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ABSTRACT

The modeling of neurobiologic brain functions such as, cognition and consciousness are important research challenges having applications to other disciplines such as, bio-inspired soft computing and, adaptive distributed computing systems. The functions of brain and distributed computing structures have resemblances. This paper proposes a computational model of cognitive function and consciousness by using algebraic methods. Furthermore, the quantum mechanical basis of the cognitive model is formulated by using linear Hermitian. A set of choice functions is computed following the neurodynamics. The neuronal excitation is modeled by using trigonometric wave functions closely matching the neuronal firing. This paper illustrates an analytical approach to model neuronal excitation and, associated cognitive functions having quantum mechanical behaviour.

Introduction

The brain is a neurological device capable of computation and, expressing cognition as well as consciousness. As the physical substrate, brain is composed of billions of neurons and they are connected by a complex neuronal network. The neurons communicate by using a biological trigger mechanism based on ion density gradient and threshold potential. However, the physical substrate of brain alone cannot explain its capability to carry out the complex cognition functions. It is proposed that, the conscious and abstract thinking can be modeled by using the global workspace (GW) formalism (Reggia, 2013;

Lin, 2004). The individual neurons in neural network implement computational mechanisms to achieve cognitive functions (Rees, 2002). The models of machine consciousness and artificial cognitive functions are developed by following artificial neural network and probabilistic reasoning employing Bayesian and hidden Markov models (Reggia, 2013; Lin, 2004; Koch, 2008). In general, the understanding and modeling of cognitive actions and consciousness require the quantitative and theoretical frameworks bridging the neurobiological functions and the computational as well as algorithmic functions (Fitch, 2014; Starzyk, 2011). The cognitive functions of brain are inherently a distributed computing mechanism, because the information processing happens at different locations in brain due to an input (Lin, 2004; Fekete, 2011). On the other hand, the quantum mechanical models are proposed to explain cognitive functions and consciousness (Kurita, 2005; Tegmark, 2000; Hameroff, 1996). This paper argues that, a brain can be viewed as a

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complex hybrid model of distributed computing machine having a quantum mechanical basis of consciousness expression. This paper proposes a novel bio-inspired distributed computational model of consciousness. Furthermore, it illustrates that there is a quantum mechanical basis of the proposed distributed computational model. The proposed model assumes that, the nodes have memory and they evolve by storing information.

Motivation

The modeling of cognitive neuro-functions and their integration into computing have given rise of machine intelligence having applications in artificial intelligence, robotics and, bio-inspired distributed computing (Reggia, 2013; Starzyk, 2011; Koch, 2008). The predictive coding model of neocortex emphasizes on existence of distributed computing into the neocortical computation (Mumford, 2010). However, the majority of existing models of cognition follow artificial neural network, which cannot explain notion of consciousness (Lin, 2004; Starzyk, 2011). There is a need to develop unified computational model of cognition having a basis in quantum theory of consciousness. This paper proposes a distributed computational model of consciousness following the functional attributes of neurobiology and, it shows that there is a quantum mechanical basis of the proposed model. A set of functions is proposed to quantify neural excitation, internalization and propagation. The main contributions of this paper are:

- Developing a computational model of consciousness by following functional neurophysiology and elements of distributed computing.

- Developing an analytical basis of the computational model in view of quantum theory.

- Developing a set of functions to quantify neurodynamics supporting the computational model.

Rest of the paper is organized as follows. Second section describes related work. Third section explains the construction of computational model of consciousness. Fourth section illustrates analytical basis of the model in view of the quantum theory. A set of choice functions and their characteristics are developed in fifth section. Sixth section describes the

analytical properties of the model. Finally, seventh section concludes the paper.

Related work

The brain is a large collection of neurons having a highly complex network. Experimental evidences show that cognitive functions of brain require extended-assembly of neurons (Pribram, 1991). The brain functions are analyzed by following the discrete stochastic pulse train model of a single neuron and, the spatially coherent phase-amplitude model (Alfinito, 2000). These models consider laws of classical physics. However, the neuronal firing has quantum properties, where superimposed ion-states of firing and resting neurons decohere fast in time (Tegmark, 2000). In general, the brain-dynamics and functions obey quantum mechanical processes (Alfinito, 2000; Kurita, 2005; Ricciardi, 1967). The quantum model of brain explains the functioning of cognition, memory and recalling, which is experimentally verified (Alfinito, 2000; Conte, 2009). Furthermore, a combination of neural network and dissipative quantum model of brain is proposed to explain quantum evolution (Alfinito, 2000; Williams, 2011).

