Superhuman Accuracy on the SNEMI3D Connectomics Challenge

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Abstract

For the past decade, convolutional networks have been used for 3D reconstruction of neurons from electron microscopic (EM) brain images. Recent years have seen great improvements in accuracy, as evidenced by submissions to the SNEMI3D benchmark challenge. Here we report the first submission to surpass the estimate of human accuracy provided by the SNEMI3D leaderboard. A variant of 3D U-Net is trained on a primary task of predicting affinities between nearest neighbor voxels, and an auxiliary task of predicting long-range affinities. The training data is augmented by simulated image defects. The nearest neighbor affinities are used to create an oversegmentation, and then supervoxels are greedily agglomerated based on mean affinity. The resulting SNEMI3D score exceeds the estimate of human accuracy by a large margin. While one should be cautious about extrapolating from the SNEMI3D benchmark to real-world accuracy of large-scale neural circuit reconstruction, our result inspires optimism that the goal of full automation may be realizable in the future.

1 Introduction

The 3D reconstruction of neurons from electron microscopic (EM) brain images is a basic computational task in the field of connectomics [1]. Ten years ago it was first demonstrated that convolutional networks could outperform other image segmentation algorithms at the task [2]. Recently the DeepEM3D convolutional net [3] approached human accuracy for the first time on the SNEMI3D benchmark challenge for segmentation of EM brain images.

Here we describe our own SNEMI3D submission, which is currently at the top of the leaderboard and has surpassed the SNEMI3D estimate of human accuracy by a large margin. Our submission is a variant of U-Net [4] and differs from other leading SNEMI3D entries [3,5] by making more extensive use of 3D convolution. For realizing the full power of 3D, we have found two tricks to be helpful. First, we introduce novel forms of training data augmentation based on simulation of known types of image defects such as misalignments, missing sections, and out-of-focus sections. Second, we train the convolutional net to predict affinities of voxel pairs that are relatively distant from each other, in addition to affinities of nearest neighbor voxels. In quantitative and qualitative comparisons, we find that both tricks produce substantial improvements in the performance of convolutional nets.

That being said, convolutional nets are typically just one stage of an image processing pipeline, and it is also important to assess the overall accuracy of the pipeline. For example, test-time augmentation
with rotations and reflections has been shown to enhance segmentation accuracy [3]. This ensemble technique presumably averages out noise in boundary predictions, at the cost of drastic increase in inference time. Here we instead apply mean affinity agglomeration as a postprocessing step, and show that it yields a comparably large gain in segmentation accuracy, while being much faster to compute.

The gain from either postprocessing technique (test-time augmentation or mean affinity agglomeration) is larger for our worst nets than for our best nets. In other words, the effects of our two training tricks are reduced by postprocessing, though they are not eliminated. In particular, for our best net, the improvement from postprocessing is relatively small. It is possible that future progress in convolutional nets will render both postprocessing techniques ineffective.

Although our SNEMI3D submission has surpassed the estimate of human accuracy provided by the SNEMI3D leaderboard, one should not jump to the conclusion that the problem of automating neuronal reconstruction has been completely solved. A human expert can still readily find mistakes in our submission, if provided with interactive 3D viewing of segments in addition to 2D views of images and segmentation. This may seem inconsistent with the SNEMI3D estimate of human accuracy, unless one appreciates that human accuracy is somewhat ill-defined. Humans vary greatly in their expertise at the task. Furthermore, accuracy depends on the procedures and software tools used to perform the reconstruction. (It is much more difficult for a human expert to find errors in our SNEMI3D submission based on inspection of the EM images alone, without access to 3D renderings of the segments.) Therefore it would be a mistake to conclude that the segmentation problem is now solved. The correct conclusion is that the SNEMI3D challenge has become obsolete in its present form, and must be modified or replaced by a challenge that is capable of properly evaluating algorithms that are now exceedingly accurate.

Having mentioned these caveats, it seems safe to say that the prospects for full automation of neural circuit reconstruction look more encouraging than ever before.

2 Residual Symmetric U-Net

2.1 Network architecture

Our network is a variant of the widely used U-Net [4]. The architecture (Figure 1) inherits three main elements from U-Net: (1) a contracting path with convolutions and downsampling, (2) an expanding path with convolutions and upsampling, and (3) same-scale skip connections from the contracting path to the expanding path. These three elements constitute a top-down refinement...
process \[7,8\] by progressively integrating higher-level contextual information with lower-level localization information in a coarse-to-fine manner.

