Frontiers in Computing and Intelligent Systems
ISSN: 2832-6024 | Vol. 4, No. 3, 2023

A Review of Medical Image Segmentation Techniques

Bihan Fan *, Ji Zhang

North China Electric Power University, Baoding 071000, China

Abstract: Medical image segmentation is a key task in medical imaging processing. It can segment different tissues, organs or lesions in medical images to provide doctors with more accurate diagnosis and treatment suggestions. With the continuous development of computer science and medical technology, medical image segmentation technology has also undergone rapid development. This article will provide an overview of medical image segmentation technology from concepts, commonly used methods, and applications, and introduce some of the latest research results.

Keywords: Medical Images; Image Segmentation; Deep Learning; Summarize.

1. Introduction

Medical image segmentation technology is an important technology in the field of medical image processing, aiming to segment different tissues, organs, or lesions in medical images for quantitative analysis and disease diagnosis [1-2]. Medical images are usually obtained through medical imaging equipment (such as X-ray, CT, MRI, etc.), and these images contain different tissues and organs in the human body. Segmentation technology can help doctors better understand the structure in images, while also helping to automate image analysis and assist in diagnosis.

Medical image segmentation technology is widely used in medical imaging, medical research and clinical practice [3-4]. It can be used for tumor detection and localization, vascular analysis, brain structure segmentation, cardiac function evaluation, and other aspects. The development of medical image segmentation technology not only improves the anatomy and functional analysis ability of medical imaging, but also provides clinicians with more accurate diagnosis and treatment basis.

2. Common Methods for Medical Image Segmentation

Medical image segmentation methods are mainly divided into threshold based, edge based, region based, and deep learning-based methods [5]. Based on these methods, researchers have introduced various improvements and made many combinations to solve various problems in image segmentation.

The threshold-based method is one of the simplest image segmentation methods. It is based on the grayscale values of image pixels and divides them into different categories by setting one or more thresholds. This method is suitable for situations where different tissues or lesions in the image have significant grayscale differences. Usually, a suitable threshold can be selected through histogram analysis. It is generally divided into two steps: one is to calculate the histogram of the image and count the number of pixels with different grayscale values. The second is to segment the image into two or more different regions by observing the histogram and selecting an appropriate threshold. Reference [6] proposes an adaptive threshold segmentation method. This method is mainly used for ultrasound medical images, including two parts: an automatic region of interest extraction method based on target area detection and an improved adaptive threshold-based ultrasound medical image segmentation algorithm. Firstly, the connectivity of the target region is detected, and the maximum connected region is iteratively determined according to the area parameter value. Then, the region of interest is extracted from the ultrasonic medical image and converted into an integral image; Solve the optimal adaptive threshold segmentation parameters through grid search method to segment regions of interest. Reference [7] proposed a multi-threshold segmentation algorithm and designed a fuzzy Kapur entropy based multi-threshold image segmentation algorithm (FKMTS) to eliminate the impact of medical artifacts on the performance of the segmentation algorithm. This algorithm solves the problem of blurring the boundary of medical image organizational structure through fuzzy Kapur entropy; In addition, on the basis of FKMTS, a fuzzy Kapur entropy multi-threshold image segmentation algorithm FKNMTS based on neighborhood information has been designed. Its core idea is to assign membership degrees of different segmentation regions to pixels, and aggregate adjacent pixels that meet the conditions through membership degrees, thereby improving the correlation of pixel membership degrees in local regions. Achieved good segmentation results.

Edge based image segmentation methods perform segmentation by detecting edges in the image. Edges are areas in an image that exhibit significant grayscale changes and can be used to segment different tissues or lesions. Commonly used edge detection algorithms include Canny operator, Sobel operator, etc. The main idea is to first smooth the image to reduce the impact of noise. Then, edge detection algorithms are used to detect edges in the image. Finally, based on the detected edges, the image is segmented. Reference [8] proposes an edge detection and precise positioning algorithm based on Sobel operator. This algorithm combines Sobel gradient map and first-order differential expected threshold to reduce noise and interference. From the perspective of probability distribution, the confidence interval of the actual edge of the image is calculated, and then the positioning estimation is performed, which can achieve high positioning accuracy. The experimental results show that this method can effectively process medical CT images with a large amount of noise and blurred target edges, and extract accurate edges. Reference [9] proposes an edge detection medical image segmentation algorithm based on an improved Canny operator, which fuses image features through multi-scale filtering and combines morphological methods for image enhancement to achieve effective segmentation of medical images. Segmentation experiments were carried out on cell microscopic images and mammography image datasets. The results show that the target edge feature points of the segmentation results of this algorithm have good continuity and strong regional closure, which solves the difficulties of edge detection of the traditional Canny operator and achieves good segmentation results.

The region-based image segmentation method divides the image into a series of continuous regions, each with similar features. This method is typically implemented using algorithms such as region growth, region splitting, and merging. The region growth algorithm starts from one or more seed points, serving as the starting point for region growth. Based on similarity criteria, each pixel is gradually connected to the seed points, and pixels with similar features are merged into a single region. The region growth is continuously iterated until all pixels are assigned to a single region. The region splitting and merging algorithm achieves segmentation by iteratively splitting and merging regions. Reference [10] proposes a laser medical image segmentation method based on region growth. This method first eliminates noise in laser images through bilateral filtering to protect edge details. Then, an improved watershed method is used to segment the laser image, and the region growth method is used to further process the image segmentation results, making the segmented target more complete. Simulation experiments show that this method achieves high accuracy in laser image segmentation and can effectively handle the impact of noise. Reference [11] proposed an interactive medical image segmentation method based on PRW region correction. This method divides seed points based on the original manual annotation information of the dataset using the RW algorithm, and converts the partitioning process into Dirichlet integrals to accelerate the solution speed; The distribution of seed points is calculated by PRW, and the target equation is solved based on the pixel distribution of the target image to obtain seed point classification. Finally, neighborhood models and region correction strategies are used to handle the similarity of adjacent pixels, construct corresponding feature potentials based on the characteristics of each region, and use connection checks to correct segmentation errors in pixels. Simulation experiments have shown that this method can achieve complete, fast, and accurate medical image segmentation.

