Replicating the Human Visual Cortex

Jack Landers, March 9, 2025

***Abstract*—The purpose of this thesis is to consider emerging technologies and their applications towards improved visual reasoning in order to enhance brain computer interfacing. We will examine how neural networks model the brain in software, and how hardware will evolve to support more complex models by collecting research on mem devices and reservoir computing. In addition, we will evaluate studies on transcranial focused ultrasound for its potential as a noninvasive mode of stimulating the visual cortex.**

***Index Terms*—mem devices, memristor, memcapacitor, transcranially focused ultrasound, artificial neural networks, deep neural networks, convolutional neural networks, reservoir computing, echo state networks, small world power law, visual cortex, optical reservoir**

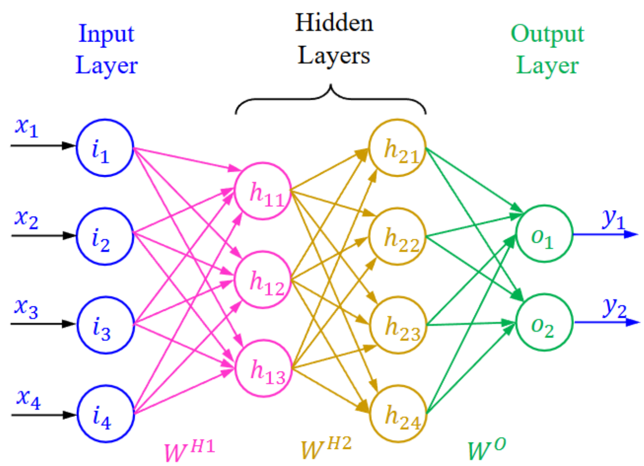
I. Introduction

It is a foreseeable future where the distance between the mind and the internet, a vast collection of memory connecting the world, closes in. We know that the brain is the source of our experience and reflection, but it is still an area of research due to the deep complexity of its nature. Should we be able to decode its connections and map the sources of various senses, then the distinction between mind and computer can be reduced. The traditional Von-Neumann computer is a digital processor that interprets collections of 1s and 0s to develop them into digital outputs so detailed that they may compare to the analog inputs that we experience, like images and music [8]. But our minds are more intricate, as we receive analog information and produce analog outputs. While it is not immediately apparent how this is superior, consider facial recognition, a process that, digitally, requires that a computer be trained on at least hundreds of images, and yet if you meet someone for just a moment, you could pick them out from a crowd in an instant. With technical innovation, this limit of digital processing will be overcome. We will explore how Non-Von Neumann architectures using mem devices have been proven to effectively replicate the architecture of the mind. As well as this, we will dive into how this can be applied to brain-computer interface technology, to integrate the mind more closely with the Internet and digital memory.

II. Neural Networks

A. Artificial Neural Networks

Artificial Neural Networks (ANNs) are a mathematical representation of how brain neurons identify patterns to perform parallel reasoning from several analog inputs. By representing this process in software, ANNs have been applied to develop the field of Artificial Intelligence for a range of technologies. The brain uses a network of trillions of synapses that connect neurons, which are electrical nodes [1]. These neurons are organized into clusters, each performing different functions



$$H^1 = \varphi^{H1}\left(I \times W^{H1} + B^{H1}\right)$$
$$H^2 = \varphi^{H2}\left(H^1 \times W^{H2} + B^{H2}\right)$$
$$Y = \varphi^{O}\left(H^2 \times W^{O} + B^{O}\right)$$

Fig. 1: A Deep Neural Network Structure, where layers of hidden neurons between the input and output neurons are trained to process information using the backpropagation of weights in machine learning algorithms. [9]

φ = Activation Function of the Layer
W = Layer Weights Matrix
B = Layer Biases Matrix
I = Input, Y = Output

within the brain. A synapse is reflected in an ANN by a weight value corresponding to the strength of the connection between the neurons. The goal is for each neuron to receive input vectors of information and process the vectors with an activation function. The output is scaled by the synaptic weight before its input to the next neuron, until the output neurons are reached. ANNs successfully achieved machine learning with the application of training using backpropagation. This is where the synapse weights are scaled after each forward pass of information from input to output by a gradient descent algorithm. The gradient descent algorithm compares the output values with expected targets and calculates an updated weight. For the network to successfully learn, there must be multiple hidden layers between the input and output neurons, each with their own set of neurons and activation function. With multiple hidden layers, the network is then regarded as a Deep Neural Network (DNN).

