Journal of Electronic Research and Application, 2024, Volume 8, Issue 6
http://ojs.bbwpublisher.com/index.php/JERA
ISSN Online: 2208-3510
ISSN Print: 2208-3502

A Review of Research on Accurate Segmentation of Multimodal Tumor Images

Hao He[1]*, Zixuan Yin[2], Mingzhu Dong[3]

[1]Anhui Institute of Information Technology, School of Computer and Software Engineering, Wuhu 241100, China
[2]Bohai University, Finance, School of Economics, Jinzhou 121000, China
[3]Hefei University of Technology, Xuancheng Campus Hospital, Xuancheng 242000, China

***Corresponding author:** Hao He, hehao206@126.com

Abstract: Accurate segmentation of tumor images is a key core technology for the diagnosis and treatment of tumor diseases. In this paper, we analyze a variety of novel and targeted algorithms to solve these problems, summarize, and elaborate the method based on multimodal tumor image processing given the characteristics of serious grayscale inhomogeneity, texture instability, and diversity complexity of tumor images.

Keywords: Multimodal; Image segmentation; Tumor image

Online publication: December 2, 2024

1. Introduction

According to the International Agency for Research on Cancer (IARC), in 2020, there will be approximately 19.2 million new cancer cases and 10 million cancer-related deaths worldwide. Tumors have become one of the major public health problems worldwide. The most common types of tumors worldwide include lung, breast, colorectal, prostate, and stomach cancers. Among these, lung cancer is one of the leading causes of cancer deaths worldwide.

In the process of computer-aided diagnosis and treatment, the precise segmentation of tumors is an important and urgent task. Firstly, the importance of precise radiotherapy. For patients with tumors that have not yet metastasized extensively, image-guided radiotherapy is now commonly used. This treatment requires tomographic images of the patient to locate tumor boundaries and organs at risk, from which the radiation dose distribution in the patient is calculated and the radiotherapy is planned. Precise radiotherapy for tumor patients is essential to avoid endangering normal organs and thus prolonging the patient's survival or even curing the tumor. However, the prerequisite for precise radiotherapy is to plan the ideal target area by precise segmentation of the tumor.

Secondly, the importance of constructing radiomics. Radiomics extensively quantifies the phenotype of tumors by analyzing a large number of quantitative features and thus the processing flow is shown in **Figure**

1, which is divided into image acquisition, segmentation, feature extraction, and quantification as well as the final analysis. As tumors need to be feature extracted and quantified, effective tumor image segmentation is the basis of feature extraction and data analysis, and is also a very important and challenging part of the whole radiomics process.

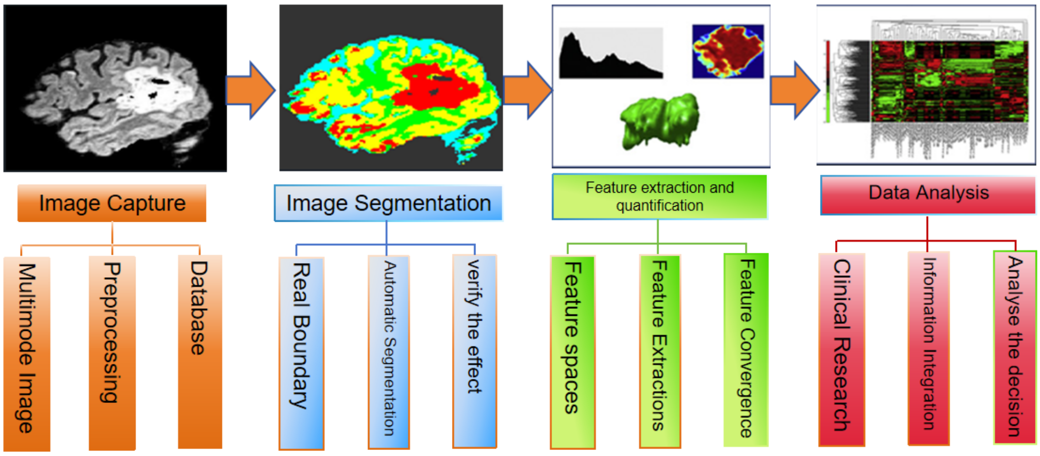

Figure 1. Oncology processing flow

Histology plays an important and challenging role as well. Due to the different textures, shapes, grayscale changes, and other differential features displayed by different patients on the tumor images, by analyzing a large number of multimodal image features, radiomics research focuses on improving the data analysis capability of medical imaging and providing more and better information than what medical experts can derive from traditional methods [1]. The construction and study of radiomics allow further algorithmic means to analyze and target oncological diseases.

