Realizing Quantum Image Analysis in Application to Connectomics

Theodore Mefford

May 14, 2018

Abstract

Exponential speed-up in image processing is highly desirable and would push the boundary of brain research by making the crucial task of automated neuron segmentation feasible for large amounts of data. This research aims to look into the potential of quantum computers to provide this capability.

1 Motivation

For over a century mankind has been dissecting brain tissue to probe the depths of how this most complex organ functions. Advancement has nearly always come hand-in-hand with technological innovation, whether it be simple stains that allow individual neurons to be seen (Golgi) or the creation of advanced automated slicing devices that can cut to a width of 50 nm (Denk).[1] The landmark research done by White and Brenner [4] circa 1980 that succeeded in completely mapping the neuron pathways of a C. Elegans worm opened the gateway to a horizon of mapping brain structure. The penultimate end of this field would be the complete mapping of a human brain, dubbed the connectome by Olaf Sporns.[3]

The work by Brenner et al. took over a decade and most of the work was manual and intensively time-consuming. It is clear that any substantial progress forward will require significantly greater technological power and nearly autonomous function. One of the forefront problems faced during this process is the analysis of individual images of a single brain slice. In order to obtain the composite structure of the brain at the neuron level, individual images need to processed by distinguishing the neuron-membrane from the background and mapping this information into a three-dimensional computational model.

The proposed research project is to pursue a more formal protocol that utilizes quantum computation capabilities to significantly speed-up the analysis of individual brain images. It

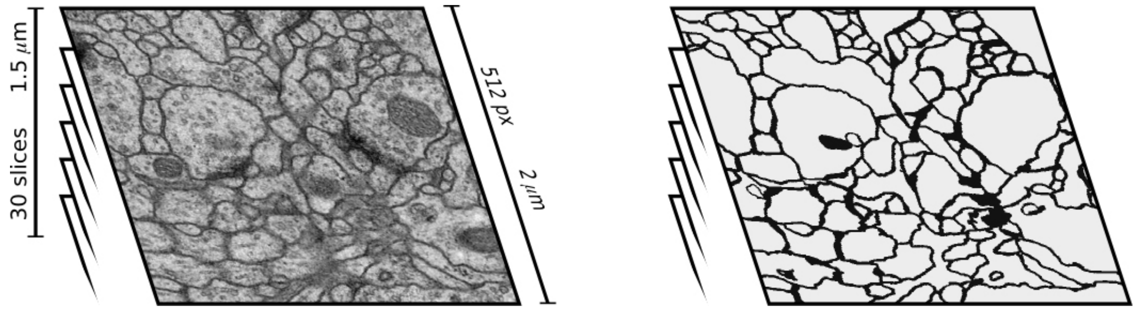

Figure 1: The goal of automated segmentation is to take a raw image of neurons (left) and accurately determine and trace where the individual neurons are into a computational model (right). [6]

is the hope that this research will provide a proof of concept that quantum machine learning will play a crucial role in the connetome project as well as other areas of neuroscience, biology and medicine, such as tumor detection[8], as a whole. Here we present an outline that quantum machine learning can be embedded into the analysis protocol. The feasibility, utility and approach of such implementation would be the result of the following research. Most boundary prediction software used in tracing neurons is based on machine learning technology so it seems probable that if quantum neural nets prove to have an exponential advantage over their classical counterparts they will be essential to many brain imaging research projects.

2 Boundary Prediction in Brain Slice Images

Many labs working on connectomics have turned to AI to train computers to see neurons, such as that of Sebastian Seung, a pioneer of connectomics.[1] As stated by Ciresan et. al in 2012 "Reliable automated segmentation of neuronal structures in ssTEM stacks so far has been infeasible. A solution of this problem, however, is essential for any automated pipeline reconstructing and mapping neural connection in 3D."[6] Classically, edge detection methods rely on the computation of image gradients by different types of filtering masks. Therefore, all classical algorithms require a computational complexity of at least $O(2^n)$ because each pixel needs to be processed.[10]

Deep Neural Nets are commonly used in the process of automatic segmentation of neuronal structures in neuroanotomy.[6] Often these neural networks operate as pixel classifiers that make decisions on grainy images of whether or not a particular pixel belongs to a neuron membrane. Each pixel is mapped to a neuron and is then followed by a succession of convolution and max-pooling layers that preserve 2D information and extract features with increasing levels of abstraction to produce a calibrated probability for each class.