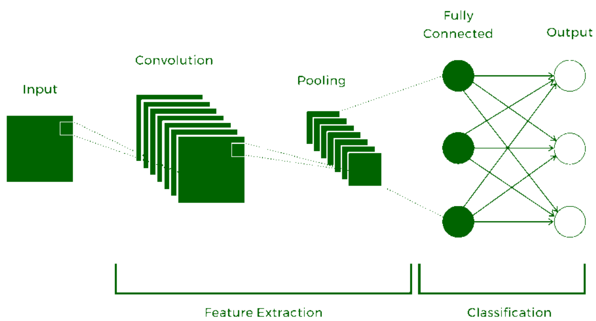


Fig. 2: A Convolutional Neural Network Structure, which uses kernels convolved with 2D pixel matrices to process visual data. [1]

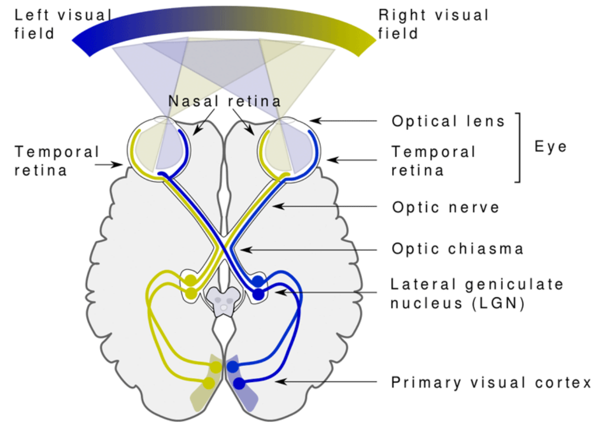


Fig. 3: A Retinotopic Map, showing how information from visual light enters the eyes to reach the primary visual cortex. [6]

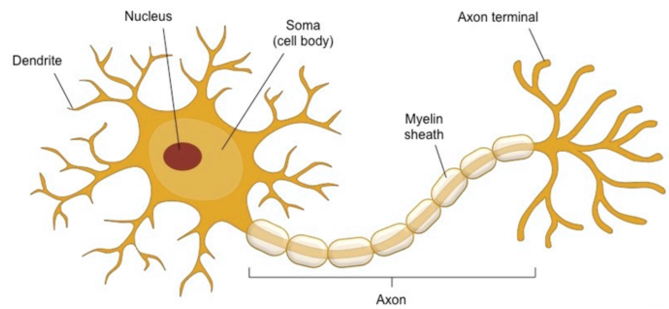


Fig. 4: A Model Biological Neuron, which exhibits electrical properties activated by chemical reactions in the brain. [1]

B. Training and Datasets

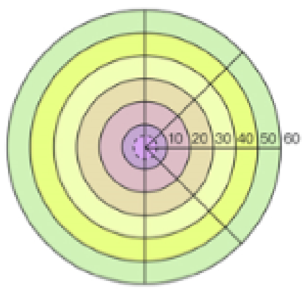
A neural network can only be as good as the data it is trained on. In order to maximize the effectiveness of training, the input and target datasets must be optimized to reduce bias. Datasets like MNIST, CIFAR, and ImageNET were created to help evaluate models learning from the same information. By reducing any noise in the data and improving labeling, the models are less likely to be confused by anomalies [21]. Vision models are also trained by augmenting the data with filters that change properties of the images so that they are less consistent, like rotating images, so that the model can recognize the object pattern at any orientation. Another issue for neural networks training is managing parameters such as the learning rate and the number of epochs. If a model trains for too long, it may begin to overfit the dataset, which leads to errors where it identifies patterns that exist for only the training data.