**Symmetric architecture** Following others \[9\], we have modified U-Net to use *same* rather than *valid* convolution. This is mainly for simplicity and convenience; it is easier to keep track of feature map sizes. Border effects may hurt accuracy, but this can be mitigated by the overlap-blend inference scheme described in Section 2.2. We further replace *concatenation* joining by *summation* joining \[9,10\] where the skip connections join the expanding path.

**Modular architecture** The basic module (Figure 1) consists of three convolution layers of equal width, interspersed with batch normalization layers \[11\] and exponential linear units \[12\]. Using the same modules everywhere simplifies the specification of our network \[13\]. The depth, or the number of layers along the longest path of the network becomes a function of how many layers the module contains and how many scales the network spans. The *scale* is determined by the number of up/downsamplings. The *width*, or the number of feature maps at each scale can be adjusted to control network’s overall capacity.

**Residual architecture** We have added a residual skip connection \[14\] to each module (Figure 1), thus making every path from the network’s input to its output a residual subnetwork \[15\]. Residual variants of U-Net were previously applied to biomedical image segmentation \[16,17\] and serial section EM image segmentation \[9,18\].

**Anisotropic 3D** A “fully” 3D U-Net \[19\] can be constructed by expanding the 2D filters for convolution and up/downsampling into 3D. To better deal with the high anisotropy of serial section EM images, we have made three design choices. First, we never downsample feature maps along the \(z\)-dimension so as to minimize the loss of information along the \(z\)-dimension with inferior quality. Second, we exclusively use 2D convolutions in the modules at the finest scale (or highest resolution) where anisotropy is maximal (light-colored nodes, Figure 1). Third, the modules in other scales always start with \(3 \times 3 \times 1\) convolution, followed by two \(3 \times 3 \times 3\) convolutions (Figure 1). With this particular choice of filter size, each module represents \(7 \times 7 \times 5\) nonlinear computation, which is slightly anisotropic. Another motivation for this particular design choice is to embed 2D features first and then refine them with residuals from 3D context.

2.2 Inference

**Blending** Our use of *same* convolutions allows us to use an output patch of the same size as our input patch, but accuracy is worse near the borders of the output patch. At test time, we perform inference in overlapping patches, and blend them using a bump function which weights the center of an output patch more strongly than its borders, \(f(\vec{r}) = \exp(\sum_{a=x,y,z} r_{ax}(p_{ax} - r_{ax})^{-t_a})\), where \(r_x, r_y, r_z\) are the local coordinates within patch, \(p_x, p_y, p_z\) are the size of the patch, and \(t_x, t_y, t_z\) control how fast the bump function decays from center to border in each dimension. We used \(t_x, t_y, t_z = 1.5\) and 50% overlap in all three dimensions.

**Test-time augmentation** Test-time augmentation has been widely adopted as an effective way of improving the quality of segmentation \[3,4,5,9\]. The most common set of transformations includes rotations by \(90^\circ\) and horizontal/vertical flips over the \(xy\)-plane, resulting in 8 variants. Zeng et al. \[3\] also added a flip in \(z\)-dimension, increasing the set size to 16. We also used the same set of transformations (16 variants) when demonstrating the effect of test-time augmentation. However, we did not use test-time augmentation when demonstrating the effect of mean affinity agglomeration, which will be described in Section 5.

3 Long-range affinity prediction as an auxiliary task

Turaga et al. \[20\] trained convolutional networks to transform an input EM image stack into an output affinity graph, which is subsequently partitioned to produce a segmentation. They included only edges between nearest neighbor voxels in the affinity graph. We additionally trained our convolutional net to predict affinities for a select group of longer edges oriented along the cardinal directions. In the \(x\)-
and $y$-directions, the edges spanned 3, 9, and 27 voxels. In the $z$-direction, the edges spanned 2, 3, and 4 voxels.

In total, our convolutional net was trained to produce twelve output images, one corresponding to each of the affinity maps in Figure 2. The long-range affinity maps (third to fifth columns) look qualitatively different from the nearest neighbor affinity maps (second column).

The long-range affinities were not used at test time. They were included in the training in the hope that they would improve accuracy at the main task, the prediction of nearest neighbor affinities. In other words, we hoped that training on auxiliary tasks would improve performance at the main task [21]. As Figure 2 shows, the auxiliary tasks exhibit considerable diversity, which could aid training.