Finally, the importance in the field of international medicine, in 2011, the think tank of genomics and the biomedical community in the United States published "Towards Precision Medicine: Building a Knowledge Network for a New Taxonomy of Biomedicine and Disease" [8]. In August 2013, the International Society of Radiology organized a forum on looking forward to the next five years of development of medical technology in Beijing. It was determined that precision medicine is the direction for the development of medical imaging in the next five years. It can be seen that the precise segmentation of brain tumors has been widely mentioned and has gradually become a research hotspot and goal in the international medical field. The research difficulties in the accurate segmentation of tumor images are as follows.

(1) In terms of the characteristics of the tumor itself, due to the unpredictable pathological process of tumor generation and growth, the irregular shape of the tumor, the irregular boundaries, and even uneven grayscale inside the tumor, and the introduction of noise in the image acquisition process, the segmentation of the tumor image is still challenging.

(2) In terms of the image data used, due to the field offset effect of the imaging device, the movement of the patient's body position, and the complexity and variability of the anatomical structure of the region of interest, the boundaries of anatomical structures become unclear and variable. For unimodal images, due to the field shift effect of the imaging device, the movement of the patient's body position, and the

complexity and variability of the anatomical structures in the region of interest, the boundaries of the anatomical structures become unclear and discontinuous. Therefore, the diagnostic and therapeutic information that can be provided by a unimodal image is very limited. Although the above image acquisition errors do not disappear for single modality images in multimodal joint segmentation, by making full use of the useful information in each modality through appropriate strategies, more accurate results can be obtained than using single modality segmentation. How to fully integrate the effective information of these different modalities becomes an important problem to be solved in the multimodal joint segmentation method.

(3) From the analysis of the actual problem of tumor segmentation, although there are many segmentation methods, Magnetic Resonance Imaging (MRI) tumor image segmentation has not yet been able to get rid of the situation of the specific analysis of the specific tasks and has not yet formed a common solution.

2. Elaboration of methodology

Currently, the commonly used image segmentation methods are broadly classified into the following five categories: thresholding-based methods, edge detection-based methods, region growth-based methods, graph cut-based methods, and elasticity model-based methods. However, traditional medical image segmentation methods include simple image segmentation methods based on thresholding and region growth, as well as more complex segmentation methods based on Statistical Shape Model (SSM) and graph cut. In recent years, level-set methods have been widely used in the field of medical image segmentation. Level set methods are mainly divided into two categories: edge-type and region-type level set methods. Edge-based methods mainly rely on the edge features of the image, including the gradient and other information to detect the target edge, which makes this type of method have an obvious disadvantage being that it does not apply to images with unclear boundaries. Region-based level set methods are divided into global, local, and hybrid models.

The Chan-Vese model proposed by Chan *et al.* as the most classical global region-based level set model makes it an important basis for local and hybrid region-based level set methods [17]. At this time, researchers proposed many local region-based level set methods to solve the problem of gray level inhomogeneity, Darolti *et al.* used to segment gray level inhomogeneous images by defining local region descriptors on the local neighborhoods around the evolutionary contours of the level set to avoid overlapping gray level distributions as much as possible [3]. Lankton *et al.* proposed to fit the target and background regions separately in the local regions around the edges of the evolutionary contours of the level set [18]. Lankton *et al.* proposed a framework to fit the target and background regions in the local region of the edges of the evolving contours of the level set so that several types of global level set methods can be applied to segment some grayscale inhomogeneous images efficiently, to solve the problem of complex grayscale interference and accurate segmentation of tumor regions in MRI images.

