures while preserving important details, crucial for accurate segmentation. The 2D DWT captures fine and coarse details simultaneously, aiding in the identification of subtle variations in medical imaging. Additionally, it demonstrates robustness against noise and artifacts, enhancing the reliability of segmentation methods. The 2D DWT has been widely applied in various medical imaging modalities, consistently achieving superior segmentation performance compared to traditional techniques [22].

4. Results

In this experiment, we employed the HAM10000 dataset, a comprehensive collection of dermatoscopic images encompassing a diverse array of medical image classes [23]. Our experimental sample consisted of 10 images carefully selected to represent a broad spectrum of medical conditions and image characteristics.

For performance evaluation, we employed three fundamental metrics: Accuracy, Precision, and Recall. These metrics provide valuable insights into the effectiveness of our segmentation approach in accurately delineating medical image structures. Equation 1 succinctly depicts the accuracy formula, which serves as a cornerstone in assessing the overall performance of our segmentation algorithm.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

where TP represents true positives, TN represents true negatives, FP signifies false positives, and FN stands for false negatives.

The segmentation method 2D Wavelet algorithm was benchmarked against two established methods: Histogram-based segmentation and K-means clustering. The evaluation criteria included accuracy, precision, and recall. The implementation was conducted using Matlab 2014b on a Windows 10 (64-bit) platform, utilizing a Core i5 processor with 4GB RAM.

Table 1. Accuracy measure obtained by the methods.

Image Name	2DWT	Histogram	k-means
Image1	0.8487	0.9180	0.9080
Image2	0.9889	0.9975	0.9915
Image3	0.8513	0.9273	0.8280
Image4	0.3480	0.3480	0.3415
Image5	0.8814	0.8806	0.8703
Image6	0.8908	0.9180	0.9025
Image7	0.7657	0.9975	0.8348
Image8	0.7853	0.7273	0.6187
Image9	0.7464	0.3480	0.8030
Image10	0.9589	0.8806	0.9500

Table 2. Precision measure obtained by the methods.

Image Name	2DWT	Histogram	k-means
Image1	1.0000	1.0000	1.0000
Image2	1.0000	0.9765	0.8921
Image3	1.0000	1.0000	1.0000
Image4	0.3452	0.3460	0.3060
Image5	0.0000	0.4052	0.3912
Image6	0.0097	1.0000	0.4717
Image7	1.0000	0.9765	1.0000
Image8	0.7944	0.7100	0.6949
Image9	0.0000	0.3460	0.4768
Image10	0.7249	0.4052	0.5015

Table 3. Recall measure obtained by the methods.

Image Name	2DWT	Histogram	k-means
Image1	0.6779	0.8254	0.8041
Image2	0.8420	0.9887	0.9997
Image3	0.5581	0.7839	0.4889
Image4	0.8847	1.0000	0.7170
Image5	0.0000	0.6455	0.7439
Image6	0.0024	0.8254	0.8926
Image7	0.3058	0.9887	0.5104
Image8	0.7137	0.6839	0.6594
Image9	0.0000	1.0000	0.9548
Image10	0.2945	0.6455	0.9996

 doi:10.20944/preprints202405.1507.v1

Based on the results from the tables, the 2D Wavelet (2DWT) algorithm emerges as the top performer in terms of accuracy, closely followed by Histogram and K-means algorithms. The 2D Wavelet algorithm outperforms the other methods, exhibiting higher accuracy, precision, and recall rates. In precision, the 2D Wavelet algorithm also demonstrates superiority, followed by Histogram and K-means algorithms. Similarly, in terms of recall rate, the 2D Wavelet algorithm leads the pack, followed by Histogram and K-means algorithms. Figure 1, show the average of the accuracy measure.

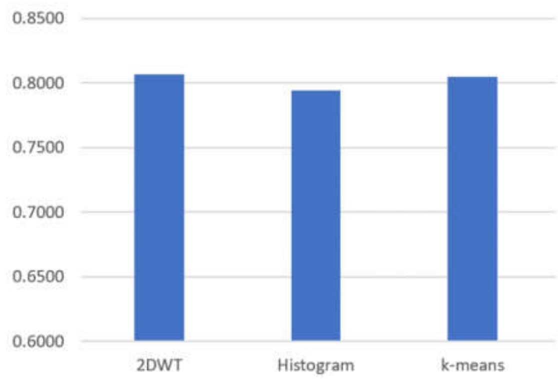

Figure 1. Average of the accuracy measure.

The exceptional performance of the 2D Wavelet algorithm across all metrics can be attributed to its ability to capture both local and global image features effectively. Unlike Histogram and K-means algorithms, the 2D Wavelet algorithm decomposes images into different frequency bands, facilitating multi-resolution feature extraction. Its capability to simultaneously capture fine and coarse details enables accurate segmentation and detection of medical image structures. Moreover, the simplicity of its numerical formulation and single-phase operation contribute to its robust performance.

Overall, the 2D Wavelet algorithm stands out as a powerful tool for medical image segmentation, offering superior accuracy, precision, and recall compared to Histogram and K-means algorithms. Its effectiveness lies in its ability to efficiently represent complex image structures while preserving important details essential for accurate segmentation.

