THE ENERGY PARADOX OF THE BRAIN

a white paper

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ABSTRACT

In order to study brain function, some researchers have attempted to reverse-engineer neuronal networks and even the brain itself. This approach has always been based on the assumption that neurons in-vivo acted like transistors in-silico. Unfortunately, this assumption has always been false and so network and whole-brain modeling have provided little practical insight with respect to actual brain function.

Neurons and transistors are very different; neurons react to processes, while transistors react to static events. Neurons vary their signaling properties continually and are able to establish and change connections, allowing them to adapt to circumstances, self-assemble, auto-calibrate and store information by changing properties according to experience (Laughlin, Sejnowski, 2003). The transistor is powerful but it will never be the ideal tool for modeling neurological processes; it is boolean and electrical, while the brain is likely unary and optical.

We argue that one must first understand the interaction between all layers of neurophysiological organization in order to build a truly useful model of the human brain. We propose that a unary system would be best suited, as it must account for activity across many layers and modalities. We assert that there must exist a fundamental switching layer within the human brain that is far faster and far more energy-efficient than any electrochemical process yet proposed. We believe this system is quantum and optical, driven by mitochondrial reactions and mediated by bistable opsins, such as neuropsin.

Keywords: axiology, fundamental code unit, neural net, neuron, neuropsin, optical brain, unary system

INTRODUCTION

Economy and efficiency are guiding principles in physiology (Weibel, 2000), just as they are throughout nature. As such, understanding the design rules and constraints that shape neuronal organization could be useful for developing a model of the overall system.

Ramon Y Cajal noted the purposed efficiency of brain design over a century ago, stating that “all of the formations of the neuron and its various components are simply morphological adaptations governed by the laws of conservation for time, space and material” (Cajal, 1995).

The brain requires nearly 20% of the body’s total energy to function, despite accounting for only 2% of the total mass. Neurons utilize significant quantities of energy to process information and so in order to maximize energy efficiency, the structure of neurons in the brain is dense. Physiochemical and structural relationships connecting resource use to performance in the brain are determined by three major constraints: (1) geometrical limitations on packaging and wiring, (2) energy consumption considerations, and (3) energy-efficient neural codes.

Operational Efficiencies

The largest use of energy in the brain is memory and computation itself, so these operations have been designed to be particularly efficient. We do not yet know how such remarkable efficiencies are obtained, but they are many orders of magnitude beyond our transistor technology. To illustrate how far apart we are, IBM and Stanford researchers used a Blue Gene/ IP supercomputer (ranked as the fourth most powerful supercomputer in the world at the time) to model and simulate a cat’s
cerebral cortex. The simulation required well over a million times more energy to power and still ran about 100 times slower than the actual cat brain (Hsu, 2009). The human brain is vastly more complex but still requires less energy than a light bulb. A computer with the same capabilities would require more than 10 megawatts (roughly the amount of energy produced by a small hydroelectric plant). The primary difference between silicon and neuron is that transistor-based networks lose most of their energy in the form of heat, while neurons are able to accomplish the same or more work without this loss. The result is radically improved efficiency.

Long-range signal processing is another expensive and key design consideration, as energy dissipates with distance. Axonal transmission across long ranges utilizes large amounts of energy, so the brain prioritizes local connectivity, organizing sensory cortical areas into columns to provide an optimal geometry for energy efficient processing (Aiello, 2001). Neurons in columns are connected to each other much more densely than neurons farther apart. Cortical columns also have dense dendritic and axon branching, enhancing the surface area for input and output and minimizing transmission length. Roughly half (50%) of the brain’s energy is spent on driving signals along axons and across synapses. Another 20% is used for brain metabolism and the remainder is dedicated to the maintenance of resting support, membrane potentials and the vegetative function of neurons and glial (Kety, 1957), (Sokoloff, 1960), (Rolfe, 1997).

