International Journal of Information Processing, 6(1), 67-75, 2012
ISSN : 0973-8215
IK International Publishing House Pvt. Ltd., New Delhi, India

Convolutional Neural Network Generated Affinity Graph based Segmentation

Leena Silvoster M and V K Govindan [a]

[a]Department of Computer Science and Engineering, National Institute of Technology, Calicut, Kerala, India, Contact: leenasilvoster@gmail.com, vkg@nitc.ac.in

The recent proliferation of Scanning Electron Microscopy (SEM) image in the field of neuroscience has attracted many neuroscientists. Segmented SEM images have played a vital role in diagnosis of diseases, treatment, computer aided surgery etc.. Machine learning system is able to learn from experience, analytical observation and other means, results in a system that can improve its own speed and performance. In this work, Convolutional Neural Network (CNN) is used for learning how to segment images. CNN extract features directly from pixel images with minimal preprocessing. It is able to recognize a pattern which has not been presented before, provided it resembles one of the training patterns. After learning (from ground-truth image), CNN automatically generate a good affinity graph from raw EM images. This affinity graph can be then paired with any standard partitioning algorithm to achieve improved segmentation. In this paper, we introduce a novel flexible and powerful combined approach, where a CNN and Connected Component(CC) algorithm are used to segment SEM images. As a preprocessing step, the image is segmented using the Edge Detection and Image Segmentation (EDISON) system, which uses mean shift algorithm. F-score of the proposed algorithm was found to be 86%.

Keywords : Convolutional Neural Network, Connected Component, SEM Image, EDISON System

1. INTRODUCTION

The influence of imaging technologies on the study of biomedical and neuroscience lead a new research area. The present day automated imaging system is able to acquire and archive tons of image data. Scientists work on imaging not only need machines, but also must have an overlook of the properties of machines. Ideally, use a computer to analyze an image with little or no expertise.

Detection of neuronal tissues is one of the challenging problems of neuroscience. Scanning Electron Microscopy (SEM) delivers image stacks with a resolution adequate to identify the components in dense neuropil. They are difficult to distinguish from each other solely on the basis of local image statistics, especially when the signal-to-noise ratio of data is low. Recent developments in imaging technology have rendered possible automated acquisition of high quality volume electron microscopy data. However, purely manual or purely automated strategies to distinguish neural tissues are likely to fail. Segmentation algorithm partitions the image into different sets of pixels which belong to distinct objects. A good segmentation algorithm will be able to answer the following:

1. Given two different segmentations of the same image, how can we differentiate the mismatches between them?

2. Given two different segmentations of two images, how can we minimize the disagreements with the ground truth?

In this paper, we present an innovative automated learning approach for the detection of the affinity graph using a Convolutional Neural Network (CNN) trained using ground truth generated by human experts. This learned CNN affinity graph can be combined with any partitioning algorithm which leads to an accurate segmentation result. Convolutional Neu-

Table 1
Comparison of results

Method	Precision	Recall	Accuracy	FP	TP	f-score
CC	0.05	0.11	0.25	0.7	0.11	0.07
CC+CN	0.56	0.10	0.37	0.07	0.06	0.10
Comb	0.64	1	0.78	0	1	0.78
New	0.76	0.99	0.79	0	0.99	0.86

needs only the threshold value of the image. Thus, the proposed approach is efficient as well as faster.

REFERENCES

1. S C Turaga, J F Murray, V Jain, F Roth, M Helmstaedter, K Briggman, W Denk and H S Seung. Convolutional Networks can Learn to generate Affinity Graphs for Image Segmentation, *Neural Computation,* (22):511-538, 2010.
2. K L Briggman and W Denk. Towards Neural Circuit Reconstruction with Volume Electron Microscopy Techniques, *Current Opinion in Neurobiology*, (16):562-570, 2006.
3. I Carlbom and D Terzopoulos and K M Harris. Computer-assisted Registration, Segmentation, and 3D Reconstruction from Images of Neuronal Tissue Sections, *In IEEE Transactions on Medical Imaging,* (13):351-362, 1994.
4. Y Mishchenko. Automation of 3D Reconstruction of Neural Tissue from Large Volume of Conventional Serial Section Transmission Electron Micrographs, *In Journal of Neuroscience Methods, Elsevier*, (176):276-289, 2009.
5. A Vasilevskiy and K Siddiqi. Flux Maximizing Geometric Flows, *In IEEE Transactions on Pattern Analysis and Machine Intelligence,* (5):1565-1578, 2002.
6. Nowlan S J and Platt J C. A Convolutional Neural Network Hand Tracker, *Advances in Neural Information Processing Systems 7, Citeseer,* 1995.
7. Garcia C and Delakis M. Convolutional Face Finder: A Neural Architecture for Fast and Robust Face Detection, *In IEEE Transactions on Pattern Analysis and Machine Intelligence,* (26):1408-1423, 2004.
8. Lawrence S and Giles C L, Tsoi A C and Back A D. Face Recognition: A Convolutional Neural-Network Approach, I*n IEEE Transactions on Neural Networks*, (8):98-113, 1997.
9. Waibel A and Hanazawa T and Hinton G and Shikano K and Lang K J. Phoneme Recognition using Time-delay Neural Networks, *In IEEE Transactions on Speech and Signal Processing*, (37):328-339, 1989.
10. LeCun Y and Bottou L and Bengio Y and Haffner P. Gradient-based Learning Applied to Document Recognition, *In Proceedings of the IEEE*, 86, pages 2278-2324, 1998.
11. Jain V, Murray J F, Roth F, Turaga S, Zhigulin V, Briggman K L and Helmstaedter M N, Denk W and Seung H S. Supervised Learning of Image Restoration with Convolutional Networks, *IEEE Press,* 2007.
12. Christoudias C M and Georgescu B and Meer P. Synergism in Low Level Vision, *In IEEE Proceedings of 16th International Conference on Pattern Recognition,* vol. 4, pages 150-155, 2002.
13. Comaniciu D and Meer P. Mean Shift: A Robust Approach Toward Feature Space Analysis, In IEEE Transactions on Pattern Analysis and Machine Intelligence, (6):603-619, 2002.
14. Meer P and Georgescu B. Edge Detection with Embedded Confidence, *In IEEE Transactions on Pattern Analysis and Machine Intelligence,* (45):1351-1365, 2001.
15. Rodríguez R and Suarez A G. A New Algorithm for Image Segmentation by using Iteratively the Mean Shift Filtering, *In Scientific Research and Essay*, (1):43-48, 2006.
16. Robust Image Under Standing Laboratory, Rutgers University, `www.caip.rutgers.edu/riul/`.
17. A Cardona, S Saalfeld, Preibisch B, Schmid A, Cheng J, Pulokas P, Tomancak and V Hartenstein. An Integrated Micro-and Macroarchitectural Analysis of the Drosophila Brain by

Computer-assisted Serial Section Electron Microscopy, *PLoS Biol,* 2010.
18. S Haykin. Neural Networks and Learning Machines, *Pearson Prentice Hall, USA,* 2008.
19. A Cardona. TrakEM2: An ImageJ-based Program for Morphological Data Mining and 3d Modeling, *In Proceeding of Image User and Developer Conference,* vol. 4, 2006.
20. M Leena Silvoster and V K Govindan. Convolutional Neural Network Based Segmentation, *In Proceeding of 5th International Conference on Information Processing,* 157:(190-194), 2011.