Guo *et al.* proposed a semi-automatic segmentation method based on the level set method, in which the initial contour is placed manually in the vicinity of the tumor contour, with the help of edge-type and region-type descriptors, to avoid overlapping grayscale distributions as much as possible [10]. The initial contour position is manually placed near the tumor contour, with the help of the idea of constructing edge-type and region-type level sets, and at the same time, the principle of combining local and global is used to construct the level set energy general function, and the final segmentation result is obtained by minimizing the energy general function. Shaheen *et al.* first extracted the multiple features of the image such as the texture, shape, and gray level, and then solved the fusion problem of the multiple features through the expectation-maximization method based on the level set method, to achieve the segmentation of the multimodal tumor. thereby achieving the segmentation of multimodal tumors [5]. The above two methods are similar to a simple cumulative fusion, and cannot effectively fuse multiple multi-features through intuitive or quantitative analysis.

However, how to make the fused features complementary is the key issue that they do not address. It is particularly noteworthy that with the recent application of the more popular machine learning algorithms in the field of image processing, level-set methods have also been widely combined with methods such as sparse representation to achieve more accurate segmentation results. Low-rank representations have begun to be used in the segmentation of complex natural images to solve some image segmentation problems based on statistical analysis. Sparse representations are efficient in segmenting image regions due to their unique dimensionality reduction ability [4]. Wang *et al.* proposed a semi-supervised segmentation method by identifying some texture blocks as training samples in advance, then training the data with the help of sparse representations, and then classifying the data efficiently to gray drive the contour evolution of the level set [19]. This type of approach is based on features such as statistical local histogram information, which on the one hand does not have targeted multi-feature extraction and multi-feature training learning. On the other hand, it lacks effective fusion. Therefore, they are ineffective for complex tumor images with severe interference and unstable grayscale. The summary is as follows.

(1) The severe grayscale inhomogeneity of brain tumor images has become a major obstacle to accurate segmentation, and the traditional level-set method can approximate the grayscale uniformity of the images to a certain extent by using the grayscale inhomogeneity correction method with local information. However, given the severe grayscale variations, discontinuous boundary contours, and unstable grayscale in some regions of the brain tumor image, and as such, makes the traditional level-set method is no longer able to accurately correct the grayscale inhomogeneity effect.

(2) Due to the instability of the texture features of the brain tumor image, the uncertainty of the scale and the direction of the image, and other factors, result in the difficulty of analyzing the determined texture patterns only by the existing static images.

(3) Although the level set method has demonstrated strong advantages in the field of image segmentation, each existing algorithm has certain limitations and it is difficult to achieve satisfactory results when segmenting general images, so the current trend is to focus on the use of multiple segmentation algorithms together, effectively combining the advantages of a variety of algorithms.

(4) How to better extract features from single-modal images, design a segmentation framework that fully leverages multi-featured images, and utilize the complementary information between multiple algorithms are key challenges in achieving higher segmentation accuracy. Although the trend in complex image segmentation research involves using multiple algorithms and features, effectively fusing these is essential for successful segmentation outcomes.

3. Conclusion

Based on the problems and challenges mentioned, the segmentation of multimodal tumor images should focus more on the combination of advanced research algorithms and level sets to solve the problem of segmentation of complex tumor images, and future research should focus on the following points.

(1) Applying the adaptive multi-scale algorithm to the level set generalization, which can determine the corresponding local processing scale for different degrees of grayscale inhomogeneity, and inhibit the grayscale inhomogeneity effect of the image to the maximum extent, to be able to adaptively solve the serious grayscale inhomogeneity problem caused by the invasive growth of some tumors and other characteristics.

(2) Use dynamic texture feature extraction as well as processing to solve the segmentation problem of static texture images. Traditional texture feature patterns, such as grayscale change information, texture primitives, neighborhood change patterns, and many more are difficult to accurately identify the tumor regions and normal tissues of complex static tumor images, which on the one hand, do not have enough patterns to be analyzed and trained, and on the other hand, lack of the comprehensiveness of the patterns. We propose to solve the segmentation problem of static tumor images by using dynamic texture patterns. Since dynamic texture mainly targets unstable texture features including unstable scale, direction, and other features, it can effectively solve the problem of texture feature instability in multimodal tumor images. Most importantly, attention should be paid to the complementary fusion of multi-features and multi-algorithms, as different targeted algorithms are proposed for different features of complex tumor images, and the comprehensive use of level set methods and novel research methods will be the development direction of MRI tumor image segmentation technology.