A large percentage of communicative energy usage is dedicated to synaptic transmission between neurons, primarily associated with the Na+/K- pumps. Energy is also required to maintain neurons at their resting membrane potential. Laughlin, et al showed that action potential propagation and postsynaptic current utilize the largest amount of energy in the cortex. It should also be noted that cortical gray matter consumes a higher proportion of energy (75%) than white matter (Aiello, 2001), highlighted by the fact that global connectivity in the cortex is very sparse: the probability of any two neurons having a direct connection is around 1:100 for neurons in a vertical columns 1 mm in diameter but only 1:1,000,000 for distant neurons. Only a small percentage of neurons in the brain have long range connections, so the focus is clearly on local processing. To overcome this wiring limitation, neurons in connected areas use synchronous firing to communicate local information globally.

Neurons also differ from transistors in that they are grown within a tightly confined, organic spaces and so are wired in 3D from day one. Microprocessor chips, on the other hand, are usually manufactured with only a few layers of planar wiring. Various studies have examined optimal geometric patterns of connectivity and find that neurons, arranged in cortical columns, strike the optimum balance between two opposing tendencies: transmission speed and component density (Mitchison, 1991), (Chklovskii, 2000), (Koulakov, 2001). Understanding the design rules underlying this micro-column organization will provide a better understanding of the brain as a whole. Even just understanding the various adaptations our brain has made in its relentless pursuit of efficiency would enable vast improvements to the design of computer hardware, software and networks.

Finally, energy concerns have also governed the design of optimal coding schemes within the brain. Neural performance correlates to the amount of energy used and is measured by
combining the speed of response with the signal to noise ratio. In terms of spiking activity, the efficiency of the neural coding process is optimized to enhance the amount of information gained from a train of action potentials over a period of time.

Another energy optimization technique used by the brain is sparse coding, where maximal information is gained from a small number of active neurons as opposed to a large population. The optimal neural code enhances the information gained from a small number of active neurons as opposed to a large population, using minimal resources and enhancing performance. It is well established that redundancy reduction is a major design principle in the cortex (Simoncelli, 2001). By maximizing the ratio between information coded and energy expended for signal transmission and resting state maintenance, sparse coding regimes improve energy efficiency (Baddeley, 1997), (Balasubramanian, 2002), (D.J., 1994). Sparse coding regimes (in which a small proportion of neurons signal at any one time) also have the additional benefit of having a large representational capacity (Levy, 1996), (Attwell, 2001). The bandwidth of neurons is higher than would be expected from sparse coding.

One final energy consideration in the brain is that of noise, such as that caused by ion channels or signaling molecules. The noise and unreliability of neural signals is largely counteracted by plasticity mechanisms that make synaptic transmission more reliable and energy efficient. Researching the constraints and rule-based optimizations within the brain provides us with a key to understanding the operation of neurological systems. These rules can provide a highly useful guide for understanding neuronal network architecture and coding.

**Operational Methods**

Neurons do not operate as transistors do. They do not statically integrate information, they are not boolean and furthermore, the electric fields generated by neuronal activity have been shown to in fact affect that same neuronal activity (Frohlich, 2010). We must therefore ask whether it is appropriate to assume a binary code or whether a more holistic view is required.

The shifting concentrations of elements within the brain, particularly within the activity of ions, create an ebb and flow of charge and energy between individual neurons. This flow of electrons and protons (as action potentials) throughout the brain gives rise to an energetic field that we call consciousness, which manifests itself in action and language. The various atoms such as hydrogen, nitrogen, oxygen, etc., each have a unique marker that defines its behavior and interactions with other atoms. This arises from protons, neutron, and electron counts and configuration and, more importantly, the ionization energy as defined by an atom’s valence (Campbell, 2010). The ionization that takes place at the valence shell also yields energy. The ionization energy related to synaptic exchange is driven by the interactions amongst neuronal molecules. So, if two atoms react and approach one another, it is
their outer shells that become involved in any chemical reactions, such as a synaptic exchange. Given these different mediums of brain function, it is imperative to map its expression within each of these domains in order to understand the brain's operation as a whole. We need to develop brain-specific information exchange models, from molecular to cognitive, to truly understand the mechanisms that underlie cognition and awareness. Something beyond binary is required.