The medical image segmentation method based on deep learning is a new image segmentation method developed in recent years. Deep learning technology learns the features and segmentation rules of images by constructing deep neural network models. This method usually requires a large amount of annotated data for training, but has achieved good results in many medical image segmentation tasks. Common deep learning models include Convolutional neural network (CNN), U-Net, etc. The specific steps are as follows: Firstly, prepare a large amount of annotation data, including input images and corresponding segmentation results; Then, a deep neural network model is constructed, including input layer, convolutional layer, pooling layer, upsampling layer, and output layer; Next, use annotated data to train the deep neural network to learn the features and segmentation rules of the image; Finally, use the trained model to segment the new medical image. Reference [12] proposes a U-net segmentation algorithm based on a hybrid state transition algorithm. Using a variable depth encoding strategy to represent the potential optimal depth and different building blocks in U-net; It uses original interactive operations to generate potential individuals, and accelerates the evolution speed of network individuals by introducing Transfer learning strategies and reducing epochs; This method was tested on cardiac MRI and liver LiTS medical image datasets, and its effectiveness was verified. Literature [13] proposed a new medical image semantic segmentation network, which is based on Convolutional neural network and Transformer, and can greatly improve the accuracy of medical image semantic segmentation. The network extracts network structure features through ResNet-50, and then uses Transformer technology to expand the Receptive field; A cascading up sampler is introduced to decode hidden features through multi-layer jump connection combination to make full use of feature extraction information at each stage. Finally, experiments were conducted on the gastrointestinal medical image segmentation dataset to demonstrate the segmentation accuracy of this method

3. Recent Research Results

In recent years, with the rapid development of deep learning technology, many researchers have achieved a series of important research results in the field of medical image segmentation. For example, researchers have proposed a deep learning model based on U-Net for segmenting lesion areas in brain MRI images. Some researchers have also applied Generative adversarial network to medical image segmentation and achieved better segmentation results. Meta AI has released a basic model in the field of visual segmentation called the Segment Anything Model, abbreviated as SAM. This model is very powerful and shows a strong ability in image segmentation tasks. It mainly uses Prompt engineering to train a large pre training model for segmentation according to prompts. This model has the potential to be applied in downstream segmentation tasks, and can be combined with other visual tasks to form new solutions for other visual tasks.

4. Conclusion

In summary, the commonly used methods for medical image segmentation include threshold-based methods, edge-based methods, region-based methods, and deep learning-based methods. Each method has its own characteristics and applicable scenarios. With the continuous development and in-depth research of technology, the methods and algorithms of medical image segmentation will become increasingly intelligent and precise. In the future, medical image segmentation technology will play a greater role in the field of medical image processing.

References

[1] Ren Chulan, Wang Ning, Zhang Yang. Overview of Medical Image Segmentation Methods [J]. Network Security Technology and Applications, 2022 (02): 49-50.

[2] Liu Yu, Chen Sheng. Overview of Medical Image Segmentation Methods [J]. Electronic Science and Technology, 2017,30 (08): 169-172. DOI: 10.16180/j.cnki.issn1007-7820.2017.08.047.

[3] Zhou Tao, Dong Yali, Huo Bingqiang, et al. A review of the application of U-Net network in medical image segmentation

[J]. Chinese Journal of Image and Graphics, 2021,26 (09): 2058-2077.

[4] Qu Binpeng, Wei Xiaojie, Miao Jia, et al. Application Practice of Image Segmentation Technology in Medical Image Processing [J]. Science and Technology Innovation and Application, 2021,11 (16): 178-180.

[5] Pan Xiaohang. Medical Image Segmentation Method [J]. Electronic Technology and Software Engineering, 2018 (11): 84-85+235.

[6] Khalid S. Research on medical ultrasonic image segmentation method based on improved adaptive threshold [D]. Beijing University of Chemical Technology, 2022.

[7] Liu Fengning Research on fuzzy multi threshold medical image segmentation algorithm [D]. Nanjing University of Posts and Telecommunications, 2019.

[8] Zeng Wenquan, He Yongjun, Yu Aimin, et al. A Sobel operator based probability estimation method for medical image edge refinement [J]. Microcomputers and Applications, 2013,32 (13): 49-52+57.

[9] Xu Li, Wu Jiamin, Yang Yang, et al. Research on Medical Image Segmentation Based on Improved Canny Operator [J]. Computer and Digital Engineering, 2023,51 (02): 456-461.

[10] Guo Dongmin, Li Lianjie, Shan Chunyan. Laser medical image segmentation based on improved watershed and regional growth [J]. Journal of Laser, 2015,36 (09): 64-67.

[11] Zhou Junjie, Peng You, Shi Yuanwu. Research on Interactive Medical Image Segmentation Based on PRW Region Correction [J]. Computer Simulation, 2022,39 (11): 235-239.

[12] Zhou Xiaojun, Geng Chuanyu, Yang Chunhua. Medical image segmentation based on state transition algorithm and U-net [J]. Journal of Central South University (Natural Science Edition), 2023,54 (04): 1358-1369.

[13] Wang Jinxiang, Fu Lijun, Yin Pengbin, et al. Medical Image Segmentation Based on CNN and Transformer [J]. Computer System Application, 2023,32 (04): 141-148.