C. Convolutional Neural Networks

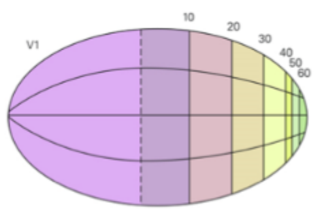
ANNs evolved further with the combination of DNNs and the convolution filter. A convolution is a mathematical operation that processes a matrix of pixel values representing an image, with a kernel, a matrix that produces an output highlighting the necessary features for a computer vision operation like edge detection or texture mapping [2]. This is such that an edge detection kernel convolved with an input picture would result in an output feature map of just the edges in the picture [22]. The use of this feature map in a DNN makes it a Convolutional Neural Network (figure 2) that can spot patterns in the original image, similarly to how the visual cortex of the brain can. However, now that the dimension of the input is a matrix and not a vector, the digital processing required becomes massive because there are so many operations involved that the information bottlenecks as data is translated between the RAM and processing units [8]. This is a limitation to the further development of computer vision technology, and it is why we humans are better at tasks like facial recognition.

III. The Visual Cortex

The visual cortex uses an estimated 4-6 billion neurons and is divided into six critical regions, identified with fMRI, to process different visual attributes [6]. Lower order areas of the visual cortex, the primary cortex (V1), V2, and V3, are precisely mapped to light sources and can be regarded as the neuron layers closest to the input [6]. The primary cortex is responsible for detecting edges, orientation, and contrast, this is much like the feature mapping process at the start of a CNN. The V1 uses contrast normalization mechanisms to help regulate brightness, ensuring neurons encode relative differences rather than absolute brightness, similar to a sigmoid activation function in ANNs. The V2 region is where we start to perform pattern recognition, it is the part of the brain responsible for object detection and classification. Next, the V3 region is associated with motion and depth, performing more complex tasks like 3D reconstruction [6]. Both V4 and V2 specialize in color perception which is used for object recognition, but fMRI studies reveal that color maps are less precise than luminance-based maps due to the complexity of chromatic adaptation in the brain [19]. The regions of the visual cortex are mapped to the projection of the visual field on the retina, and changes in eccentricity of visual stimuli correspond to activity in pathways associated with these visual field maps. In the primary visual cortex, the image is projected by cortical magnification in the retina. This passes more information from the focal point of the image to the brain and packs the peripheral vision more densely, so that more neurons can be used to process the focal area. The visual field is mapped in every region of the visual cortex allowing for spatially localized computation. Areas of the visual cortex can be specialized to certain visual experiences, which we know from studying certain neurological disorders such as loss of motion perception or loss of the ability to read words [19].



(a) Retinal Eccentricity, color mapping the visual field



(b) Cortical Magnification, a color mapped projection of the visual field image on the visual cortex

Fig. 5: Comparison of Retinal Eccentricity and Cortical Magnification, showing the proportion of magnification that the regions of the visual field undergo when projected to the visual cortex. [6]

A. Neuron Behavior

Cortical neurons are sensitive to changes in brightness in order to perform edge detection. This is our natural ability to grayscale such that our brain applies more significance to these differences in brightness that CNNs preprocess images to optimize for [5], [22]. Comparably, the primary visual cortex uses specialized neurons named double opponent cells to optimize color perception. These cells are linked to two receptors that each detect different colors in the visual field. This makes them especially sensitive to color contrast, so double opponent cells are necessary for using color in object classification [4]. When replicating neurons, we also have to consider that they do not have a digital behavior, but are analog. When a neuron fires its signal is characterized by an electrical pulse upon stimulus, which could fail to surpass the threshold for action potential [5]. For this reason, a neuron is commonly activated by multiple input activations simultaneously. As well as this, there is a refractory period before reaching a resting state, so the neuron has the possibility to change spontaneously without external stimuli. The neuron's analog pulse strengthens the synaptic connection in

