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A overview of the use of multi-modality fusion and deep learning for medical picture segmentation

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SUMMARY

Due to its ability to provide multiple information about a target (tumor, organ, or tissue), multi-modality is frequently utilized in medical imaging. In order to improve the segmentation, multimodality segmentation involves fusing multiple information sources. In recent times, approaches based on deep learning have demonstrated cutting-edge results in image classification, segmentation, object detection, and tracking tasks. Multi-modal medical image segmentation has recently also piqued the interest of deep learning researchers due to their capacity for self-learning and generalization across large amounts of data. We present an overview of deep learning-based methods for the multi-modal medical image segmentation task in this paper. Multi-modal medical image segmentation and the general principle of deep learning are first discussed. Second, we compare and contrast the outcomes of various fusion strategies and deep learning network architectures. Because it is straightforward and focuses on the subsequent segmentation network architecture, the earlier fusion is frequently utilized. However, the later fusion places a greater emphasis on the fusion strategy in order to learn the intricate connection that exists between the various modalities. If the fusion technique is effective enough, later fusion can generally yield more accurate results than earlier fusion. Additionally, we talk about some typical issues with medical image segmentation. In conclusion, we offer a synopsis and some perspectives on the upcoming research.

Keywords: Deep learning, Medical image segmentation, Multi-modality fusion

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INTRODUCTION

With the development of medical image acquisition systems, multi-modality segmentation has been the subject of extensive research. Probability theory, fuzzy concepts believe functions, and machine learning is two examples of successful image fusion strategies. For the techniques in view of the likelihood hypothesis and AI, various information modalities have different measurable properties which make it hard to display those utilizing shallow models. The fuzzy measure measures the degree of membership in relation to a decision for each source in the methods based on the fuzzy concept. The combination of a few sources is accomplished by applying the fluffy administrators to the fluffy sets. Each source is first modeled by an evidential mass in the belief function theory methods, and then the DempsterShafer rule is used to fuse all sources. The selection of the evidential mass, the fuzzy measure, and the fuzzy conjunction function is the primary obstacle to utilizing the belief function theory and the fuzzy set theory. However, the mapping can be directly encoded by a deep learning-based network. As a result, the deep learning-based approach has a great chance of achieving superior fusion results to those of conventional approaches.

DESCRIPTION

A number of deep convolutional neural network models, including AlexNet, ZFNet, VGG, GoogleNet, Residual Net, DenseNet, FCN, and U-Net, have been proposed since 2012.In addition to offering cutting-edge performance for image classification, segmentation, object detection, and tracking, these models offer a novel perspective on image fusion. Their success can be attributed primarily to the following four factors: First, advances in neural networks are the primary factor in deep learning's remarkable success over traditional machine learning models. Deep learning learns high-level features incrementally from data, eliminating the need for domain expertise and hard feature extraction. Additionally, it provides comprehensive solution to the issue. Second, the model can be trained 10 to 30 times faster on GPUs than on CPUs thanks to the development of GPU-computing libraries. Additionally, GPU implementations are provided by open source software packages. Thirdly, researchers can train and test new versions of deep learning models by using publicly accessible datasets like ImageNet. Finally, the final success of deep learning can be attributed to a number of efficient optimization techniques, including dropout, batch normalization, Adam optimizer, and others. We can also update the weights and get the best performance using the ReLU activation function and its variants [1].

Medical image researchers have also attempted to apply deep learning-based approaches to medical image segmentation in the brain, pancreas, prostate, and multi-organ. This was motivated by the success of deep learning. For diagnosis, monitoring, and treatment, medical image segmentation is a crucial component of medical image analysis. The objective is to label each image pixel, which typically involves two phases: first, finding the unhealthy tissue or areas of interest; Second, narrow down the various anatomical structures or areas of interest. In the medical image segmentation task, these deep learning-based methods have outperformed conventional methods. Utilizing multi-modal medical images has become a growing trend strategy for better segmentation and diagnosis. On July 17, 2019, a query was made for a comprehensive literature review using the keywords "deep learning," "medical image segmentation," and "multi modality."We can see that the quantity of papers builds consistently from 2014 to 2018, and that implies multi-modular clinical picture division in profound learning are acquiring increasingly more consideration as of late [2,3].

We compare the scientific output of the image segmentation community, the medical image segmentation community, and the medical image segmentation using multi-modality fusion with and without deep learning to better comprehend the scope of this research field. As can be seen from the graph, the number of papers using methods other than deep learning is decreasing or even trending downward, whereas the number of papers using deep learning methods is rising across all research fields. Due to the limited datasets, classical methods still hold the upper hand, especially in the medial image segmentation field; however, we can clearly see an increasing tendency toward methods that employ deep learning. Medical image analysis uses computed tomography (CT), positron emission tomography (PET), and magnetic resonance imaging (MRI).Multi-modal images, in comparison to single images, aid in the better representation of data and the network's discriminative power by bringing together information from multiple perspectives and enabling the extraction of features from those perspectives [4-6].

The MR image can provide a good soft tissue contrast without the use of radiation, whereas the CT image can diagnose muscle and bone disorders like bone tumors and fractures. While functional images like PET can provide quantitative metabolic and functional information about diseases, they do not have anatomical characterization. X-ray methodology can give reciprocal data because of its reliance on factor procurement boundaries, for example, T1-weighted (T1), contrast-upgraded T1-weighted (T1c), T2-weighted (T2) and Liquid weakening reversal recuperation (Energy) pictures.T2 and Flair can detect a tumor with peritumoral edema, whereas T1 and T1c can only detect the tumor core without it. As a result, using multi-modal images can make clinical diagnosis and segmentation more accurate and reduce information uncertainty. In, we talk about a few popular multimodal medical images. The earlier fusion is straightforward, and the majority of works employ it for segmentation. It focuses on the subsequent designs of complex segmentation network architectures but does not take into account the relationship between various modalities and does not investigate how to fuse various feature information to enhance segmentation performance. However, because each modality is used as an input to a single network that is capable of learning complex and complementary feature information from each modality, the later fusion pays more attention to the fusion problem. If the fusion method is effective enough, the later fusion can generally achieve better segmentation performance than the earlier fusion. Furthermore, the choice of fusion technique is dependent on the problem at hand [7-10].

CONCLUSION

Deep learning-based medical image analysis is also the subject of a few additional reviews. However, the fusion strategy is not their primary focus. Examples include Litjens et al. reviewed the most important ideas about deep learning in medical image analysis. Bernal and co. gave an overview of deep CNN for MRI analysis of the brain. For the purpose of medical image segmentation, we concentrate on fusion techniques for multi-modal medical images in this paper. The remainder of the paper is organized as followed. Multi-modal medical image segmentation and the general principle of deep learning are discussed in Section 2.We explain how to prepare the data before feeding it to the network in Section 3.The comprehensive multi-modal segmentation network based on various fusion strategies is discussed in depth in Section 4.We talk about some common issues that have arisen in the field in Section 5.In conclusion, we provide a synopsis and talk about the outlook for the future in the field of multi-modal medical image segmentation.

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