4 Data augmentation

Following standard practice, we augmented our training set using random rotations by $90^\circ$ and flips in $x$-, $y$-, and $z$-dimensions. We also applied warping and brightness and contrast perturbations using code from ELEKTRONN[^2], an open source deep learning framework. These kinds of augmentation have been widely used when training convolutional networks on serial section EM images[^3][^4][^5][^9].

We also introduced three novel types of data augmentation. These were motivated by the necessity of dealing with common image defects: misalignments, missing sections, and out-of-focus sections. However, we speculate that these kinds of data augmentation may end up improving accuracy even at locations without image defects, because they force networks to maximally exploit 3D context.

**Misalignment** Misalignments of serial section EM images can lead to severe merge and split errors. Robustness to misalignment is important for accuracy, though a training set may contain very few examples of misalignment. To deal with this problem, we introduced a simulated misalignment in every training sample. Specifically, we picked a random $z$-location in each input patch and then applied random translations along the $x$- and $y$-direction[^3]. The pixel displacement in each direction

[^2]: http://elektronn.org/
[^3]: The same transformation is applied to both the input image and target label stacks. The target affinity graph is then dynamically generated from the transformed label.
was chosen independently from the discrete uniform distribution between 0 and 17. We generated two different types of misalignment: (1) slip-type misalignment applies the random translation only at the randomly chosen \( z \)-location, whereas (2) translation-type misalignment additionally applies the same translation to every slice below the \( z \)-location.

**Missing section**  
Missing section is another common mode of failure in serial section EM imaging. In some cases, the whole sections are missing, or sections could be partially missing due to error of imaging. In other cases, sections become so severely damaged that it is preferable to remove their content - either partially or fully. When reconstructing large image volumes, accounting for these errors can be critical for performance. Since our training set did not contain any missing section, we introduced **missing section** augmentation. We picked random \( z \)-locations up to five slices in each input patch and introduced partial or full missing section independently. We found that filling out missing sections with zero intensity values distorted the input distribution too much and damaged inference performance when paired with batch normalization. Therefore, we drew random fill-out values uniformly from minimum (zero) to maximum (one) intensity.

**Out-of-focus section**  
During automated EM imaging, the microscope focus may occasionally fail and yield blurry images. We modeled this error process using simple Gaussian blurring. As in missing section augmentation, we picked random \( z \)-locations up to five slices and applied a 2D Gaussian blur filter either partially or fully. The standard deviation of Gaussian filter was randomly sampled from the uniform distribution between zero and five pixels.

5 **Mean affinity agglomeration**

Oversegmentation into supervoxels followed by agglomeration has been proposed as a strategy for segmenting EM images [22, 23, 24, 25]. In this approach, each pair of adjacent supervoxels receives an agglomeration score, and the pair with the highest score is greedily merged at each step. Previous work has emphasized learning of the scoring function, often using hand-designed features as input. We have found that scoring a pair of supervoxels with a single hand-designed feature, the mean affinity of all edges between the supervoxels, often produces good agglomeration accuracy. The analog of mean affinity for a boundary map is already used as a feature in the GALA agglomeration package [23, 25], and was previously used to segment natural images [26].

The rationale is that mean affinity smooths out noise in the affinity map that could lead to merge errors. Anecdotally, we have found that it is surprisingly difficult to substantially outperform mean affinity agglomeration by learning from GALA-type features. This is perhaps because the quality of convolutional network output has improved so much in the years since GALA was introduced.

6 **Experiments**

6.1 **Dataset**

The SNEMI3D challenge provides a single labeled image stack of size \( 1024 \times 1024 \times 100 \) for training and the same-sized image stack for testing. The voxel resolution is \( 6 \times 6 \times 29 \, \text{nm}^3 \), which roughly amounts to an anisotropy factor of 5. We further divided the training stack into top 80 slices for training and bottom 20 slices for validation.

6.2 **Model comparison**

We systematically examined the effect of our proposed data augmentation and long-range affinity by comparing networks trained with different setups. \( \text{aug}0 \) refers to the nets trained with none of our proposed augmentation, and \( \text{aug}3 \) refers to those trained with all of them. Note that both setups still include the basic types of data augmentation described in Section 4: rotation, flip, warping, brightness and contrast augmentations. Postfix -long is used to indicate whether the net was trained with long-range affinity. By combining these setups, we trained a total of four nets on the SNEMI3D training set, namely, \( \text{aug}0 \), \( \text{aug}0\text{-long} \), \( \text{aug}3 \), and \( \text{aug}3\text{-long} \).