**MODELING THE BRAIN**

We are proposing the use of a unary system to model the various mediums of brain function (physiology, neuronal activity, molecular chirality, frequency oscillations, etc) in a mathematically uniform manner. A method for efficient coding at the level of neurolinguistics is explained below.

Throughout the brain there are various forms of activations (electrical, chemical, biological), each of which contributes individually or within groups to the formation of new concepts, which in turn define a positive or negative mental state. This mental state may be calculated by the MSI algorithm (Howard, 2012).

A series of these activations forms an activation set and this set then represents a connected structure for each activated region, defined in terms of a node. The circumference of this node changes based on the duration of the region being activated and reflexivity changes based on the re-activation of this region at different instances. Each node represents a form of activation and can be connected to any other node, which can vary in shape and time orientation. The segment connecting the various nodes to one another represents the time orientation. Once this connection is formed, a new activation set is created and this set can then be connected with other activation sets and create a concept set. Nodes within the same set all add together based on a unary computation, are weighted by a statistical coefficient and finally represented in terms of waveform signals to produce a resultant active node.

The figure below shows two different concept sets \{1, 2\} each consisting of two or more activation sets. These sets have been generated through the interaction of neural activity at the various cognitive levels. Each node of those sets represents an active region that is either dependent on other regions to complete its “cognizant” state or is self-dependent but cannot form a comprehensive notion. Two active states that are can form a uniform concept interact together to define a concept set.

Each node within this model represents an active region of the brain and each of the activities in these regions, naturally, consumes energy. Throughout the various stages of our analysis, energy is being both generated and propagated from the molecular level to every signal mechanism. Looking closely at the activation sets, we can clearly distinguish the various levels of interaction ranging from biochemical and electrical up to cognitive and linguistic, as each simply represents the activation of various brain regions. Components at each level interact with one another in a unary structure, producing a consistent function of activity. The various levels that activate each of these brain regions form a unitary operation that affects the brain at all levels.

A concept set is a set of concepts derived from connected-activated sets, which produce an axiological value that represents a mood state once projected onto a positive and negative plane. The concept set is defined by the activation set with higher value. A concept can therefore be formed when other activation sets are elements of it but their contribution (effect) is diminished by another, dominant set. The value of the resultant concept set can have various ranges from positive infinity to negative infinity and only becomes unitary positive or negative after projection. This method allows correlated and dependent concept sets to form conceptual metaphors that remains
consistent in terms of axiological value, despite time changes. For example, to determine the axiological value of a concept such as “Sky”, we would need to understand that the concept of “Sky” is a resultant of various activation sets in which each contribution was based on the level of its activation within a specific time frame and orientation. If we were to consider another concept alongside, such as “Dark”, most likely the same computation applies but a negative axiological value would be assigned. At another point in time and according to the same patient the concept “Morning” could be formed based on these two concepts and result in a positive axiology, as a “Dark Sky” might resemble the end of a day and hence the coming of a positive “Morning”.

This axiological value is valid within these time-division constraints and it might change if the constraints were to change, similarly for other patients. The use of a learning algorithm will thus enhance our computational accuracy while reducing evaluated errors for specific individuals.

Hence, we will introduce a mathematical framework for Unary Topological Axiologies (UTA) describing mental states. Its mathematical structure can be defined in terms of instantaneous and continuous representations. Begin with a set $S$ (unaccountably infinite) representing brain regions, which may be activated by some means. We introduce a $\sigma$-algebra $A$ on this set, and call the elements $a \in A$ activation sets (by definition $a \subset S$). Now introduce a second set $W$ whose elements are labeled concepts in the brain, which correspond to words.