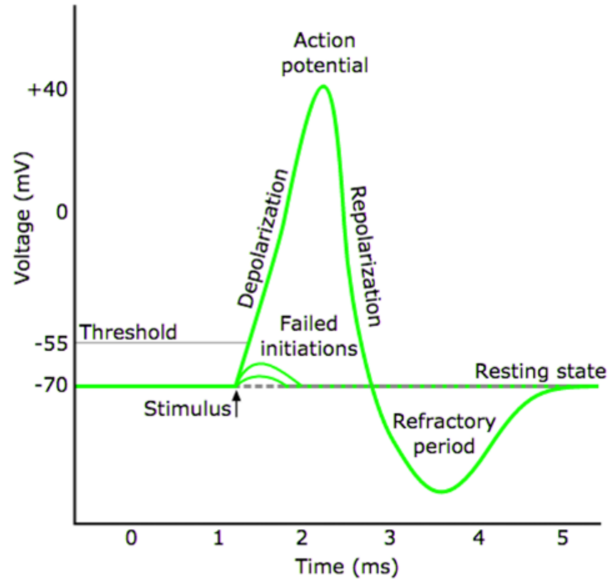


Fig. 6: A Neural Pulse, which is activated when sufficient stimulation from input neurons break the threshold voltage, depolarizing the neuron and passing the information forward to the next neuron in an analog signal. [5]

what is referred to as the Spike-Time-Dependent-Plasticity, our biological learning mechanism [5]. This is wherein if a presynaptic neuron's spike precedes a postsynaptic neuron's spike within a narrow time window, the synapse is typically strengthened, deemed long-term potentiation. But in contrast, if the presynaptic spike follows the postsynaptic spike, the synapse may weaken. This timing-dependent adjustment is crucial for memory formation, acting as a real time update to synaptic weight [7].

IV. Mem-Devices

As Artificial Intelligence is produced at scale, these neural networks are limited by their massive demand for hardware [8]. Although current software models are nearing the number of neurons in the brain, digital processors are magnitudes less efficient, requiring over 7 million times as much energy for data centers that are hectares large [3].

Mem-Devices are nanoscale circuit elements that have the ability to remember their previous states. This has enormous application potential for processing neural networks, because it is similar to the functionality of biological neurons. With Mem-Devices brain structures can now be duplicated in hardware rather than just in software simulations [9]. They are modeled as traditional circuit elements, but with a changing internal state.

A. Memristors

Currently, the memristor is the first of the mem-devices to have been fabricated. The memristor can be described by two equations, depending on its application, the flux controlled model, and the charge controlled model. In both cases, the resistance of the device is consequently a function of the

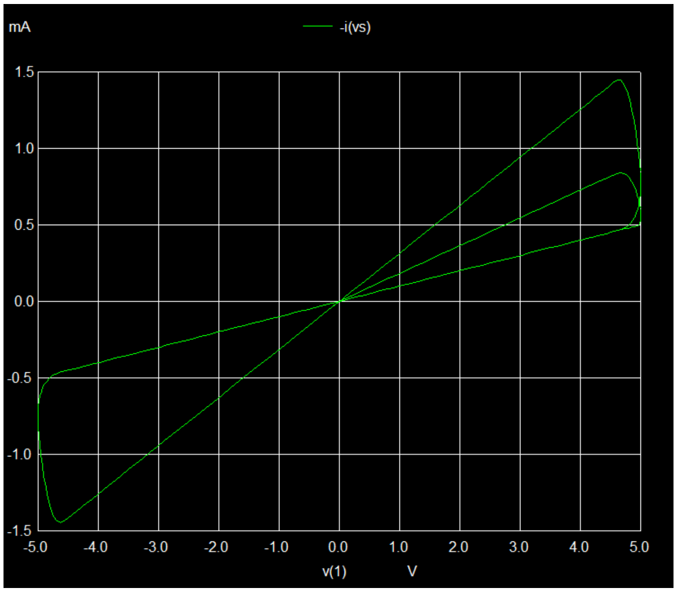


Fig. 7: Current with Respect to Voltage in a Bipolar Threshold Memristor. The relationship is nonlinear in what is known as a Hysteresis response caused by the element's resistance depending on both input current and previous voltage

