

DEEP FEATURE REPRESENTATION FOR THE COMPUTATIONAL ANALYTICS OF 3D NEURONAL MORPHOLOGY

Zhongyu Li^{1,*}, Chaowei Fang^{2,*}, Shaoting Zhang¹

¹Department of Computer Science, University of North Carolina at Charlotte, USA

²Department of Computer Science, The University of Hong Kong, China

ABSTRACT

With the ever-increasing number of digitally reconstructed neurons, computational analytics of 3D neuronal morphology has become a new avenue to understand neuroanatomical structures and functional properties. However, traditional methods cannot well identify and represent neuronal morphology, especially when tackling large-scale and diverse neuron datasets. In this paper, we propose a deep learning based framework for the representation of 3D neuron morphology. At first, considering the neuronal tree-structures are usually very sparse in 3D space, we project each 3D neuron into 2D images with three angles of view. The projective strategy can preserve the spatial morphologies from the original data. Subsequently, as there are no sufficient annotations for each neuron, we introduce an unsupervised deep neural network to automatically learn neuron features from the projected 2D images. The deep features are then combined with traditional features for accurate neuron representation. Experimental results validate the effectiveness of our method by searching similar samples on a public database including 58,000 neurons. Moreover, we demonstrate that the traditional hand-crafted features are complementary with deep features in the representation of 3D neuron morphology.

Index Terms— Neuron morphology, deep learning, feature representation, computational neuroanatomy

1. INTRODUCTION

Understanding neuron morphology is a fundamental task to explore neuronal circuits, functional and physiological properties. Recent frontiers in neuron tracing and reconstruction (e.g., BigNeuron [1], NeuroMorpho [2]) have greatly facilitate the research of neuron morphology. Increasing number of neurons are digitally reconstructed and added to the public repositories with tens of thousands of neurons [3, 4]. For each reconstructed neuron, their morphologies are recorded in a SWC format file including a set of neuron nodes with segment types, locations, radius, and connections [5]. Accord-

ingly, these morphological data can bring new opportunities for neuron mining and knowledge discovery. For example, finding neuron sharing similar morphologies, correlating neuronal morphologies with functional properties, all these tasks require methods to identify and represent neuron morphology.

In recent years, neuron morphology has been investigated based on computational models and machine learning techniques. Scorcioni et al. [6] first developed L-measure tool for the quantitative measurement of neuromorphology, which can compute neuroanatomical parameters from 3D reconstructed neuron data. Costa et al. [7] proposed the concept of neuromorphological space and identified the most important geometrical features in neuron cell, including neuron’s total length, branch numbers, etc. With these measurement based features, multiple methods have been proposed for the analytics of neuron morphology. For example, Wan et al. [8] developed *BlastNeuron* for the comparison, retrieval and clustering of 3D neuron morphology. In *BlastNeuron*, they employed L-measure tool and moment invariants as morphological features for similarity search. Costa et al. [9] presented *NBLAST* to measure pairwise neuronal similarity by considering both position and local geometry, decomposing neurons into short segments. To improve the analytical efficiency, Mesbah et al. [10] first introduced hashing methods, i.e., hashing forest, to transform neuron features into binary codes. More recently, Li et al. [11] proposed feature hierarchy to group neuronal features into different similarity levels for more accurate representation and retrieval.

By employing quantitative measurements as neuron features, the above methods have achieved many successes in the research of neuron morphology. However, with the continuously expanding of neuronal amounts and varieties in databases, neurons belonging to different categories can express similar morphologies (indicating small inter-class variances), while neurons belonging to same categories can express different morphologies (indicating large intra-class variances) [12]. Thus, traditional “hand-crafted” features may not work well in the exploration of large-scale neuron databases. On the other side, deep learning has become a kind of advanced techniques for the feature representation in many fields, such as computer vision, medical image analysis, and speech recognition [13]. Nevertheless, directly applying deep

*Indicates equal contribution.