We begin with a predefined distance $d$. As an example, $d$ could be Euclidian distance, but exploring other possibilities could also be an interesting thing to do. We define $B$ as the R3 unity sphere representing the brain.

$$B = S(0,1) = \{ b \in R^3, d(0,s) < 1 \}$$

We then define a set $S$, representing brain regions (which may be activated by some means) as the set of every open subset included in $B$.

$$S = \{ b \in B, \forall x \in s, \exists \varepsilon \in R^+, S(x,\varepsilon) \subset B \}$$

From that set $S$, we create $S'$, as the union of every finite extract from $S$. We then have

$$S' = U_{n=1}^{\infty} \{ (s_1, \ldots, s_n) \in S^n \}$$

We introduce $A$, a $\sigma$-algebra on that set, and call the elements $a \in A$ activation sets (by definition, $A \subset S$). The choice of this $\sigma$-algebra is still yet to finalize, but we will here define it as $S$ power set, which seems to be a natural candidate.

$$A = P(S') = \{ E \mid E \subseteq S' \}$$

As the result is well known, we won’t take the time to prove that a set’s power set defines a $\sigma$-algebra on the latter, but verifying it is quite trivial.

We now introduce a second set $W$ whose elements are labeled concept, physical process, and linguistic linkages that tend to occur at given mind states.
We assume the existence of a subset of $A$, such as we can define a bijective function $P$ that verifies

$$P: \tilde{\alpha} \in \tilde{A} \rightarrow w \in W$$

We call $P$ the concept activation mapping, and the elements of $A'$, action potentials. Now let $\tilde{P}: w \in W \rightarrow \tilde{\alpha} \in \tilde{A}$ be a mapping we call the brain activation mapping. We define $\mu$, a measure on $S$ ($\mu$ could be the discrete measure associated to $S$), and $F: A \rightarrow \{+, -\}$ to be a parity mapping. From these elements we define an axiology (i.e. a mapping $\Xi: W \rightarrow \{+,-\}$ generated by computing). We then have

$$f(\omega) = \int_a F(s) d\mu$$

Where:

$$a = P'(\omega)$$

Then we project:

$$\Xi(\omega) = \text{sign}(f)$$

Below is a representation of such symbols (Hsu, 2009)

<table>
<thead>
<tr>
<th>symbol</th>
<th>description</th>
<th>properties</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S$</td>
<td>brain regions</td>
<td></td>
</tr>
<tr>
<td>$A$</td>
<td>activation sets</td>
<td>$a \in A \Rightarrow \alpha \in S$</td>
</tr>
<tr>
<td>$\mathcal{A}$</td>
<td>concept activation sets</td>
<td>$\mathcal{A} \subset A$</td>
</tr>
<tr>
<td>$W$</td>
<td>concepts</td>
<td></td>
</tr>
<tr>
<td>$P$</td>
<td>concept activation mapping</td>
<td>$P: \tilde{\alpha} \in \tilde{A} \rightarrow w \in W$</td>
</tr>
<tr>
<td>$\Xi$</td>
<td>axiology</td>
<td>$\Xi: W \rightarrow {+,-}$</td>
</tr>
<tr>
<td>$\mu$</td>
<td>weight mapping</td>
<td></td>
</tr>
</tbody>
</table>

The model for two populations of neurons to address connections to neighboring networks of actions, or neuron column, assumes a constant production efficiency, meaning potentiation or activation ratios. This efficiency also holds at (-10mv) with (+) displacement and at (-20mV) with (-) displacement as in the classical Lotka–Volterra equations, which succinctly utilize the energy flow principle: in essence, we are energy processors (Howard, 2011).

$$\frac{dx}{dt} = -bx - f(x)y \quad (1a)$$

$$\frac{dy}{dt} = -ef(x)y - dy \quad (1b)$$

Here the system is divided into two levels, (x and y are their respective densities or biomasses in the same units) and the yield constant or the production efficiency ($e$), manifests the second law of thermodynamics ($0 \leq -e < 1$). Since $e$ is a constant and the functional response of 1a, $f(x)$, is a monotone non-decreasing function, it follows that higher density never decreases the flow of energy to the next level. In fact, all relationships are considered as a $(+, -)$ type, as indicated by the signs of the off-diagonal terms in the community matrix or Jacobian system (Laughlin, 2001).