After a brain slice has been prepared, it is imaged using a serial-section Transmitted Electron Microscopy (ssTEM) to a pixel resolution size of approximately 4 x 4 nanometers.[6] (see Figure 1 left) The goal is to assign each pixel to a class, either *membrane* or *non-membrane*. Using the raw intensity value of the pixels as inputs, a deep neural net computes the probability p of each for being in the membrane class. The classifier is trained with test images and is then applied to all of the image's pixels to generate a map of *membrane* probabilities. Postprocessing techniques now provide a binary membrane segmentation. (see Figure 1 right) Repeating this process for many successive images of neurons allow for the creation of a three-dimensional rendering of the neuron network structure. Of equal importance to a visualization of the structure is being able to decipher the connectivity matrix, whose entries describe the strength of synaptic connection between each neuron with every other, from these images.

3 Quantum Image Analysis and Pattern Recognition

The idea behind quantum image processing (QuIP) is to take a classical image end encode it into a quantum system via a classical-to-quantum interface, perform processing on it, and measure or read out the result through a quantum-to-classical interface.[9] The advantage that quantum entails over classical is that the processing step may utilize quantum algorithms that have an exponential speed-up over corresponding classical processing and can thus handle images and algorithms that may have otherwise been unmanageable. At present, using quantum computation for boundary detection has not been extensively researched with only several groups in China publishing on the topic[10][11][12] while other, unuseful in this case, forms of quantum image recognition have been considered [14]

The use of quantum systems for image processing and boundary detection has begun to be explored [10] and shows promise to provide exponential speed-up over classical counterparts. The essential ideas is to store pixel values in the probability amplitudes and the position in the computational basis states of the Hilbert Space. A 2D image with n x m pixels is considered as a single vector $\vec{f}$ where the columns have been concatenated to form an n x m vector. Now, $\vec{f}$ can be mapped onto a pure quantum state $|f\rangle=\sum_{k=0}^{2^n-1} c_k|k\rangle$ where the computational basis $|k\rangle$ encodes the position of each pixel, and the coefficient c_k encodes the pixel value.[10] This is called the *flexible representation of quantum images.*[13] An advantage this provides is that by using the quantum superposition of a qubit sequence to store the position information of all the pixels, FRQI allows all of them to be operated on simultaneously rather than individually. With the image data in quantum form, it can now be postprocessed by various quantum algorithms.[16] (see Figure 2 left)

The research by Xi et al.[10] proceeds to use a quantum Hadamard edge detection (QHED) algorithm that generates a quantum state encoding the information about the boundary. However, this is performed on an image with a well defined boundary so analysis of brain images will need to involve more sophisticated techniques since the edges are not well defined. One approach may be to follow the protocol currently being employed (described in section 2) but use a quantum neural net as the pixel classifier. If the entire state of the quantum system can be operated on simultaneously to perform the classification than this would provide the desired speed-up over the classical analogue which must evaluate every pixel individually.

4 A Potential First Experiment

Quantum technology has seen rapid development in the last decade and the hardware necessary to perform proof of concept quantum edge detection algorithms may already be developed. As an example we consider implementing the scheme presented in the previous section on a 51-atom quantum simulator. [15] This system consists of an array of individually trapped cold atoms with strong, coherent interactions enabled by excitation to Rydberg states.(see Figure 2 right a) It realizes a programmable Ising-type quantum spin model with tunable interactions. The Hamiltonian for this system is

$$\frac{H}{\hbar} = \sum_i \frac{\Omega}{2}\sigma_x^i - \sum_i \Delta_i n_i + \sum_{i<j} V_{ij} n_i n_j \tag{1}$$

where Δ_i are the detunings of the driving lasers from the Rydberg state (Fig 2 right b), σ_x^i describes coupling of the ground and Rydberg state that is driven at Rabi frequency Ω_i and V_{ij} is the interaction between atom i and atom j. V_{ij} can be controlled by physically altering the distance between atoms or by coupling to a different Rydberg state. This tunability provides the means to perform quantum gate operations on the quantum states and will serve as the image processor.