Funding

2022 Scientific Research Project of Anhui Higher Education Institutions (Natural Science), "Construction and Application of Multimodal Medical Tumor Image Segmentation Model Based on Improved U-Net Model" (Project No. 2022AH051889).

Disclosure statement

The authors declare no conflict of interest.

References

[1] Lambin P, Rios-Velazquez E, Leijenaar R, et al., 2012, Radiomics: Extracting More Information from Medical Images using Advanced Feature Analysis. European Journal of Cancer, 48(4): 441–446.

[2] Siegel R, Naishadham D, Jemal A, 2013, Cancer Statistics. CA: A Cancer Journal for Clinicians, 63(1): 11–30.

[3] Darolti C, Mertins A, Bodensteiner C, et al., 2008, Local Region Descriptors for Active Contours Evolution. IEEE Transactions on Image Processing, 17: 2275–2288.

[4] Gao Y, Bouix S, Shenton ME, et al., 2013, Sparse Texture Active Contour. IEEE Transactions on Image Processing, 22(10): 3866–3878.

[5] Ahmed S, Iftekharuddin KM, Vossough A, et al., 2011, Efficacy of Texture, Shape, and Intensity Feature Fusion for Posterior-Fossa Tumor Segmentation in MRI. IEEE Transactions on Information Technology in Biomedicine, 15(2): 206–213.

[6] Liu Y, Sadowski SM, Weisbrod AB, et al., 2014, Patient-Specific Tumor Growth Prediction using Multimodal Images. Medical Image Analysis, 18(3): 555–566.

[7] Parisot S, Wells W, Chemouny S, et al., 2014, Concurrent Tumor Segmentation and Registration with Uncertainty-Based Sparse Non-Uniform Graphs. Medical Image Analysis, 18(4): 647–659.

[8] National Research Council, 2011, Toward Precision Medicine: Building a Knowledge Network for Biomedical Research and a New Taxonomy of Disease.

[9] Doyle S, Vasseur F, Dojat M, et al., 2013, Fully Automatic Brain Tumor Segmentation from Multiple MR Sequences using Hidden Markov Fields and Variational EM. Proceedings of MICCAI-BRAST, September 22–25, 2013.

[10] Guo X, Schwartz L, Zhao B, 2013, Semi-Automatic Segmentation of Multimodal Brain Tumor Using Active Contours. Proceedings of MICCAI-BRAST, September 22–25, 2013.

[11] Iftekharuddin KM, Zheng J, Islam MA, et al., 2009, Fractal-Based Brain Tumor Detection in Multimodal MRI. Applied Mathematics and Computation, 207(1): 23–41.

[12] Li C, Kao C, Gore JC, et al., 2008, Minimization of Region-Scalable Fitting Energy for Image Segmentation. IEEE Transactions on Image Processing, 17(10): 1940–1949.

[13] Li C, Huang R, Ding Z, et al., 2011, A Level Set Method for Image Segmentation in the Presence of Intensity Inhomogeneities with Application to MRI. IEEE Transactions on Image Processing, 20(7): 2007–2016.

[14] Li CY, Wang X, Eberl S, et al., 2013, Robust Model for Segmenting Images With/Without Intensity Inhomogeneities. IEEE Transactions on Image Processing, 22(8): 3296–3309.

[15] Zhang H, Ye X, Chen Y, 2013, An Efficient Algorithm for Multiphase Image Segmentation with Intensity Bias Correction. IEEE Transactions on Image Processing, 2(10): 3842–3851.

[16] Wang W, Hua M, 2013, Extracting Dominant Textures in Real Time With Multi-Scale Hue-Saturation-Intensity Histograms. IEEE Transactions on Image Processing, 22(11): 4237–4248.

[17] Chan TF, Vese LA, 2001, Active Contours without Edges. IEEE Transactions on Image Processing, 10(2): 266–277.

[18] Lankton S, Tannenbaum A,2008, Localizing Region-Based Active Contours. IEEE Transactions on Image Processing, 17: 2029–2039.

[19] Wang B, Gao XB, et al., 2010, A Unified Tensor Level Set for Image Segmentation. IEEE Trans. Syst. Man Cybern. PartB: Cybern., 40(3): 857–867.

Publisher's note

Bio-Byword Scientific Publishing remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.