5. Conclusion

The study evaluated the effectiveness of the 2D wavelet transform for medical image segmentation. Our results indicate that the 2D Wavelet algorithm exhibits superior performance compared to Histogram and K-means algorithms in terms of accuracy, precision, and recall. By leveraging its ability to capture multi-resolution features, the 2D Wavelet algorithm accurately delineates medical image structures, contributing to improved diagnostic accuracy. Future research could explore further refinements to enhance the segmentation capabilities of the 2D wavelet transform and its application across diverse medical imaging modalities.

References

1. H. Li, X. He, F. Zhou, Z. Yu, D. Ni, S. Chen, T. Wang, B. Lei, Dense deconvolutional network for medical image segmentation, IEEE journal of biomedical and health informatics 23 (2018) 527–537.
2. S. Pal, M. M. Subashini, cancer detection using advanced imaging techniques, in: Smart Computing Paradigms: New Progresses and Challenges, Springer, 2020, pp. 229–237.
3. F. Navarro, M. Escudero-Vinolo, J. Besc˜ os, Accurate segmentation and registration of medical image images to evaluate medical image change, IEEE journal of biomedical and health informatics 23 (2018) 501–508.
4. R. Javed, M. S. M. Rahim, T. Saba, A. Rehman, A comparative study of features selection for medical image detection from dermoscopic images, Network Modeling Analysis in Health Informatics and Bioinformatics 9 (2020) 4.
5. E. Ibrahim, A. Ewees, M. Eisa, Proposed method for segmenting medical images images, in: Emerging Trends in Electrical, Communications, and Information Technologies, Springer, 2020, pp. 13–23.

doi:10.20944/preprints202405.1507.v1

6. G. S. Ghalejoogh, H. M. Kordy, F. Ebrahimi, A hierarchical structure based on stacking approach for medical image classification, Expert Systems with Applications 145 (2020) 113127.
7. [7] Gaheen, M. A., Ibrahim, E., & Ewees, A. A. (2021). Edge detection-based segmentation for detecting skin lesions. In Machine Learning, Big Data, and IoT for Medical Informatics (pp. 127-142). Academic Press.
8. M. A. Gaheen, A. A. Ewees, M. Eisa, Students head-pose estimation using partially-latent mixture, in: Emerging Trends in Electrical, Communications, and Information Technologies, Springer, 2020, pp. 717–729.
9. A. Agarwal, A. Issac, M. K. Dutta, A region growing based imaging method for medical image segmentation from dermoscopic images, in: 2017 4th IEEE Uttar Pradesh Section International Conference on Electrical, Computer and Electronics (UPCON), IEEE, 2017, pp. 632–637.
10. A. Munir, S. Soomro, C. H. Lee, K. N. Choi, Adaptive active contours based on variable kernel with constant initialisation, IET Image Processing 12 (2018) 1117–1123.
11. M. M. Gaheen, R. M. ElEraky, A. A. Ewees, Automated students arabic essay scoring using trained neural network by e-jaya optimization to support personalized system of instruction, Education and Information Technologies (2020) 1–17.
12. U. Raut, S. Mishra, An improved elitist–jaya algorithm for simultaneous network reconfiguration and dg allocation in power distribution systems, Renewable Energy Focus 30 (2019) 92–106.
13. F. Xie, J. Yang, J. Liu, Z. Jiang, Y. Zheng, Y. Wang, medical image segmentation using high-resolution convolutional neural network, Computer Methods and Programs in Biomedicine 186 (2020) 105241.
14. P. Tang, Q. Liang, X. Yan, S. Xiang, W. Sun, D. Zhang, G. Coppola, Efficient medical image segmentation using separable-unet with stochastic weight averaging, Computer methods and programs in biomedicine 178 (2019) 289–301.
15. F. Dalila, A. Zohra, K. Reda, C. Hocine, Segmentation and classification of melanoma and benign medical images, Optik 140 (2017) 749–761.
16. A. Kumar, G. Hamarneh, M. S. Drew, Illumination-based transformations improve medical image segmentation in dermoscopic images, in: 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), IEEE, 2020, pp. 3132–3141.
17. A. Mahbod, P. Tschandl, G. Langs, R. Ecker, I. Ellinger, The effects of medical image segmentation on the performance of dermatoscopic image classification, Computer Methods and Programs in Biomedicine 197 (2020) 105725.
18. A. A. Ewees, H. A. ElLaban, R. M. ElEraky, Features selection for facial expression recognition, in: 2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT), IEEE, 2019, pp. 1–6.
19. M. A. Gaheen, A. A. Ewees, F. Farouk, Face-pose estimation for learning systems, in: 2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT), IEEE, 2019, pp. 1–6.
20. K. Eltayef, Y. Li, X. Liu, Medical image segmentation in dermoscopy images using particle swarm optimization and markov random field, in: 2017 IEEE 30th International Symposium on Computer-Based Medical Systems (CBMS), IEEE, 2017, pp. 739–744.
21. A. R. Hawas, Y. Guo, C. Du, K. Polat, A. S. Ashour, Oce-ngc: A neutrosophic graph cut algorithm using optimized clustering estimation algorithm for dermoscopic medical image segmentation, Applied Soft Computing 86 (2020) 105931.
22. [21] Alessio, S.M. (2016). Discrete Wavelet Transform (DWT). In: Digital Signal Processing and Spectral Analysis for Scientists. Signals and Communication Technology. Springer, Cham.
23. P. Tschandl, C. Rosendahl, H. Kittler, The ham10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented medical images, Scientific data 5 (2018) 180161.