The scheme for using this cold atom array for the task of automatic segmentation of neuronal structures is as follows. First, configure the cold atom array by loading the atoms into a tweezer array. Next, use raw pixel data from the neuron image to initialize the atomic Rydberg states. Now the selected edge detection algorithm is performed by evolving the array under $U(t)$ with tunable parameters $\Delta(t), \Omega(t)$, and V_{ij}. The final state is now read out using fluorescence imaging.

At present only arrays of neutral atoms with Rydberg excitations have been developed but

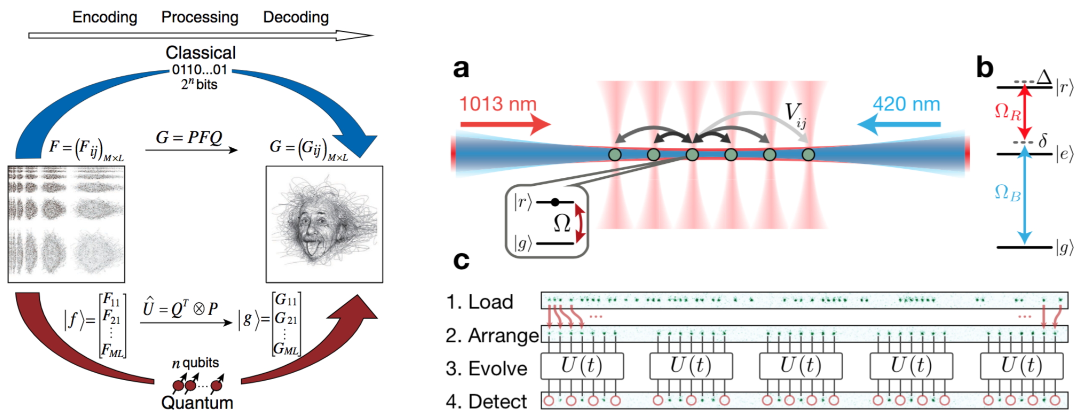

Figure 2: (Left) A comparison of quantum vs classical image processing where image is encoded in n qubits rather than 2^n bits and is analyzed via a unitary operation $\hat{U}$. (Right) Ion trap scheme that could potential encode a quantum image. Images from [10][15]

there is positive outlook that two-dimensional arrays will greatly strengthen the capabilities of these systems. It is believe that "with increased loading efficiencies, the robust creation and control of arrays of hundreds of atoms is feasible."[15] A two-dimensional quantum simulator with a qubit number in proportion to the image size seems like a natural system for this type of image analysis to done. A classical image would be directly encoded onto the two-dimensional quantum work space, processed, and read out classically. The quantum system would act as a "sieve" through which stacks of neuron images would pass through and be segmented. There are significant challenges in the way of accomplishing this [9], particularly with decoherence and measurement issues, but it does not appear to be impossible.

5 Goals

At present the connectome project is far beyond practical. Quantum computers may or may not shift the possibility that the human brain's structure can be mapped by aiding in the automation of image analysis. Knowledge of this potentiality is crucial as it would provide an overall perspective on whether connectome research is worth pursuing or whether other approaches to understanding the brain are more promising and worthy of immediate attention and resource allocation.

The goal of this research is to explore the effectiveness of quantum algorithms in boundary detection with the particular application to neuron tracing. It is desired to develop a specific protocol to achieve this goal as well as quantify the speed-up that this would potentially provide, given the proper hardware. Combined with further research into the progress of image acquisition techniques, this would enable a prediction of the feasibility, time, time-line, and cost to accomplish the mapping of the human connectome. Following this research it would be imminent to work with experimental groups to develop image encoding, processing and read-out on a small scale of several pixels/qubits.