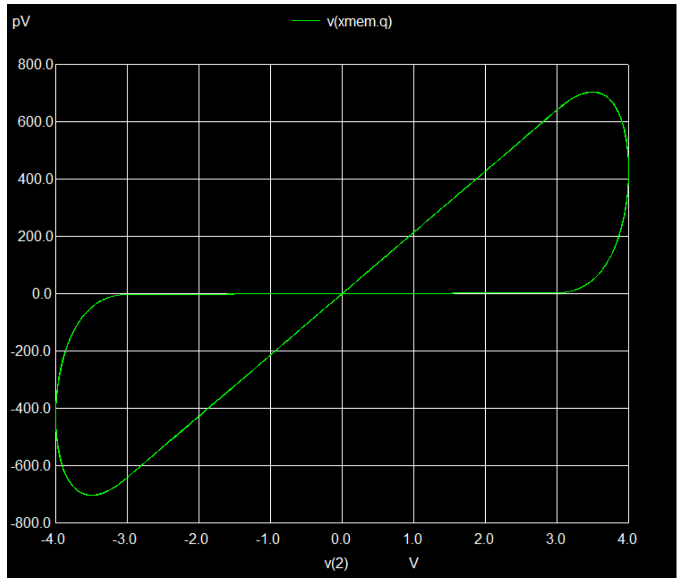


Fig. 8: Charge with Respect to Voltage in a Bipolar Threshold Memcapacitor Hysteresis response, where charge to voltage is not linear like a regular capacitor, because it is reliant on the mem-device's previous state. (Charge is modeled in spice as the voltage at node mem.q)

previous resistance state, and the voltage across the device. With this, the memristance value is often calculated using a window function of the device's properties to determine where the momentary resistance lies between its minimum and maximum [9]. The Hysteresis response shown in figure 7 depicts how the current voltage relationship is nonlinear, because the resistance is dependent on if the voltage has increased or decreased from the previous state.

The memristance in a charge-controlled model is given by:

$$V(t) = M[q(t)] \cdot I(t) \tag{1}$$

Where the memristance $M(q)$ is defined as:

$$M(q) = \frac{d\phi(q)}{dq} \tag{2}$$

Here:

- $V(t)$ is the voltage across the memristor,
- $I(t)$ is the current through the memristor,
- $q = \int I(t)\,dt$ is the charge,
- $\phi = \int V(t)\,dt$ is the magnetic flux linkage.

This charge controlled model is necessary for interpreting the state of the resistance in the case of a neural network, because they track how the accumulation of current to the system changes the state. This state change can be used to represent the effect of a forward pass on the neuron's weight.

Memristors have been fabricated with the DC magnetron sputtering of Hf-Nb thin-film alloys to exhibit the bipolar threshold switching similar with non-volatile memory behavior [17]. Magnetron sputtering is already used in CMOS fabrication lines so it can be easily integrated for the manufacturing of memristors. Anodic oxidation is then used to form the Hf-Nb alloy into a uniform oxide layer, allowing for the deposition of platinum electrodes on top of the memristive material, acting as individual memristors [17]. This electrochemical method enables precise control over the oxide layer's thickness and composition, which is crucial for tailoring the memristive behavior of the devices.

B. Memcapacitor

Similarly, mem-capacitors have been shown to exhibit such a state change with incredible energy efficiency, but are in earlier stages of development [9]. The state of a memcapacitor, its memcapacitance, is reliant on the previous state of the device's charge, resulting in a nonlinear charge to voltage ratio, which can be seen in the hysteresis response in figure 8.

The memcapacitance is given by:

$$V(t) = \frac{1}{C[q(t)]} \cdot q(t) \tag{3}$$

Where the memcapacitance $C(q)$ is defined as:

$$C(q) = \frac{dq}{dV(q)} \tag{4}$$

Here:

- $V(t)$ is the voltage across the memcapacitor,
- $q(t)$ is the charge stored in the memcapacitor,
- $C(q)$ is the charge-dependent memcapacitance,
- $I(t) = \frac{dq}{dt}$ is the current through the memcapacitor.