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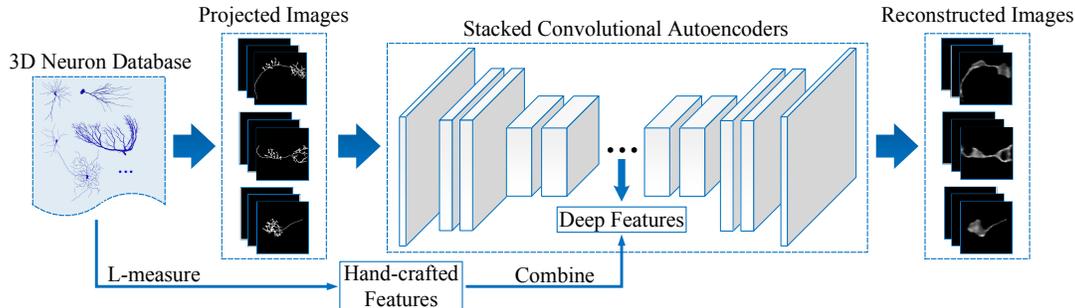


Fig. 1: Overview of the proposed framework for the feature representation of 3D neuron morphology.

learning in the 3D neuron morphology still faces two major problems: 1) the tree-structure of neurons are usually very sparse in 3D space, which are not suitable for training the 3D neural network; 2) the spatial information of neuron nodes, i.e., location, radius, and connection, need to be considered but are hard to be embedded in deep models.

To address the above problems, we develop a deep learning based framework for the feature representation of 3D neuron morphology. As shown in Fig. 1, to overcome the tree-structural sparsity, we first transform 3D neurons into 2D images through orthogonal projection. The spatial information of neuron nodes can be greatly preserved by projecting nodes' coordinates, radius, and connections in three angles of view. The computed 2D neuron images are subsequently set as input to train our unsupervised deep neural network, i.e., stacked convolutional autoencoders (SCAEs). The network learns to recover the input image by exploring intrinsic deep feature representation among neuron morphologies. After training the SCAs model, our learned deep features are combined with the traditional hand-crafted features for comprehensive and accurate representation of neuron morphology. The combined features can be further used for similarity searching and knowledge discovery.

2. METHODOLOGY

3D Neuron Projection: according to Fig. 1, the first step in our framework is to project 3D neurons into 2D images. In general, 3D neuron morphological data are stored in the SWC format file which includes hundreds to tens of thousands of nodes. For each node, its spatial information is determined by the location (i.e., x, y, z coordinates), radius (indicating the thickness of neuronal dendrite), and connection (i.e., the connectivity with parent nodes). Therefore, unlike previous 3D deep learning problems which can directly handle the point sets, we need to consider neuronal nodes and their composed tree-structures in 3D neuron morphology. Here, we present a neuron projection strategy which can transform 3D neuron data into a suitable modality for deep feature representation.

Given a 3D neuron data, we first employ the principal component analysis (PCA) algorithm to shift and rotate the

neuron into a normalized axis, since some of the original neurons are not oriented properly. Then all the neuronal nodes are orthogonally projected into three angles of view, i.e., the x-y, x-z, and y-z plane respectively, based on their coordinates after PCA orientation. The three angles' projection can greatly preserve the spatial information. Moreover, considering the projected image haven't reflected neuron's original tree-structure, we introduce two operations for each node in images: 1) embedding each node's radius in the image, where all pixels within the node's radius are assigned as 1; 2) each node is connected to its corresponding parent node, where all pixels residing on the line segment connecting the two nodes are assigned to 1. After the above operations, three grayscale images can be generated from a 3D neuron data. The grayscale images can preserve the original neuronal spatial information and tree-topological structure as much as possible, and also transform the 3D neuron data into a usable modality for deep learning.

Deep Feature Representation: after 3D neuron projection, we can employ the generated 2D images to train deep neural network for the neuronal feature representation. In recent years, there are varieties of deep neural networks that designed for different datasets and tasks. In current neuron databases, there are no sufficient annotations to identify and classify each neuron, which only provides coarse brain regions, cell types, etc. Thus only unsupervised deep neural network can be used. Besides, neuron's tree-structures, e.g., dendrites and bifurcations, should also be considered in the network. Here, we introduce the stacked convolutional autoencoders (SCAs), which can explore the intrinsic structure of neurons in an unsupervised manner.