This research takes as it's ultimate goal that of connectomics: the complete mapping of the human brain. A subgoal necessary to reach this end is exponential, automated image analysis of brain slices. This work would be a first step towards this. A long term outlook of this research line is as follows: survey existing quantum machine learning algorithms and quantum hardware, identify a particular set that demonstrates feasibility and scalability in the near future, experimentally demonstrate exponential speed-up on real sample images, scale-up and use original images from research by White and Brenner to create a rendering of the C. Elegans nervous system, continue scaling. Eventually it is hoped that the entire brain rendering process may be automated into a black box with a brain going in and a computational model coming out. This would be a revolution in behavioral cognitive research as it would allow data taken during a beings lifetime, that has poor resolution but good time resolution, to be mapped with postmortem structural data that has extraordinary spatial resolution but no time resolution. It would also enable structural differences between various individuals (mice) to be compared and used to formulate quantitative theories on how brain structure and connectivity can manifest cognitively and behaviorally.

An immediate benefit that may come of this research is that it may clarify what type of quantum hardware is best suited for quantum image recognition. If it provides exponential speed-up, quantum image recognition is of such importance that it would be well worth-while pursuing a particular system even if it had no other applications. It may not be necessary to have a truly universal quantum computer to perform this task and existing quantum architecture may be capable. These are issues worth exploring and if successful would have a large impact to many research communities, including connectomics.

The end product of this research would be an extensive outline and outlook of the application of quantum machine learning techniques to connectomics research. It would provide quantum protocols to accomplish neuron image analysis and discuss hardware upon which this could be achieved. Ideally, it would provide preliminary experimental results of quantum image recognition to a brain slice image. With a well defined quantum edge detection protocol and with small images, it may be possible to obtain prelimary results on systems such as those being used by Hannes Bernien at Harvard that use 51 qubits. [15] Protocols that depend upon steepest descent and optimization may be tested on a D-Wave system if server time can be obtained.

6 Budget

The expense of this research would entail the salaries of one post-doctoral researcher, \$65k, and one graduate researcher, \$35k, for the duration of one year for a total of \$100k. At the end of one year results will be presented and a proposal for further research will be presented.

7 Conclusions

To progress in connectomics it will be necessary to harness more powerful technology to ease and speed up the process of data acquisition and analyzation of brain matter. The proposed research intends to push the development of quantum pattern recognition, with particular application to edge detection and neuron tracing, forward as quickly as possibly by clearly identifying algorithms and quantum hardware that can be used to accomplish this goal. Pushing beyond this stage will enable closely connected collaboration with experimental groups to begin physically realizing quantum image recognition capabilities.

If we believe Sebastian Seung when he states that "if connectomics experiences sustained exponential progress, then finding entire human connectomes will become easy well before the end of the twenty-first century"[1], then quantum computers, which are coveted for their exponential speed-up, may likely have a role to play.

References

[1] S. Seung, *Connectome: How the Brain's Wiring Makes Us Who We Are*, Houghton Mifflin Harcourt, (2012).

[2] O. Sporns, *Discovering the Human Connectome*, The MIT Press, (2012).

[3] O. Sporns, D. Chialvo, M. Kaiser, and C. Hilgetag, *Organization, development and function of complex brain networks*, TRENDS in Cognitive Sciences Vol.8 No.9 September (2004).

[4] J. G. White, E. Southgate, J. N. Thomson, S. Brenner, *The structure of the nervous system of the nematode Caenorhabditis elegans* Phil. Trans. R. Soc. Lond. B 1986 314 1-340; DOI: 10.1098/rstb.1986.0056, (Nov 12 1986).

[5] Brenner S. *The genetics of behaviour.* Br. Med. Bull. 29, 269-271, (1973).

[6] D. Ciresan, A. Giusti, L. Gambardella, J. Schmidhuber, *Deep Neural Networks Segment Neuronal Membranes in Electron Microscopy Images* NIPS, 2852-2860, (2012).

[7] J. Long, E. Shelhamer, T. Darrell, *Fully Convolutional Networks for Semantic Segmentation* CoRR, abs/1411.4038, (2014).

[8] Havaei, Mohammad et al., *Brain tumor segmentation with Deep Neural Networks* Medical Image Analysis, Volume 35, 18-31, (2017).

