On Discretized Time-Local Waveforms In The Brain And Neural Theory

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*Abstract*—The nature of unsolvable problems depends on the kind of unsolvability. These problems cannot be solved; thus, they are not problems, rather they are constraints, or domains or ranges. Further, these problems are already solved upon creation, as they were not created, they arise as natural mathematical law as a result of axioms. The fears associated with Artificial Intelligence and its development to the point of superintelligence and beyond are dramatically under estimated, while simultaneously being inevitable. Thus, discussion in regard to these control ‘problems’ should be instead in regard to the control ‘situation’ and our responsibility in the continued management of AI tech knowledge.

Keywords—artificial intelligence; superintelligence; the control problem; unsolvability; control situation; global technology management; GAIA; MAIA

First off, this paper will discuss the nature of nerve signals in light of papers discussing the theory behind EEG. Then the paper moves on to discussing the current (and, in my opinion, flawed) viewpoint of nerve signals as brainwaves (frequencies). Further, after mathematically analysing an EEG reading for a healthy person undertaking a mindfulness task a theoretical model for the brain’s electromagnetics is proposed. After considering infinite infinities for wavelet transformations expressed by the mathematics behind the mother and father root wavelets a single specific wavelet transformation is proposed for analysis of brain activity and mental function.

A number of tasks are performed by a single person and a series of deep neural networks trained on the signals in a linear, frequency and wavelet form, as well as combinations of each of these, even a neural net that uses all three. The many paths of attack are then compared for predictive accuracy.

# Nervous Excitation

Considering brain signals under the model of chemical flow with action potentials; neurons as black boxes. Nerve impulses have been reported to flow at rates of 0.9 m/s to 90 m/s generalized as being speeds for pain and muscles, respectively[3].

Assuming a purely resistive flow, a model that is inherently flawed, yet yields a boundary for the simplest approach, with combined capacitive, inductive, and resistive circuit components being a model with a wider range of application, yet also incomplete.

(1)

With such a purely resistive flow and neurons having an average diameter of 1-20 micrometers for an axon and 4-100 micrometers for a soma, it is easy to see that the latitudinal neuronal flow becomes 90 MHz for a fast twitch thick nerve down to 45 kHz for a slow twitch thin nerve and the longitudinal flow is in proportion to the length of the neuron rather than the diameter. This number is not representative of how many pulses a nerve fiber can take in a second, but, inclusive of Nyquist’s sampling theorem, it closely represents how fast of a measurement is required to not lose information on the (assumed non-fractal, for simplicity) electrical flow through each nerve. Thus, it appears only the highest frequency ADC (analog-digital converter) components should be used for determining single axon action potentials.

Latitudinal neuron electrical flow is important to be able to measure as this will determine the sample rate necessary to observe dendritic dominance – the proportion of dendritic selectivity of individual neural cell bodies as well as the proportion of neural cell selectivity of individual dendrites. To be able to isolate between the forks of an axon a more precise model of neural electrical function can be used to better determine relationships between mind and brain.

Another way of determining a loss-less informational recording of an analog signal in neurons could be through the use of waveform duration, even though it’s not a sinusoidal waveform, thus there is more information than specified by the following calculation. Recorded waveform durations have been in the range of 150-500 micro seconds, this comes out to 4 kHz to 7 kHz needing Nyquist’s sampling theorem to be included on top of this (a multiplication factor greater than 2).

Thus, it appears feasible and worthwhile to record at frequencies greater than that of High Gamma as referred to by numerous brainwave theorists of the past.

# Information Resolution

Information is resolved from a voltage recording in proportion to the non-compressible digital space used to remember (memory that gets actuated) the raw data. There are the bitrate of each sample, the sample rate per second, and the number of channels recording that determine the information resolved:

(2)

On Discretized Time-Local Waveforms In The Brain And Neural TheoryAbstract

After reading numerous EEG articles incorporating Machine Learning, what was hypothesized as the key variable in obtaining useful data, the sample rate, was almost always neglected in being mentioned. One particular article suggested that sample rates around 128 Hz (sic) was all that was needed for an EEG. However, seeing as epilepsy can be quite reliably diagnosed from an EEG at this rate, and EEGs vary from person to person, it was hypothesized that a person’s identity could not be fingerprinted from a large pool with a sample rate so low. At 256 samples per second, a 1 second reading could not identify between 122 people, on any of their 64 channels, all obtained from a public data set. Thus, a ‘back of the envelope’ calculation is given for what may be a more useful theory in recognizing that the EEG is very complex and higher sample rates and bits per sample will likely give more useful information, hopefully to the point of decoding thoughts on the order of 1 in 70,000 as would be needed for the English language. The code used is now open source (without license) and online in the case that someone has access to a more powerful computational device or a more information-rich dataset. 1-5% accuracy was found in fingerprinting an individual at this level. The winner on average was the two derivative measures (5% accuracy). The winner on a single channel was the final custom wavelet of a derivative. (7% accuracy). Less than 1% accuracy is considered random.