The general structure of SCAs is illustrated in Fig. 1. From left to right, the network can be roughly divided into encoder and decoder two parts. The encoder subnetwork contains 6 convolution layers and 5 maxpooling layers, which transforms a 256×256 grayscale image into a $128 \times 4 \times 4$ tensor which is further embedded into a 2048 dimensional feature vector via a fully connected layer. The decoder subnetwork is designed for recovering the grayscale image from the output of encoder network with 1 fully connected, 5 up-sampling, 6 convolution and 1 deconvolution layers. In ad-

dition, we employ batch normalization and ReLU activation right after each convolution. We adopt the tanh function to reconstruct the grayscale image for the deconvolution in the last layer of decoder subnetwork. After training the SCAEs network, the decoder part can be removed. The deep feature of each input neuron image would be the output of encoder subnetwork, i.e., a 2048 dimensional feature vector. The network is optimized through SGD algorithm using L_1 loss function,

$$L = \|\mathbf{x} - \text{Decoder}(\text{Encoder}(\mathbf{x}, \theta_e), \theta_d)\|_1, \quad (1)$$

where \mathbf{x} is the input 2D neuron image, θ_e, θ_d is the parameter of encoder and decoder subnetwork respectively.

Feature Combination: for a 3D neuron data, its deep feature can be computed by sequentially combining the three grayscale image features using the trained SCAEs model. As the unsupervised deep neural network usually cannot explore the fine-grained details in image data, our SCAEs may also not work well in fully representing the 3D neuron morphology. Therefore, we propose to combine the deep features with traditional hand-crafted features for more accurate neuronal representation. For the deep features, we first employ the PCA algorithm to reduce the dimension from thousands to tens. This operation can alleviate noise and redundancy in original deep features and also keep a similar feature size with the hand-crafted features. For the hand-crafted features, we compute the quantitative measurements in each 3D neuron through the L-measure tool, including global, branch, and bifurcation three levels of measurements. Then, we combine the deep feature with the hand-crafted feature to represent the 3D neuron morphology. Advantages of this feature combination step will be demonstrated in the experiment.

3. EXPERIMENTS

Experimental Setting: in the experiment, we adopt the NeuroMorpho database [3] to validate the performance, which is the largest collection of publicly accessible 3D neuronal reconstructions and associated metadata. Particularly, we consider in total 58,414 valid neurons for feature representation and evaluation (excluding neurons that cannot be read and measured by the L-measure tool [6]). In the 3D neuron projection, we project and normalize each neuron into three images with the size of 256×256 . For our SCAEs, we set a weight decay of 10^{-4} and momentum of 0.9. The whole neural networks are trained end-to-end in 60 epochs with an initial learning rate of 0.01. We randomly select 30,000 neurons to train the SCAEs model, i.e., 90,000 projected images in total. For the hand-crafted features, we employ the L-measure tool to extract 38 quantitative measurements, following the setting with previous articles [8, 9, 11], which have achieved the best representational performance in several neuron analytical tasks. All experiments are carried out on a desktop with 1.6GHz processor of twelve cores and 128G RAM.

Table 1: Average precision of four methods under different number of top similar retrieval results.

	top-10	top-20	top-30	top-50
Deep-fea	0.6851	0.5534	0.4729	0.3710
MIPS-fea	0.8396	0.7605	0.6920	0.5982
Hand-fea	0.8586	0.7776	0.7239	0.6407
Comb-fea	0.9130	0.8377	0.7943	0.7337

Validations and Discussions: to evaluate the performance of neuronal feature representation, we employ the metric of neuron morphological retrieval, i.e., similarity searching in a neuron database. Particularly, we compare the performance of four methods related to neuronal feature representation and retrieval, including our deep features, our combinational features, the above 38 dimensional hand-crafted features [8, 9, 11] and the MIPS based binary codes [11], which are abbreviated as Deep-fea, Comb-fea, Hand-fea, and MIPS-fea respectively. Hand-fea and MIPS-fea are both the state-of-the-art for neuronal retrieval. We select the *Drosophila Melanogaster*'s projection neurons as queries for which the brain region is the olfactory antennal lobe, and the cell types are principal cell and uniglomerular projection (233 such projection neurons in total, denoted as uPNs). This selection of query neurons is also consistent with previous articles [8, 9, 11], since uPNs are the one kind of most fine-grain identified neurons in the NeuroMorpho database.