[9] M. Mastriani, *Quantum Image Processing?* Quantum Information Processing, Volume 16, Number 1, Page 1 (2017) https://arxiv.org/ftp/arxiv/papers/1512/1512.02942.pdf

[10] Xi-Wei Yao et al., *Quantum Image Processing and Its Application to Edge Detection: Theory and Experiment* PHYSICAL REVIEW X **7**, 031041, (2017).

[11] Z. Yi, LU Kai and G. YingHui, *QSobel: A novel quantum image edge extraction algorithm* Science Chine Informaton Sciences Vol 58, (Jan 2015).

[12] X. Fu, M. Ding, Y. Sun, and S. Chen, *A new quantum edge detection algorithm for medical images* Proceedings of SPIE - The International Society for Optical Engineering, (Oct 2009).

[13] P.Q. Le, F.Y. Dong, K. Hirota, *A flexible representation of quantum images for polynomial preparation, image compression and processing operations* Quantum Inf. Process. **10**(1), 63-84 (2011)

[14] H. Neven, G. Rose, and W. G. Macready, *Image recognition with an adi- abatic quantum computer. I: Mapping to quadratic unconstrained binary optimization* arXiv:0804.4457, 2008.

[15] H. Bernien et al., *Probing many-body dynamics on a 51-atom quantum simulator* Nature volume 551, pages 579584 (30 November 2017) doi:10.1038/nature24622.

[16] Rebentrost, M. Mohseni, and S. Lloyd, *Quantum Support Vector Machine for Big Data Classification*, Phys. Rev.Lett. 113, 130503 (2014).

[17] P. Wittek, *Quantum Machine Learning*, Elsevier Inc (2004)

[18] J. Biamonte, P. Wittek, N. Pancotti, P. Rebentrost, N. Wiebe, and S. Lloyd, *Quantum Machine Learning*, Nature **549**, 195-202 (2017); arXiv:1611.09347.

[19] Dong-Ling Deng et al., *Exact Machine Learning Topological States*, arXiv:1609.09060v1, (2016).

[20] A.W. Harrow, A. Hassidim, and S. Lloyd, *Quantum Algorithms for linear systems of equations*, arXiv:0811.317v3, (2009).

[21] J. Biamonte, P. Wittek, N. Pancotti, P. Rebentrost, N. Wiebe, and S. Lloyd, *Quantum Machine Learning*, arXiv:1611.09347v1, (2016).

[22] V. Ivancevic, T. Ivancevic, *Quantum Neural Computation*, Springer, (2010).

[23] M. Schuld, I. Sinayskiy, F. Petruccione, *The quest for a Quantum Neural Network*, arXiv:1408.7005v1, (2014).

[24] R. Rojas, *Neural Networks: Chapter 13, The Hopfield Model*, Springer-Verlag, Berlin, (1996).

[25] X.D. Cai et al, *Entanglement-Based Machine Learning on a Quantum Computer*, arXiv:1409.7770v3, (2015).

[26] A.L. Barabasi, *Network Science*, Cambridge University Press, (2016).

[27] A.L. Barabasi, *Network Medicine*, Harvard University Press, (2017).

[28] A.L. Barabasi, *Network Medicine: a network-based approach to human disease*, Nature Reviews Genetics 12, 56?68, (2011).

[29] Vedran Dunjko and Hans J. Briegel, *Machine learning and artificial intelligence in the quantum domain*, arXiv:1709.02779v1, (2017).

[30] E. Farhi, J. Goldstone, S. Gutmann, H. Neven, *Quantum Algorithms for Fixed Qubit Architectures* arXiv:1703.06199v1, (2017).

[31] Vedran Dunjko, Jacob M. Taylor and Hans J. Briegel, *Quantum-Enhanced Machine Learning* Phys. Rev Lett.117.130501

[32] Harmut Nevin, *An Update from the Google Quantum Artificial Intelligence Lab*, http://kits.ucas.ac.cn/index.php/events/talks-2/62-an-update-from-the-google-quantum-artificial-intelligence-lab-jul-5-2017, (2017).

[33] Christopher Monroe, *"Modular Ion Trap Quantum Networks: Going Big"* GoogleTechTalks, (May 26, 2015).