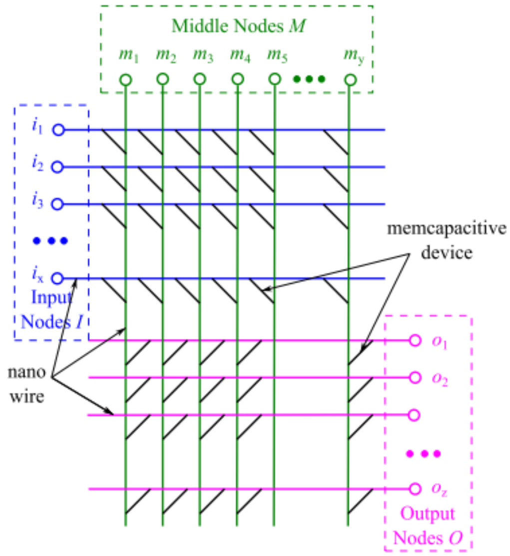


Fig. 9: A Memcapacitive Crossbar Array, which has been developed to simulate a feed forward neural network using memcapacitors in a highly energy efficient hardware replica. [9]

These equations capture how the accumulation of charge influences the capacitance state. This state change can be used to represent dynamic synaptic weights, where the modulation of charge reflects the adaptive learning behavior of artificial neurons [7].

The memcapacitor crossbar array developed by Hwang et al. uses memcapacitor cells consisting of a multilayer stack for storing electrical charge [**?**]. This is manufactured in a process that is similar to CMOS development using techniques, such as oxidation, sputtering, atomic layer deposition, and ion implantation [**?**]. By trapping or releasing charge, the capacitance of each cell can be precisely adjusted, enabling the memcapacitor array to mimic the spiking synaptic weights of biological neurons. In order to implement the memcapacitors into a fully connected circuit network, researchers connect mem-devices in a crossbar array by combining the cells in a charge-trap NAND flash (CTF) structure, which places the mem-devices in series with one another for each respective neuron, naturally summing the potential difference of their outputs [9]. While the activation function cannot be simply applied to this output, as in software, the controlled structure has been simulated to exhibit the same nature as networks already used in software today. This network performs only 1.13% less accurately than ideal software comparisons, with extremely high energy efficiency due to it operating primarily through dynamic, rather than static power [18].

V. Reservoir Computing

Alternatively, mem-devices could be used for reservoir computing techniques, where the elements are connected in an unstructured manner. The benefit of reservoir computing is the significant reduction in training required. DNNs and RNNs are slowed by the dependency on backpropagation through time, but with a reservoir this is only necessary at the inputs and outputs. This would more accurately reflect the structure of neurons in the brain which are still effectively learning. Due to their randomly connected nature, reservoirs are also recursive, meaning that information can continue to cycle through the network and be retained in the system over a long period of time, rather than just the previous time step in what is known as an echo state network [10]. In neuroscience, neuron structure is modeled as a Small World Power Law network, where the connection of neurons is described by their randomness and locality. Locality describes how many connections a neuron has to neighboring neurons that are considered close. Randomness is determined by how distinct from a fully connected network a neuron is, with respect to how many long distance connections it has to other neurons that are not simply neighboring. This introduces the concept of clustering, whereby not only are reservoirs random connections between neurons, but also somewhat layered as their localization is only broken by a few random neurons. Such clusters represent the nature of the visual cortex regions whereby collections of neurons process information for a specific task, while some neurons pass on the signals to the next region. This is the more natural approach to processing the layers of a CNN, as each time step between layers is now determined by the probability of the cluster passing the information on, against continuing to process it [10]. Cluster network topologies are superior over processing one layer at a time, as it improves parallelism while also introducing recurrence. In software, the cluster network variables can be considered hyperparameters which we can optimize for with machine learning tools like Ray and Optuna, to perfect the model properties. On top of clustering reservoirs, to replicate the visual cortex the analog nature of the neuron has to be simulated and mem-devices can achieve this by exhibiting the Spike Time Dependent Plasticity model of a neural pulse (figure 6) in hardware [7]. This is evidenced by the hysteresis responses shown in figures 7 and 8, where the mem-devices have a threshold dependency and an adaptive state.