Taking biophysical and biochemical measurements of membrane conductance and transmitter release, one is able to calculate the number of ions and molecules that are used to generate signals in known components, such as synapses, dendrites and axons. These numbers define energy usage in terms of the ATP.
that must be hydrolyzed to maintain ionic concentration gradients and recycle signaling molecules (Howard, 2011).

In additional, evidence of optical signaling systems have been found within self-regulating cycles of photon-mediated events in the neocortex. One such cycle is mediated by sequential interactions among 3 mitochondrial sources of endogenously-generated photons during periods of increased neural network spiking activity: (a) near UV photons (~380 nm), a free radical reaction byproduct; (b) blue photons (~470 nm) emitted by NAD(P)H upon near-UV photons absorption; and (c) green photons (~530 nm) generated by NAD(P)H oxidases, upon NAD(P)H-generated blue photon absorption (Howard, 2015).

We propose that in neocortical networks, meaningful information is transmitted via this photonic activity, which is then transduced into synaptic membrane potential changes via a cGMP-dependent mechanism similar to that of the retina, with a photostimulation-catalyzed G protein/cGMP phosphodiesterase activation. This activation regulates membrane potential via closure of cGMP-gated ion channels, while photonic control is mediated by the bistable photopigment neuropsin (OPNS), within neocortical synapses. Photonic signaling may generate information regulating neuroplastic brain change, both during memory formation and also in adaptive response (Howard, 2015).

These biological, fundamental signaling layers (chemical, electrical, optical etc) seem consist of a unary mathematical coding language (+/-) ≡ (on/off states of coding elements). A developed theory of this proposed neurological coding language has been published as the “Fundamental Code Unit” (FCU) and “Brain Code” (BC), by Howard (2012). An hypothesized correlate to this theory was that quantal (photonic) signaling mechanisms, akin to those occurring in retinal rods, could serve as a facilitator for unary neural coding in the mammalian neocortex. These recent findings involving the signaling cycle between neuropsin and NAD(P)H oxidases seems to prove this photonic theory true.

**Coding Efficiency**

Basic biophysics links energy usage to two fundamental measures of signal quality: signal-to-noise ratio (SNR) and bandwidth (a measure of speed of response). Extra energy is required to improve the SNR because reliability increases as the square root of the number of stochastic events that are used to generate signals. Each stochastic signaling event, such as opening an ion channel or releasing a synaptic vesicle, requires extra energy. Raising bandwidth also requires extra energy. The membrane time constant must be reduced by increasing conductance and thereby increasing ionic current. So, minimizing the SNR and bandwidth will save energy (Laughlin, 2001).

One method of energy efficient coding at the cellular level in the brain is exemplified by the method in which the brain processes information: integrating from various sources and then firing action potentials. This is highly efficient. Considering the fact that the brain is being continually bombarded with a torrent of information coming in from literally millions of different sensory areas and inputs, the most energy-efficient method to code information is for neurons to be activated only when they receive important information. One way to achieve this is to transmit information by firing action potentials only for important inputs and not for every input that comes into the brain. This method keeps
irrelevant information from being coded. Neurons receive inputs from different sources and each of these inputs carries a different weight, translated by the size of neuronal depolarization. If inputs are strong enough in size (i.e. for important information), neurons are depolarized sufficiently to reach firing threshold and thus fire an action potential that is transmitted in the network. If the input is not strong enough (i.e. for unimportant information), neurons do not reach threshold and do not fire action potentials.

Energy-efficient neural codes increase the ratio between the amount of information coded by neurons and the amount of energy required. The ability to represent information depends on the number of recognizably different patterns of spikes that can be generated in a useful time interval. This number —the ‘representational capacity’ — is a fundamental measure of neural performance (Laughlin, 2001). It defines the number of situations and actions that neurons can specify, and is closely related to the number of bits coded.

