MINI EXAM ESSAY

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MRBrainS13 Segmentation Method Essay

Introduction

In this essay I will discuss about three brain segmentation methods which were submitted into MRBrainS13 Brain Segmentation Challenge. This challenge evaluate each brain segmentation methods by measuring how well the method segments and classify these three following classes in MRI brain image : cortical grey matter and basal ganglia (GM), white matter and white matter lesions (WM), and cerebrospinal fluid in extracerebral spaces and ventricles (CSF). A set of three evaluation metric is designed for standardized evaluation on each proposed segmentation method: Dice coefficient (value closer to 100 percent is better), Modified Haussdorf Distance(smaller value is better), and Absolute Volume Difference(smaller value is better).

Segmentation Methods Overview

The first brain segmentation method is *Multi-stage voxel classification method* which was inspired by brain segmentation method developed for neonatal infants. The main difference between adult and neonates MRI brain image is inverted contrast between grey matter and white matter in neonate brain image, hence the usage of T2 image in neonates. Other than the contrast difference, there is no significant difference between adult and neonate brain image. This segmentation method utilizes supervised voxel classification in subsequent stages by exploiting spatial and intensity information.

The segmentation sequences in this method are :

1. Creating a brain mask for defining a region of interest, by registration operation involving training images.
2. First segmentation stage, by computing features based on spatial and intensity data from image. Computed results then used for voxel classification using kNN classifiers.
3. Second segmentation stage, previous features in first stage are used again here, in addition to Gaussian filter up to and including second order, applied to the posterior probabilities of first stage classifier. The second stage mainly classifies unclassified voxels in first stage.

4. Third segmentation stage, which is similar to the second stage, only extra feature: shortest Euclidean distances to each of the three binary segmentations. The result of third stage is four class of segmentation : GM, WM, CSF, and background.

The image data used in the trial are TFE T1-IR from 20 patients (one image set each). Five images from five patients are used for ground truth(manual segmentation) by using freehand spline drawing tool. Other fifteen image sets are used for testing and evaluation.

This segmentation method excels in terms of Dice coefficient and MHD for GM, WM, and cerebrum among other competing methods in MRBrainS13 challenge. However, technically the method requires training data for brain mask generation, despite that the segmentation method do not involve machine learning or neural network tools.

The second brain segmentation method is *Parallel Multi-Dimensional LSTM method*. LSTM (Long Short-Term Memory) networks are recurrent neural network (RNN) initially designed for sequence processing. Using the Multi-Dimensional LSTM expands the capability of the network, by making entire spatio-temporal context of each pixel in an image perceivable by the network. This method utilizes modified version of regular multi-dimensional LSTM, called PyraMid-LSTM, which makes the segmentation process easier to parallelize on GPUs. Shape of scanned contexts in PyraMid-LSTM is triangle-shaped, making the network sensitive to triangle-shaped structure in the image. This means that the is *Parallel Multi-Dimensional LSTM method* can be classified as graph-based segmentation method.

Segmentation sequences are:

5. Augmentation, flipping along x-direction to adjust the image position.
6. Pre-processing, by smoothing and histogram equalization.
7. Training the neural network.
8. Use the test images to validate the result.

For the trial using this method, 3D T1-weighted scan, T1 weighted inversion recovery scan , and fluid-attenuated inversion recovery scan were used. Training scans used are 5 volumes of each scan, and manually segmented through nine labels: cortical gray matter, basal ganglia, white matter, white matter lesions, cerebrospinal fluid, ventricles, brainstem, and background.

This method excels in terms of ability to take each pixel's entire spatio-temporal context into account, as opposed to conventional convolutional neural network. However, since this segmentation method utilize artificial neural network, large number of training data is required to make segmentation accurate even in case of pathological brain image. User input must be done carefully since the nature of neural network and graph-based segmentation relies heavily on the qualified input.

The third brain segmentation method is *Hybrid ANN-based Auto-context method* which was developed by STH team. This method integrates volumetric shape models into a supervised ANN (Artificial Neural Network) framework, which make it unique compared with typical machine learning-based brain segmentation methods. This method of segmentation also combines model-based and contour-based segmentation methods.

The segmentation process begins by pre-processing steps to ensure that the image data features are normalized and ready to be extracted. After pre-process stage, feature extraction starts by statistical shape-fitting process guided by image intensity and sending the signed distance maps of several key features. Additional conventional image features also extracted from the images. The extracted features then sent into the ANN as its input. Shape context information (based on level set) is feed into the ANN to help it learn the local adaptive classification rules based on a certain sample point instead of universal rules. Post processing steps were taken for the ANN results, so that the segmentation can be displayed in informative manner and validated (with the ground truths).

The data from MRBRainS13 were used, consisting of 20 3T MRI brain segmentations from 20 different patients. The ground truth of this method's trial were five segmentations taken from MRBrainS13 data, segmented manually by experts.

This method performs greatly in terms of accuracy and training-testing time—which was considerably shorter than other similar methods. However more random samples are needed, because in case of patient with MS lesion, the system could not perform the classification as good as other patients. Also, inhomogeneity correction was depended heavily to third party resources. Skull stripping process is also prone to error.

Result Discussion

Table 1. Segmentation Scoring and Ranking in context of gray matter (GM) segmentation.

