Semi-Supervised Learning for Electron Microscopy Image Segmentation

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Introduction

In the research field called connectomics, it is aimed to investigate the structure and connection of the neural system in the brain and sensory organ of the living things, and understand their functions. The method for investigating the neural structure varies depending on the scale, serial block-face scanning electron microscopy (SBF-SEM) is used when the target is sensory organs of small size organisms such as ants. In general, hundreds of consecutive images taken are reconstructed into three-dimensional.

Since the annotation is time-consuming task, automation by machine learning has been attempted in recent years. Many of the things that have been proposed so far are based on supervised learning, using a large amount of data labeled by experts in advance, and end-to-end learning with deep neural network has especially achieved significant results (Chen et al. 2016). However, in the case of using SBF-SEM, there is an outside chance of imaging due to the difficulty of hardening tiny sensory organs. And in most cases, therefore, a large amount of training data can not be prepared. Furthermore, labeling for training samples also places a heavy burden on experts.

In this paper, we propose a method of performing neuronal segmentation on all images for 3-D reconstruction from a very small number of training samples. This makes it possible to automatically segment neuronal regions using only a small amount of labeled data.

Related Work

Regarding the task of neuronal cell segmentation, various methods have been proposed with the related competition such as ISBI Challenge. In particular, since a method proposed by (Ciresan et al. 2012) achieved the high precision, most of newly proposed methods have been based on deep neural network. And recently, examples of achievements in recent years are Deep Contextual Network (Chen et al. 2016) and U-Net (Ronneberger, Fischer, and Brox 2015).

Though both of them have characteristics in terms of the network structure respectively, their networks are based on the Fully Convolutional Network (Long, Shelhamer, and Darrell 2015), and the feature maps obtained in the middle layers are directly leveraged by the skip connection. On the latest study, much deeper network with residual connection has been proposed to pursue further improvement (Xiao et al. 2018). However, these previous studies are based on a sufficient amount of training samples, which makes it hard to use for researchers who can not readily prepare a large amount of labeled data. Our proposed method is usable even in such cases because of leveraging a few labeled samples.

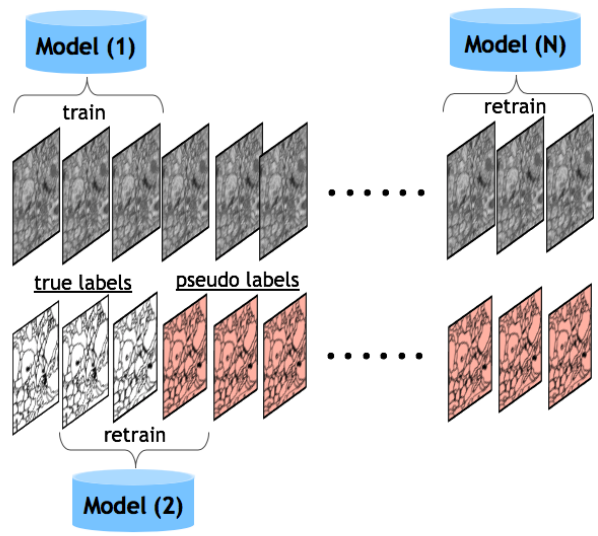

Figure 1: An overview of proposed method. Three labeled sample is used for first training, and trained model predicts a label of next sample. Then the model is retrained with next three samples to make a next pseudo label.

Proposed Method

The task addressed by aforementioned studies is regarded as pixel-wise classification, and according to the earlier study, it is possible even with a small amount of data (Ciresan et al. 2012). Therefore, we propose a semi-supervised learning (SSL) algorithm which learns and infer all data with pseudo labeling (Lee 2013) using a small number of consecutive training samples. An outline of the SSL algorithm is shown in Fig 1 and Algorithm 1. Firstly, supervised learning is suf-

Algorithm 1 SSL for neuronal image segmentation

Set the number of data N, and labeled samples M
Set the serial images $\boldsymbol{X} = [\boldsymbol{X}_1, ..., \boldsymbol{X}_N]$
Set the corresponding labels $\boldsymbol{T} = [\boldsymbol{T}_1, ..., \boldsymbol{T}_N]$
for $i = 1$ to $N - M$ **do**
  Train model with $(\boldsymbol{X}_{i:i+M-1}, \boldsymbol{T}_{i:i+M-1})$
  Predict the label from $\boldsymbol{X}_{i+M}$
  $\boldsymbol{T}_{i+M} \leftarrow$ predicted label
end for

ficiently performed using a few consecutive labeled training samples. Then, the inference result for the next one image is set as a pseudo label. Next, the model is retrained with next training samples including pseudo labels. This procedure is repeated until all pseudo labels are predicted. Although what to use for the training model is arbitrary, it is desirable to use one based on Fully Convolutional Networks (Long, Shelhamer, and Darrell 2015) because of its capability of end-to-end learning.

Experimental Results

We evaluated our approach on the dataset of ISBI 2012 EM Segmentation Challenge. The training dataset consists of a stack of 30 slices. Our Performance on the 30th slice was measured by metrics Rand Score Thin (V^{rand}) and Information Score Thin (V^{info}). The detail of their definitions is referable in (Arganda-Carreras et al. 2015) Additionally, we used another image dataset of olfactory sensory unit in the Japanese carpenter ant, taken by Ozaki laboratory in Graduate School of Science, Kobe University (Takeichi et al. 2018), and it consists of a stack of 377 slices. The performance of our inference on the 100th slice in this dataset was measured by Intersection over Union. In training process, Deep Contextual Network was used as training model. Each training phase in our SSL, we trained the model for 200 epochs with the batch size of 3. See (Chen et al. 2016) for details about the network structure and hyperparameter setting.

Table 1 and 2 show the quantitative result of our performance on two datasets respectively. Comparison model was trained with only three labeled samples without semi-supervised method. Our method outperformed the comparison model on both datasets. It leads to the conclusion that our approach is effective in case we have few labeled samples.

Future Work

In our experiments, while our method was shown the effectiveness of training with a few labeled samples, the accuracy was not sufficient yet. In the future, we will consider the task characteristic that there is spatial correlation between slices. Leveraging recurrent neural networks or 3-D convolutional neural networks are likely to exert their abilities.

Also, in order to perform pseudo labeling more accurately, it will be necessary to apply some kind of post-processing.

Table 1: Results in ISBI 2012 dataset (only the first three labels were used). The evaluation metrics were calculated on the 30th prediction

Method	V^{rand}	V^{info}
Supervised learning	0.0645	0.1353
Semi-supervised learning	**0.7310**	**0.2167**

Table 2: Results in the dataset of olfactory sensory unit in the Japanese carpenter ant (100/377 slices and the first three labels were used). The evaluation metrics were calculated on the 100th prediction

Training method	Intersection over Union
Supervised learning	0.3426
Semi-supervised learning	**0.5314**

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