Model selection and hyperparameter search were strictly performed on the validation set. We have only submitted the result of \( \text{aug}3\text{-long} \) to the SNEMI3D challenge leaderboard (Table 1). We
subsequently performed extensive quantitative comparison on AC3, a labeled image stack of size \(1024 \times 1024 \times 256\) that was made publicly available along with the publication of Kasthuri et al. [27]. It should be noted that although AC3 is a superset of the SNEMI3D test set, we used it only for the post-challenge analyses after submitting our SNEMI3D results.

6.3 Training procedures

Our networks were trained using the binomial cross-entropy loss with class-rebalancing. The network weights were initialized as described in He et al. [28]. We used the Adam optimizer [29], starting with \(\alpha = 0.01\), \(\beta_1 = 0.9\), \(\beta_2 = 0.999\), and \(\epsilon = 0.01\). The step size \(\alpha\) was halved when validation loss stopped decreasing, up to four times. We used a single patch of size \(160 \times 160 \times 18\) (i.e. minibatch of size 1) to compute gradients at each training iteration. We trained our nets until convergence using the Caffe deep learning framework [30]. The total number of iterations for each training setup ranged from 500K to 700K. Each training took about five days on a single NVIDIA Titan X Pascal GPU.

6.4 Postprocessing

We used an edge-weighted graph implementation of watershed algorithm [31] to produce initial oversegmentation. We chose parameters \(T_{\text{min}} = 1\%\), \(T_{\text{max}} = 80\%\), \(T_{\text{size}} = (800, 20\%)\), and \(T_{\text{dust}} = 600\). Note that relative percentiles computed from the output affinity distribution were used instead of absolute parameter values. We picked the best performing segmentation threshold optimized on the validation set when generating our SNEMI3D submissions.

6.5 Evaluation

The SNEMI3D leaderboard measures segmentation quality based on the adapted Rand F-score [32, 33]. For the post-challenge analyses on AC3, we adopted the variation of information (VI), an information theoretic metric, to measure segmentation quality [23, 34]. VI is defined by

\[
\text{VI}(S, T) = H(S|T) + H(T|S),
\]

(1)

where \(S, T\) are two segmentations to compare. Suppose that \(S\) is a segmentation produced by an automated method and \(T\) is the ground truth. Then the conditional entropy \(H(S|T)\) measures oversegmentation errors (splitters), and \(H(T|S)\) measures undersegmentation errors (mergers).

7 Results

Table 1 summarizes the SNEMI3D challenge leaderboard after our submission of aug3-long. Our result was ranked first place on the leaderboard, and strikingly, it has surpassed the human accuracy value provided by the challenge organizer. To the best of our knowledge, this is the first demonstration that a fully automated algorithm can surpass human accuracy in the dense neural circuit reconstruction on any publicly available benchmark EM dataset.

Comparing our method against the former leading entries [3, 5] further demonstrates the effectiveness of our approach. The number of trainable parameters of our “deeply” 3D net is an order of magnitude smaller than the 2D [5] or “shallowly” 3D [3] convolutional nets. Our proposed mean affinity

\[Zeng et al. [3] used an ensemble of three convolutional nets, each taking as input one, two, and three consecutive slices. Their net has 3D convolution only in its initial layers, where anisotropy is maximal and thus the efficacy of 3D convolution would be minimal.

| Group name | Rand error | Trainable parameters | Test-time augmentation |
|------------|------------|----------------------|------------------------|
| Ours (test-time aug.) | 0.02576 | 1.5M | 16 variants |
| Ours (test-time aug.) | 0.02590 | 1.5M | 8 variants |
| Ours (mean affinity aggl.) | 0.03332 | 1.5M | 1 variant |
| ** human values ** | ** 0.05998 ** | – | – |
| DIVE [3] | 0.06015 | 18M × 3 models | 16 variants × 3 models |
| IAL [5] | 0.06561 | 35M | 20 variants |
Table 2: Variation of Information (VI) measured on AC3.

|                                         | aug0   | aug0-long | aug3   | aug3-long |
|-----------------------------------------|--------|-----------|--------|-----------|
| Baseline (1 variant)                    | 0.935  | 0.656     | 0.637  | 0.529     |
| Test-time augmentation (16 variants)    | 0.607  | 0.578     | 0.552  | 0.500     |
| Mean affinity agglomeration (1 variant) | 0.568  | 0.554     | 0.546  | 0.513     |

Figure 3: The effect of test-time augmentation (top) and mean affinity agglomeration (bottom) measured on AC3.

agglomeration is also quite remarkable because it could achieve superhuman accuracy without the need for the costly test-time augmentation (Table 1).