Segmentation Method	**GM Segmentation score**			**Total GM-segmentation Score**	**Local GM-segmentation Rank** (among 3 methods)	**Global GM-segmentation Rank** (Among all methods in MRBrainS13)
	DC (%) (Dice coefficient)	HD (Hausdorff Distance)	AVD (Absolute Volume Difference)			
Hybrid ANN-based Auto-context method	84.77	1.71	6.02	39	**1**	**10**
Multi-stage voxel classification method	85.77	1.62	6.62	39	**2**	**11**
Parallel Multi-Dimensional LSTM method	84.82	1.70	6.77	50	**3**	**16**
Note : For the rank score, smaller value of score means better segmentation capability						

In Table 1, we can see that *Hybrid ANN-based Auto-context method* and *Multi-stage voxel classification method* scores same segmentation score in context of GM segmentation. *Parallel Multi-Dimensional LSTM method* scores the lowest in GM segmentation.

Table 2. Segmentation Scoring and Ranking in context of white matter (WM) segmentation.

Segmentation Method	**WM Segmentation score**			**Total WM-segmentation Score**	**WM-segmentation Rank**	**Global WM-segmentation Rank**
	DC(%)	HD	AVD			
Multi-stage voxel classification method	88.66	2.07	6.96	41	**1**	**11**
Parallel Multi-Dimensional LSTM method	88.33	2.08	7.05	50	**2**	**15**
Hybrid ANN-based Auto-context method	88.45	2.34	7.67	62	**3**	**19**
Note : For the rank score, smaller value of score means better segmentation capability						

In Table 2, we can see that *Multi-stage voxel classification method* performs better than the other two methods in terms of WM segmentation. The difference between first and third rank is quite noticeable. However, the difference between the first rank and the second rank is very small, especially if we look in the difference of HD values and AVD values. This implicitly shows that voxel- and graph-based performs relatively better than hybrid form of model-based segmentation in distinguishing WM.

Table 3. Segmentation Scoring and Ranking in context of cerebrospinal fluid (CSF) segmentation.

Segmentation Method	CSF Segmentation score			Total CSF-segmentation Score	CSF-segmentation Rank	Global CSF-segmentation Rank
	DC(%)	HD	AVD			
Parallel Multi-Dimensional LSTM method	83.72	2.14	7.09	14	**1**	**2**
Hybrid ANN-based Auto-context method	82.77	2.31	6.73	24	**2**	**7**
Multi-stage voxel classification method	81.08	2.65	9.77	49	**3**	**17**
Note : For the rank score, smaller value of score means better segmentation capability.						

In table 3, we see that by CSF segmentation, *Parallel Multi-Dimensional LSTM method* perform the best segmentation. In global ranking, the method also excels by placed in second rank. In other side, the third rank, *Multi-stage voxel classification method* performs the worst, especially if we look at its AVD value which is significantly higher than the other two methods. Its global rank also differs significantly with other two higher ranking methods.

Table 4. Overall Segmentation Scoring and Ranking.

Segmentation Method	Rank score (Segmentation capability)			Overall Rank Score (Sum of rank score)	Final Rank (Local)
	GM	WM	CSF		
Parallel Multi-Dimensional LSTM method	50	50	14	114	**1**
Hybrid ANN-based Auto-context method	39	62	24	125	**2**
Multi-stage voxel classification method	39	41	49	129	**3**
Note : For the rank score, smaller value of score means better segmentation capability					

In Table 4, we can see that *Parallel Multi-Dimensional LSTM method* achieved the lowest segmentation score, which ultimately place this method in the number one rank among the three segmentation method that we discuss in this essay. If we look closely at individual ranking in each classes(WM, GM, and CSF), the *Multi-stage voxel classification method* actually performs the best in GM and WM segmentation. However, the method ranks the lowest in CSF segmentation, with the significant score difference with other two. This means, by excluding CSF segmentation, *Multi-stage voxel classification method* should be the best segmentation method. Practically if we look at Table 1 and Table 2, the method also performs greatly as the best segmentation method in both WM and GM class. In conclusion, if we stick to the ranking system of MRBrain13, *Multi-stage voxel classification method* is the worst segmentation method among the three. However, if we only want to segment GM and WM class, it is the best method.

Additional Commentary

It is *important to note* that MRI images from other research center / challenge possibly use different MRI machine, different parameters (i.e. TE and TR time settings), and different range of human subjects for brain images. If we were to applying the segmentation methods from MRBrainS13 into other brain MRI images from other research centers, there are things to considers :

a) The pre-process stage in most methods will likely to require a change or modification, because the raw image will be different in terms of pixel intensity or image contrast.
b) In case of model-based segmentation method, the (previously trained)models of brain tissue will likely to become less relevant. The model should be re-trained into a condition that the model represents the brain tissue shapes from the new MRI images.
c) In case of segmentation method using neural network as a classification tool, the training should be done again with the new training data (such as image pixel or feature) so that the network adapt the new brain tissue segmentation.
d) Other segmentation method ranking such as pixel/voxel-based, graph-based, and contour-based will also prone to minor change due to different brain images. However, the impact won't be as significant as in model-based segmentation.

In conclusion, if we were to use the MRBrainS13's segmentation methods without any modification with the data from other research center, the ranking of model-based segmentation method and any methods which utilize artificial neural network will likely to drop below the current ranking in MSBrainS13.

References

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