A. *Optical Reservoirs*

Optical reservoirs are also non Von Neumann architectures that model echo state networks, but rather than mem-devices use optical components. An opto-electronic oscillator modulates a laser input with a time-stepped output to create a feedback loop. Inputs can be encoded with the laser and, with the time multiplexing of the feedback loop, can exhibit properties of a learning neuron. However, neurons in this case are virtual and only simulated by the system, to be read out by photodiodes. The advantage of using an optical system is its higher capacity for speed, and while not as energy efficient as memcapacitors, it would still be a significant advantage over digital Turing computation [11]. Because it is operating at the speed of light, the optical reservoir could have the speed to replicate as many neurons as are in the brain, but this would come at the expense of scale, as the necessary optical equipment is much more large and power consuming than memcapacitors.

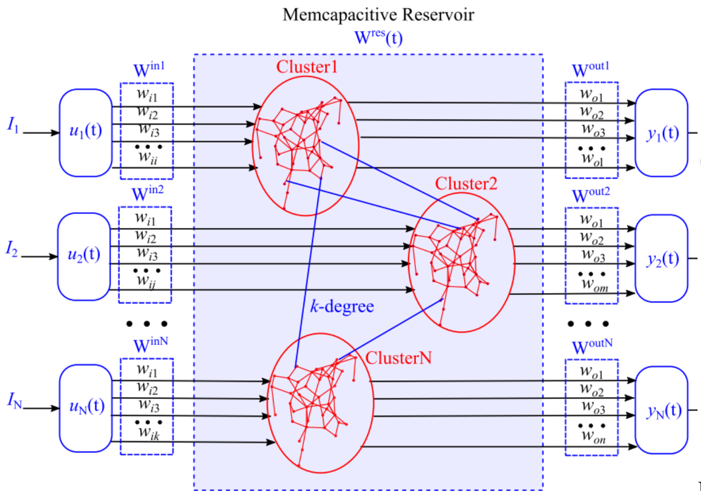


Fig. 10: A Small World Power Law Cluster Network, a reservoir computing network simulated in software to most effectively represent how our biological brains compute, which could theoretically be developed using memcapacitive devices, like a crossbar array. [10]

VI. Transcranial Focused Ultrasound

While mem devices and reservoirs have the potential to develop an artificial visual cortex, there is still a limitation to the speed at which computers can communicate this information with us. This is where the emerging field of brain computer interfacing comes into consideration. The success of electrode brain computer interfacing has come to be widespread, but the need for surgical implantation is invasive and impractical for future commercial applications at scale. Current research in Transcranial Focused Ultrasound (tFUS) aims to overcome this. Ultrasound waveforms can be focused to result in varying cortical activity patterns, using pulsed waves at frequencies higher than 100Hz, which produce prolonged low frequency responses [14]. This also provides better spatial resolution alternative electrical or magnetic stimulation techniques. The mechanism behind ultrasound neuromodulation is acoustic radiation force, where mechanical pressure is applied to the neuron, causing it to activate [12]. Studies found that this produced negligible thermal increases in the brain and no cavity or bubbles, meaning that it won't cause physical damage to the excited neurons. This shows promising results for non-invasive visual prosthesis as it can be used to activate the visual cortex. It was tested on the Rhesus Macaque, primate relatives to humans, by activating neurons in the frontal eye field of their frontal cortex [14]. Such activation was shown to produce consequent neural activity in the V4 of their visual cortex, showing dependency on the signal sent to the frontal eye field, and proving an influenced presence of visual stimuli. Transcranially focused ultrasound was then also investigated on humans. Participants were monitored to confirm that their primary visual cortex was activated by the tFUS, and both fMRI and EEG recordings. Furthermore, they exhibited that with this activation participants observed visual effects that aligned with the presence of the tFUS signal and proved it against a placebo control group [15].

