ISSN 1746-7659, England, UK
Journal of Information and Computing Science
Vol. 17, No. 2, 2022, *pp*.138-153

Gaussian Mixture Model Loss Functional for Brain MRI Segmentation With Deep Learning

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(Received October 11, 2022, accepted November 29, 2022)

Abstract: Because of the excellent performance and fast speed of deep neural network, U-Net has become the most popular network framework for medical image segmentation. For various specific image segmentation tasks, researchers have proposed a series of U-Net related methods. However, on the one hand, due to the inherent limitations of convolutional neural networks, the variants of U-Net still cannot model long-range information well while maintaining detailed texture information. On the other hand, since medical images are difficult to obtain a large number of high-quality semantic pixel-level annotations, it is difficult to use supervised deep learning networks. To address these issues above, we proposed a modified U-Net structure and a Gaussian mixture model (GMM) based loss function. This modified U-Net can be well applied to brain MR image segmentation, which can not only restore the detailed information well, but also take into account the relatively large-scale local information. The proposed GMM loss can be used for unsupervised training of neural networks. It effectively alleviates the shortcomings of difficult access to medical image annotation data and improves the performance of deep neural networks. In the experiments in this paper, the GMM loss function can also be used as a regular term to assist supervised learning to achieve better results. Experimental results on brain MR images demonstrate the superior performance of the proposed model.

Keyword: Semi-supervised learning; Unsupervised Deep learning; Modified U-Net; Gaussian mixture model

1. Introduction

Image segmentation is the division of an image into a set of non-overlapping regions. Accurate medical image segmentation technology can help doctors make accurate clinical diagnosis. Magnetic resonance imaging (MRI) has high resolution and high contrast, so it is often used as a theoretical study of medical images. MR images of the brain are segmented into three non-overlapping parts, including white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF), which is important for physicians studying brain disorders. However, due to machine imaging, MRI also has some problems such as uneven gray scale, blurred border, complex texture and noise, which brings severe resistance to the task of brain MRI segmentation.

In recent years, a large number of deep learning-based methods [1] have emerged for brain MR image segmentation, in order to improve the accuracy of image segmentation results. Most of these methods are based on the supervised convolutional neural network (CNN), which has become popular in recent years, which requires high data set size [1,2]. But the cost of acquiring massive labeled datasets is relatively high and labor-intensive for medical images,.

In the case of limited amount of labeled data, it is difficult to make it difficult to reach the correct decision boundary by training the deep learning model., as shown in Fig. 1(a). To overcome this problem, many

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researchers use data augmentation [3,4] to solve the overfitting problem and obtain more precise decision boundaries, which can be found in Fig.1(b). However, these studies still fail to reach a better decision boundary [5]. In order to solve the problem of insufficient labeled datasets, a large number of weak/semi-supervised image segmentation methods have been proposed [6,7,8]. These image segmentation methods require very little high-quality labeled data, which makes the application of deep learning methods in various image segmentation tasks gradually expand, such as brain MR image segmentation.

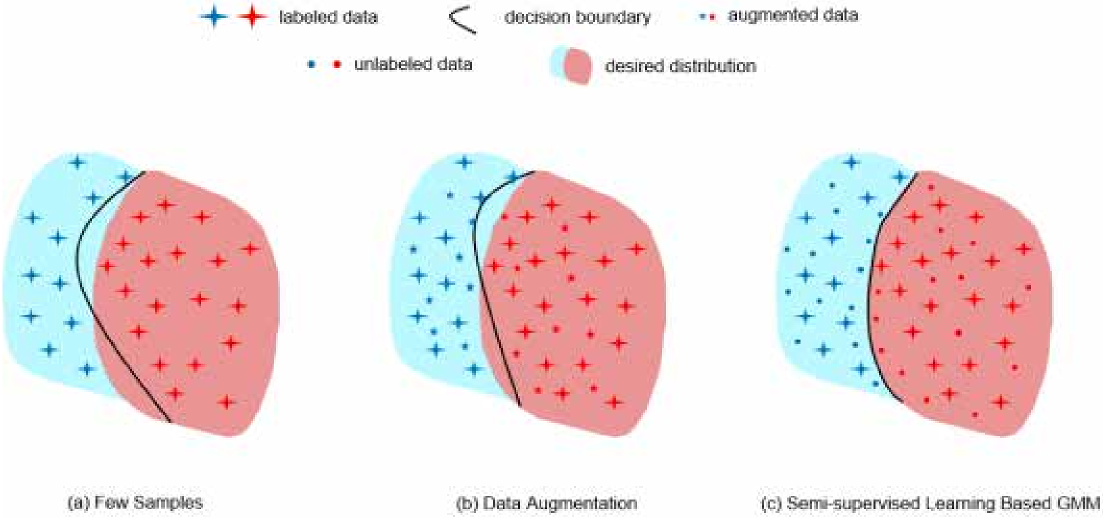

Fig. 1 Comparison of feature visualization.

Based on the observation of traditional image segmentation methods, the classic finite mixture model method for image segmentation is unsupervised [9,10,11,12,13,14]. However, these classical algorithms are computationally complex, and it is very easy to obtain local optimal solutions. In addition, they only consider the individual characteristics of a single individual rather than the common characteristics of image sets, so they are relatively limited in semantic image segmentation.

Through observations from previous studies, we found that classical finite mixture models can help improve the performance of CNN-based deep learning image segmentation models, especially when training data is small. Therefore, we propose a loss function based on the Gaussian mixture likelihood function and couple it to any deep learning network. The proposed loss function is matched with the deep learning network model, which not only utilizes the rich semantic information of the network, but also avoids the shortcomings of insufficient spatial information of the limited mixture model. If learning in a supervised way, our loss function will act as a regularization term, because the loss function considers the feature of pixel similarity, so it can improve the accuracy of the entire image segmentation model. Moreover, because our proposed loss function is a self-supervised loss, we can easily graft it to other deep learning networks for semi-supervised or unsupervised learning. Our method can obtain the best boundary, as shown in Fig.1(c).

In recent years, deep learning-based methods, especially U-Net based methods [2], have been successfully applied to brain MR image segmentation and achieve outstanding performance. However, these methods have deep semantic gaps between the encoders and decoders [15]. Furthermore, the skip connections used in the U-Net can not retrieve the spatial information lost by pooling operations [2]. In order to deal with these problems, many improved U-Net methods have been proposed [15,16,17,18]. Zhou et al. [16] proposed nested and dense skip connections to capture fine-grained details of the objects. Chen et al. [19] used the transformers to improve the U-Net and can preserve more detail information; however, this method has high computational complexity [21]. In this paper, we proposed a modified U-Net, which can effectively makes up for the defect of U-Net modeling long-distance information. Compared with transformer-based models, our method contains fewer parameters and is easier to converge.

2. Backgrounds