Model comparison on AC3  More detailed quantitative comparison between our models is shown in Table 2 and Figure 3. On the basis of this comparison, we can make the following claims. (1) Our proposed data augmentation significantly improves model performance (aug0 vs. aug3, aug0-long vs. aug3-long). (2) Training with long-range affinities substantially improves model performance (aug0 vs. aug0-long, aug3 vs. aug3-long). (3) Test-time augmentation boosts model performance at the expense of 8-16× inference cost. (4) Mean affinity agglomeration is also very effective at boosting model performance. Notably, mean affinity agglomeration was so effective that the performance gap between the four models was more or less neutralized (Table 2 and Figure 3). Viewing from a different standpoint, mean affinity agglomeration produces diminishing returns as the underlying model keeps improving.

Effect of misalignment augmentation  We performed a couple of additional analyses to demonstrate the effectiveness of our proposed data augmentation. First, we systematically simulated the two types of misalignment (translation and slip) on the validation set and examined how robust the different models are. As we expected, the models trained with misalignment augmentation were substantially more robust to the misalignment errors (yellow and purple curves, Figure 4). One exception is that aug3 started to become worse than aug0 and aug0-long beyond a certain extent of slip-type misalignment (yellow curve in the right panel of Figure 4). We have not had a chance to investigate why this particular exception occurred. Nevertheless, it is apparent that the combined use of our proposed data augmentation and long-range affinity makes the model superbly robust to the misalignment errors (purple curves, Figure 4).

Effect of missing section augmentation  To examine how robust the different models are against missing section errors, we introduced one, three, and five consecutive partial missing sections at the center of the validation set. Figure 5 qualitatively illustrates each model’s prediction on the middle part of the missing sections. Interestingly, the models trained without missing section augmentation (aug0 and aug0-long) still managed to fill out the missing part to some extent when only a single
Figure 4: Robustness to misalignment errors quantified on the validation set. Left: \textit{translation}-type misalignment, right: \textit{slip}-type misalignment. Here we used mean affinity agglomeration as a postprocessing.

Figure 5: Robustness to missing sections. Every result displays an affinity graph as an RGB image (R: $y$-affinity, G: $x$-affinity, B: $z$-affinity). Yellow-colored regions indicate the discrepancy between $z$-affinity and others. Missing section augmentation enables nearly perfect completion of the missing part when only a single section is missing (aug3 and aug3-long, top right corner).

section was missing (top row, Figure 5). However, both models immediately failed at more than two consecutive missing sections. In contrast, the models trained with missing section augmentation (aug3 and aug3-long) were substantially more robust even against multiple consecutive missing sections. Again, the combination of our proposed data augmentation and long-range affinity produced the best result (aug3-long, the last column in Figure 5).

8 Discussion

8.1 Failure modes

What do the remaining errors look like? We observed that most of them fall into one of the four categories: (1) errors caused by severe image defects, (2) truly hard cases due to the limitations of serial section EM imaging (e.g. extremely thin neurites that are parallel to the sectioning plane), (3) weakness of mean affinity agglomeration on self-touching objects (e.g. dendritic spines contacting the
dendritic shaft from which they originated), and (4) object classes that are largely underrepresented in the training set such as glial cells surrounding blood vessels and soma-soma contacts.

We found that severe image defects are likely to cause bad misalignment errors, which cannot be properly handled by the nearest neighbor affinity graph representation. An obvious solution is to develop better image alignment algorithms that are robust to such image defects. Another interesting possibility suggested by our result (Figure 5) is to completely remove the image regions encompassing the defects and associated misalignment errors, and then just let convolutional networks handle the missing sections. Iterative refinement based on recursive/recurrent computation may be the key to such a pattern completion approach.

8.2 Future directions

A key ingredient that is still missing in the current automated pipeline for neural circuit reconstruction is an automated way of detecting and correcting the remaining errors. Meirovitch et al. [35] have recently proposed a primitive rule-based error detection and a flood-filling [36] style approach to extend broken axons. Supervised learning with deep neural networks may be applicable to the fully automated error detection, which can potentially be useful for guiding focused human proofreading.

Given automatically detected errors, a coupled automated error correction based on another set of deep neural nets can also be conceivable. Flood-filling network [36] is a strong candidate for such tasks because it can focus on a single erroneous object at a time and perform perceptual/attentive computation that resembles the human way of correcting errors. It is not even necessary that the error detector and corrector be separate models.

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