Keywords—EEG, sample rate, fingerprintingFirst off, this paper will discuss the nature of nerve signals in light of papers discussing the theory behind EEG. Then the paper moves on to discussing the current (and, in my opinion, flawed) viewpoint of nerve signals as brainwaves(frequencies). Further, after mathematically analyzing an EEG reading for a healthy person undertaking a mindfulness task a theoretical model for the brain’s electro-magnetics is proposed. After considering infinite infinities for wavelet transformations expressed by the mathematics behind the mother and father root wavelets two single specific wavelet transformations are proposed for analysis of brain activity and mental function. A number of tasks are performed by a single person and a series of deep neural networks trained on the signals in a linear, frequency and wavelet form, as well as combinations of each of these, even a neural net that uses all three. The many paths of attack are then compared for predictive accuracy.

2.4.1 Nervous ExcitationConsidering brain signals under the model of chemical flow with action potentials; neurons as black boxes.

Nerve impulses have been reported to flow at rates of 0.9m/s to 90 m/s generalized as being speeds for pain and muscles, respectively[3].Assuming a purely resistive flow, a model that is inherently flawed, yet yields a boundary for the simplest approach, with combined capacitive, inductive, and resistive circuit components being a model with a wider range of application, yet also incomplete. With such a purely resistive flow and neurons having an average diameter of 1-20 micrometers for an axon and 4-100 micrometers for a soma, it is easy to see that the flow per neuron becomes 90 MHz for a fast twitch thick nerve down to 45 kHz for a slow twitch thin nerve. This number is not representative of how many pulses a nerve fibre can take in a second, but, inclusive of Nyquist’s sampling theorem, it closely represents how fast of a measurement is required to not lose information on the (assumed non-fractal, for simplicity) electrical flow

through each nerve. Thus, it appears only the highest frequency ADC (analog-digital converter) components should be used for determining single axon action potentials.2.4.2 Flawed Brainwave ModelNow, this involves a similar reasoning to that of Ambient noise (without60Hz power signals nearby) whereby a Short-Time-Fourier Transformation provides a number of different results to a standard Fourier Transformation. With the brainwave model, it is suggested that alternating current is a good and reliable way of looking at the signals within the brain. Now, the issue is that with these differences between an STFT and an FT it is mathematically unquestionable that the supposed brainwaves appear different depending on the sampling size. That is to say, the core signals moving within the brain are not actually brainwaves, they are something different. Thus, the standard approximation of a non-serialized capacitive and inductive model of the brain is highly flawed. That is to say, if an alternating current were applied to the brain in one area and tested in another, the output difference would be non-AC. AC and DC operations for current are only useful in resistive and capacitive or inductive models, but in more complex configurations, like that with many different molecules and macromolecules present in the liquid and solid and otherwise components of cell structure and extracellular matrix, a different way of looking at the brain is needed. This is perhaps why tests on tACS and tDCS are often producing poor and conflicting results.

2.4.3 Novel Wavelet Transformation

Now, Wavelet Transformations appear theoretically best for dealing with mapping an Action Potential at the various amplifications that are proportional to the distance away from the measurement electrodes. As there are many infinites of different types of wavelets, it is hard to choose one that fits the action potential signal. What has been simply called a custom tailed and custom tailless wavelet have the following specifications and appear not too dissimilar to the action potential:

Dec\_lo = [a, a/2], Dec\_hi = [-b, a],

Rec\_lo = [a/2, a], Rec\_hi = [a, -b]

(tailed)

Dec\_lo = [a, a/2], Dec\_hi = [-b, a],

Rec\_lo = [a, a/2], Rec\_hi = [a, -b]

(tailless)

Where:

dec\_lo (decomposition low pass filter), dec\_hi (decomposition high pass filter)

rec\_lo (reconstruction low pass filter), rec\_hi (reconstruction high pass filter)

And this is a non-orthogonal wavelet (ie the low-pass and high-pass aren’t symmetric)

With values for (a) and (b) sitting at around 0.7 and 0.9. However, this has only been tested with an artificial neural network on individual EEG channels and the custom tailed wavelet transformation applied on-top of a derivative operation had the best single channel result of 5 times improved accuracy than a standard symlet (9) and daubechies (1) wavelet transformation. However, results like these are best reconfirmed with a much larger data set in all repeat recording sample size, bits per sample, samples per second and number of seconds of recording. The operations took 14 hours on a 2.9 GHz i5, so with the drastic increase in scale, a number of GPUs would be required. If a mathematician who really understands the Wavelet Transformation could find one that more closely represents that of an Action Potential, it may perform better still. However, even the Wavelet Transformation is not ideal as this does not take into account what happens to the signal after the nerves generate it and it is permeated through the brain and skull for an EEG sensor to record it. That being said, the question is what are we aiming to record, something that results in a predictive model for brain function, or something that measures the direct activity of individual nerves, or something that gets both. Either way, the differences between the STFT and FT show a flaw in the logic of the brainwave model, as there is no difference between the two for standard AC signals. That being said, this does not preclude the chances of acquiring significance after a number of tests have been performed. But it is certainly clear that EEG studies have been moving slowly, if at all, under this observational model. Using the Wavelet Transformation allows for that improved resolution at what would be higher frequencies in the FourierTransformation. This is of particular importance with mental illness (schizophrenia)30

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and meditation (transcendental) where activity is shunted to higher and higher frequencies. Ideally, a researcher would compare the analytical results of using a WaveletTransformation with that of a Fourier Transformation, in attempting to detect patient-identity (as done here) or brain-states or thought-content, however in this study, knowing that there is a flaw as evidenced by the differences between STFT and FT, work was only done on improving which of the infinite WT’s to use.

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