Table. 1 presents the average retrieval precision of the four comparative methods. The average retrieval precision is defined as the average percentage of same class neurons in all retrieved neurons after evaluating the 233 uPNs. For a query uPN, the top-10 retrieval precision denotes the percentage of uPNs in its 10 most similar neurons (except itself) after the feature comparison with the whole 58,414 neurons based on the Euclidean distance. For the Deep-fea, we employ PCA to compress the original deep feature into 40 dimensions. The Comb-fea is the combination of Deep-fea and Hand-fea. The MIPS-fea generates 32 bits of binary codes as neuronal features. According to Table. 1, the Comb-fea can achieve the highest retrieval precision compared with other three methods. The Deep-fea also achieve reasonable retrieval precision, which validates that the deep learning based methods are effective for the feature representation of neuron morphology. The results are mainly benefited from our designed 3D neuron projection strategy, which can preserve the tree-topological structure of 3D neuron morphology in 2D binary images. The introduced SCAEs model has the ability to explore neuronal dendrites and bifurcations for more accurate representation.

More importantly, for the results of Comb-fea, we find that the retrieval performance has a significant improvement after combining our deep feature with the traditional hand-crafted feature. As shown in Fig. 1, the left three grayscale images are projected from the original 3D neuron, while the right three are the corresponding reconstructed images after

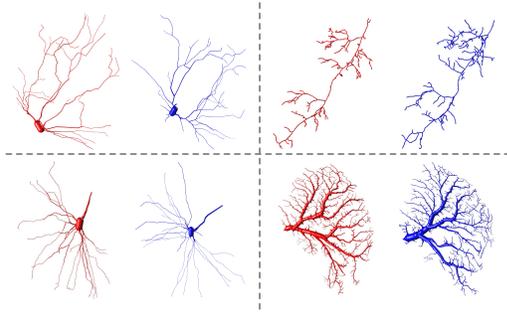


Fig. 2: Four query neurons (red) and their corresponding most similar neurons (blue) after searching in the NeuroMorpho [3] database, which illustrate the morphological similarity after using the proposed feature representation method.

the SCAEs decoder. It can be observed that the reconstructed images are able to preserve the overall structure from inputs, while most fine-grained details are lost. These results indicate that our learned deep features are more likely to explore and represent holistic structures in neuron morphologies. In contrast, the holistic structures in traditional hand-crafted features are represented by several primary measurements, e.g., neuron’s total height, length, volume, etc, which can not well identify and discriminate neurons in large-scale databases. Therefore, the traditional hand-crafted features and our deep learning based features are complementary with each other in the representation of 3D neuron morphology.

In addition, we randomly select four neurons as queries and provide their most similar neurons after retrieval using our combined features. The neurons are displayed in Fig. 2 using the Vaa3D software [14], where the reds are queries and the blues are retrieved neurons. Fig. 2 validates that our feature representation method can effectively find morphologically similar neurons in large-scale databases. These results are useful in many neuron analytical tasks. For example, the similar neurons can be employed for neuron comparison to further analyze and explore the association of detailed arborization patterns and functional properties [8].

4. CONCLUSIONS AND FUTURE WORKS

In this paper, we attempt to employ deep learning techniques in tackling the feature representation of 3D neuronal morphology. A generalized framework is proposed based on the neuronal projection, unsupervised deep neural networks and feature combination, which achieve superior performance compared with the state-of-the-art. Nevertheless, there are several aspects that can be explored to further improve the performance. For example, in 3D neuron projection, the three grayscale 2D images are related to each other, since they are reflections of a common neuron in different view angles. These relations should be considered and utilized in the deep neural network. Additionally, our current framework cannot

achieve the fully automatic feature representation. In the future, we will study how to embed hand-crafted features in a deep neural network to compute neuron features end-to-end.

5. REFERENCES

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