Sparse coding methods, in which information is represented by the activity of a small proportion of neurons in a population, greatly increase energy efficiency. The optimum distribution of activity depends on the ratio between the signaling cost of making a spike and the fixed cost of maintaining a neuron in readiness to spike. When spikes are expensive and the fixed cost is negligible, a ‘grandmother neuron’ code is cheapest (Laughlin, 2001). This code associates each unique event with a single active neuron.

Efficient coding is also found in repolarization. Once neurons fire an action potential, the membrane potential returns to its original level of polarization due to the outflow of potassium ions. Depolarization of the membrane opens voltage-gated sodium and potassium channels and the sodium channels snap shut at the peak of the action potential. This process allows for new incoming information to be coded in the brain as neurons are ready to be depolarized again and fire the next set of action potentials.

One of the most efficient coding systems is at the neuromuscular junction, where virtually every action potential in the presynaptic motor neuron triggers an end plate potential in the postsynaptic muscle cell. At this junction, none of the energy utilized to fire an action potential is wasted, as it would be at central synapses (where the postsynaptic neuron commonly receives signals from many presynaptic neurons). As the system is unary, a single neuron can be affected simultaneously by signals received at multiple excitatory and inhibitory synapses.

As Cajal suggested, the structure of a neuron is related to its functional role. Axons, dendrites and dendritic spines are all important structures for increasing processing capabilities of a neuron. Cortical columns in the brain are optimized to process specific input features and are designed to enhance efficient coding by the way in which neurons are wired in the column (Laughlin, 2001). The goal of energy efficient brain processing is for output information to match the rate of input and to connect the two streams of information, output and input, while utilizing minimal anatomical space.

Another method for energy efficient coding is at the level of neural oscillations. One is able deduce brain states and brain regions involved in different mood states by measuring neural oscillations. Neural oscillations have been shown to determine brain function and different oscillations have different functions in different brain regions.
Oscillations range from low delta, theta, alpha, beta and high gamma. Delta waves (<4Hz) are important for low level arousal activity. Theta waves (4-8Hz) are important for creative and intuitive thinking. Alpha waves (8-12Hz) are important for meditation and relaxation and beta waves (13-30Hz) are important for mental activity processing. Gamma waves (>30Hz) are important for high-level information processing.

Changes in normal neural oscillations can reflect neurological disorders in the brain. It is therefore imperative to understand the nature of such frequencies, their causes, their ranges, and the relation of each range to each disorder. As specific oscillations are associated with specific mood states, the energy utilized for a specific mood state can be measured. Energy utilized by neural oscillations can be measured in terms of energy output in single ATP transactions during a single wave in an oscillation and thus correlated to the corresponding mood state.

An example of an energy expensive mood state would be a state that scores high – in the MSI algorithm such as depression while an example of a inexpensive mood state would be the state that scores 0. This suggests that in order to maintain low energy during high cognitive tasks, it is better to keep mood states open and aware in stressful scenarios as to not lose energy.

CASE STUDY: CHRONIC PAIN

Chronic pain is a debilitating condition that could be due to neuropathic or nociceptive conditions. There do not exist any direct objective neural correlates to pain in the brain. A recent study by Green, et al identified a neural signature of brain wave activity (8-12Hz) in the sensory thalamus and periaqueductal gray (PAG), the region that is significantly correlated to subjective neuropathic pain intensity. Green, et al showed that deep brain stimulation and local field potential analysis were able to cause an increase in amplitude of 10Hz, observed in both sensory thalamus and PAG. In addition, they also found that in the power spectra there was an increase in 8-12Hz activity in the PAG and an increase in the 17-30Hz activity in sensory thalamus.