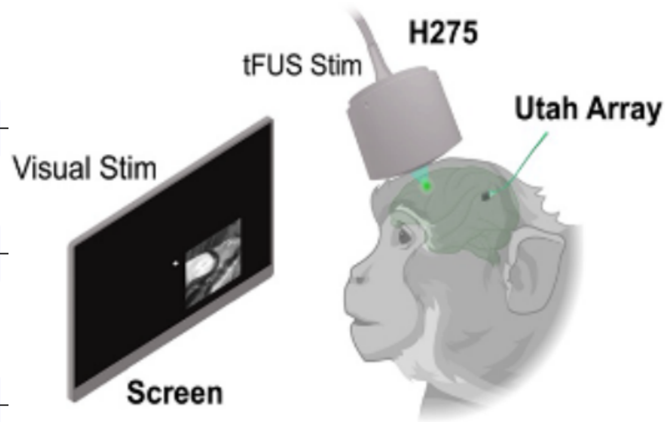


Fig. 11: Experimental Procedure on Rhesus Macaque, where transcranial focused ultrasound on the frontal eye field was proven to induce visual stimulation that matched the responses from visual stimulation which was produced by a screen. [14]

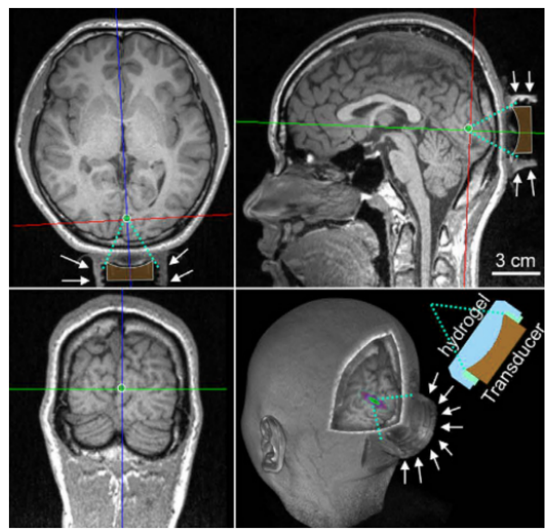


Fig. 12: An MRI of Human Testing. Transcranial focused ultrasound was directed at the primary visual cortex and both EEG and fMRI confirmed neuron activation with negligible adverse affects. Participants confirmed visual stimulation occurred. [15]

VII. Potential Applications

With the combination of these developing technologies, advancements in the medical industry can flourish and many viable commercial applications will follow. As mem-devices are produced at scale, reasoning will massively increase as processors can perform tasks in the same manner that the brain does. Furthermore, with the advent of these non Von-Neumann processors, the visual cortex can be more accurately reflected in hardware so that the computational advantages of our biological minds can be harnessed in our devices [8]. One example might be in cameras where images would no longer have to be converted to digital information to be processed. With this, research can begin to improve visual prosthetics for the blind that can produce tFUS stimulations that have the complexity to provide artificial sight [15]. Such technology could also be repurposed for augmented vision enhancing what we already see by overlaying digital information into brain perception regions. This extends beyond the visual cortex as capabilities improve, where information can be projected directly to further parts of the brain. In addition, the replaying of cortical activation patterns could be used for simulating memories and dreams, either in the brain or on hardware. Aside from brain computer interfacing, modeling synaptic connections opens up potential for neuroscientists to improve our understanding of degenerative brain diseases, and with artificial neurons the brain can be easily repaired.

VIII. Conclusion

Overall, brain activity is in the early stages of being replicated. Researchers have successfully modeled the neurons of a fruit fly, but the processing power to achieve this for trillions of human neurons is lacking [20]. Mem devices and reservoir computing open up the potential to reconstruct regions of the brain in hardware not just software. Replicating the brain can help us map the very source of our thoughts and consciousness. Already, we have harnessed the virtual world to extend our memories by storing information on devices, and accelerated how we share it with the propagation of signals. Advancements in brain computer interfacing and analog computation, will enable researchers to synchronize the processing of information performed digitally and naturally. It is a near future when the barriers between mind and machine could be overcome, and with it, the latency of communicating ideas and the fading of our memories, will reduce.

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