Treatment for chronic pain could be enabled with neurofeedback systems, as once the abnormal increase in 8-12Hz and 17-30Hz activity is detected in the PAG and sensory thalamus, neurofeedback via transcranial magnetic stimulation (TMS) or ultrasound could be employed to decrease and eliminate abnormal oscillations. It is important to determine the cause of this abnormal enhancement in 8-12Hz activity and why this increase results in perception of chronic pain. The causes of altered oscillation might be due to changes in neurotransmitter concentration or availability, or perhaps ion channel changes.
CONCLUSION

The human brain differs fundamentally from current silicon-based attempts to mimic it on a number of levels. Apart from the fact that neurons are organized and networked differently from transistors and other man-made computational hardware, there exist several inherent differences at the unit level between in-vivo and in-silico computational examples. In this paper, we have argued that these fundamental differences account for the staggering superiority of the brain to date, both in terms of cognitive performance and energy efficiency. In addition, the optimal coding schemes for the neural networks in the brain that drive cognition make highly dynamic use of energy and cellular resources based on the qualities of the information being conveyed, thus enabling optimization on both the hardware and configuration levels. Specifically, sparse coding regimes that capitalize on a small number of active neurons instead of activating entire networks, as well as the redundancy-minimizing connectivity and placement of neurons, both contribute to the computational advantage of the human brain.

We take this conclusion a step further by proposing that in order to successfully close this gap, the mathematical characteristics of neurological networks and coding schemes must be first understood and then made the basis for future hardware-based computational cognition.

In our case study of chronic pain, we apply the specific brain wave oscillation patterns identified by Green et Al. to the specific mechanisms that drive this perception – neurotransmitter concentration and, potentially, ion channel alterations. This phenomenon provides a clear and intuitive stimulus/response feedback system against which to test various neurological mechanisms for their effects on the brain, and is a prime example of the type of inference that is needed in order to determine its deeper cognitive characteristics.

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Newton Howard, a former US government officer, is a Professor of Computational Neuroscience and Neurosurgery at the University of Oxford and the Director of the Synthetic Intelligence Lab at the Massachusetts Institute of Technology (MIT). While a graduate member of the Faculty of Mathematical Sciences at the University of Oxford, England, he proposed the Theory of Intention Awareness (IA), which made a significant impact on the design of command and control systems and information exchange systems at tactical operational and strategic levels. He then went on to receive a PhD in Cognitive Informatics and Mathematics from La Sorbonne, France where he was also awarded the prestigious Habilitation a Diriger des Recherches for his work on the Physics of Cognition (PoC) and its applications to complex medical, economical and security equilibriums.

In 2009 Dr. Howard founded the Mind Machine Project at MIT; an interdisciplinary initiative to reconcile natural intelligence with machine intelligence. In 2011 Dr. Howard established the Brain Sciences Foundation (BSF), a not-for profit, multidisciplinary research foundation dedicated to developing novel paradigms that enable the study of both mind and brain and ultimately the treatment of neurological disorders.

In 2014 Newton received a Doctorate in Neurosurgery from Oxford University from the department of neurosurgery, focused on the early detection of neurodegenerative diseases. Dr. Howard works with multi-disciplinary teams of physicists, chemists, biologists, brain scientists, computer scientists, and engineers to reach a deeper understanding of the brain. Dr. Howard’s research efforts aim to improve the quality of life for so many who suffer from degenerating conditions currently considered incurable. Advancing the field of brain sciences opens new opportunities for solving brain disorders and finding new means for developing artificial intelligence. Dr. Howard’s most recent work focuses on the development of functional brain and neuron interfacing abilities. To better understand the structure and character of this information transfer he concentrated on theoretical mathematical models to represent the exchange of information inside the human brain. This work, called the Fundamental Code Unit (FCU), has proven applicable in the diagnosis and study of brain disorders and has aided in developing and implementing necessary pharmacological and therapeutic tools for physicians. He has also developed individualized strategies to incorporate solutions for psychiatric and brain prosthetics. Through collaborative research efforts with MIT and Oxford University, Dr. Howard has been working on interventions for early detection and novel treatment strategies for neurodegenerative diseases and affective disorders.
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