There is a relation between the microstructure of cerebral cortex of brain and consciousness where, the neurodynamics are controlled by quantum mechanical processes involving wave functions (Beck, 1992; Beck, 2001; Conte, 2009). The model of cognitive neurodynamics is constructed as a composite wave function with differentiated quantum probability amplitudes of excitations (Beck, 1992). The exocytosis is a quantum phenomenon and cognition is a resulting manifestation in brain (Beck, 1992). This is because, the functions of some of the physical substrates of brain can be explained by using quantum theory and these substrates are responsible to exhibit consciousness and memory (Beck, 2001). It is proposed that microstructure of neurons in brain contains microtubules where the cognitive functions are expressed due to quantum coherence as well as decoherence processes (Hagan, 2002). The Penrose-Hameroff model proposes that cognitive functions and consciousness of brain are achieved by quantum computation involving objective reduction (OR) within the microtubules of neurons (Hameroff, 1996). The Orch OR model indicates that tubulins may exist in quantum superpositions of two or

more conformal states and can function as quantum bits (Hameroff, 1996). They interact non-locally (with quantum entanglement) and, highly entangled tubulins are superpositioned to reach a threshold exhibiting consciousness. Evidently, there is a close relationship between the quantum theory and consciousness of brain (Filk, 2009). Moreover, the indeterminism at cognition functions can be evaluated by employing quantum mechanical formalisms and probability amplitudes of inner-products of wave functions (Conte, 2009; Conte, 2004). Thus, the quantum mechanical model plays a key role in understanding cognition and consciousness involving physical substrates.

On the other hand, the computational models of cognition and consciousness are formulated explaining determinism and indeterminism in neurological functions. The computational models of neurological cognitive actions are formulated by using finite state automation along with push-down stack (Fitch, 2014; Arbib, 1979; Poeppel, 2005). According to this approach, a single neuron is modeled as the tree-shaped computing structure (Fitch, 2014). The tree-model tries to map the physiological structure and functions of neurons into the computational structure while explaining neurological cognitive functions. The model of consciousness based on artificial neural network (ANN) is proposed following global-workspace (GW) formulation in order to understand mechanisms of abstract thinking (Sun, 2007). The predictive coding model of neocortex is proposed to explain the neurological cognition at functional level (Mumford, 2010; Mumford, 1992). The predictive coding model is a generalized model incorporating the elements of distributed computation. It is observed that, at algorithmic levels, the cognitive functions become computationally intractable although living species perform such functions without delay (Rolls, 2001). The computational cognitive models to predict intention are based on pattern matching and sequence analysis (Bonchek-Dokow, 2014). However, the questions about similarities and differences between quantum models and computational models of cognitive functions and consciousness remain unattended.

Computational model of consciousness

The consciousness is a neurobiological phenomenon in brain based on physical substrate

comprised of complex neural network involving billions of cellular neurons. The brain receives inputs from environment through the sensors and the neurological network processes the input signals generating conscious outputs. The neural structures of brain as well as various experimentations suggest that, the information processing in brain is inherently a bio-distributed computation (Fitch, 2014; Pribram, 1991; Mumford, 2010; Baars, 2007). The brain can be viewed as a complex graph. Let N be a set of specialized functional nodes in brain connected by neural network represented by graph $G=(N, L)$ where, the edge-set $L \subset N^2$. The schematic diagram of computational graph-model of brain is illustrated in Figure 1.
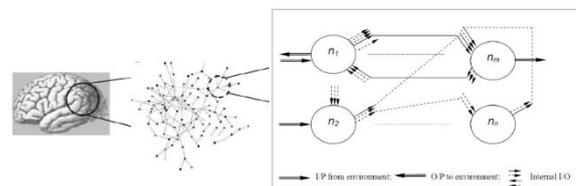

Figure 1. Computational graph model of brain.

Each node $n \in N$ of G has a set of output channels (O_n) selected from the power-set $P(O_n)$ defined over output channels. The inter-nodal signal transmission is a boolean-valued function $(\gamma_t(.))$ and, the corresponding transformation function is $(\sigma(.))$. Let $I_{\alpha n}$ be a set of inputs to a node $n \in N$. The excitation at n is generated due to internalization of an input $x \in I_{\alpha n}$ through fuzzy membership function $\mu_n(.) \in [0, 1]$ associated to the respective node. The specific excitation of a neural node in brain is defined as, $\delta : I_{\alpha n} \to S$ where, $S \subset Z$. The value of local excitation at n due to an input is $\lambda_n \in [-u, v]$ where, the excitations are bounded in the limits $(u, v \in Z)$. The triplet function governing the overall functional dynamics in G is given by Eq. (1) where, ω_{Gn} represents outputs of $n \in N$ to environment, $f_n(.)$ is a selection function at n, $Y \subset P(O_n)$, $h \in f_n(.)$ and, I_{nt} is set of inter-nodal signals/messages generated by $n \in N$ at time t:

$$\lambda_n = \sigma(\mu_n(\delta(I_{\alpha n})), \omega_{Gn})$$
$$f_n : (\delta(I_{\alpha n}), \lambda_n) \to Y$$
$$\gamma_t : (I_{nt}, h) \to \{0, 1\} \tag{1}$$

Let $g: \lambda_{\Sigma n} \to R$ be a consciousness generating function depending upon the values in the row-matrix $\lambda_{\Sigma n} = (\lambda_n, \lambda_1, \lambda_2, \ldots\ldots, \lambda_m)$, $m = |f_n(.)|$ at a node $n \in N$ at any time t. The neural output at time $t + a$ $(a > 0)$ due to an excitation at time t from a conscious brain is computed by, $\beta_n|_{t+a} = g(\lambda_{\Sigma n}|_t)$ where, $\beta_n|_{t+a} \in [-r, r]$, $r \in Z^+$. Let, an ordered pair $\psi_{n,t+i} = <I_{\alpha n}|_t, \beta_n|_{t+i}>$ represents memory in n for $i > 0$. Thus, the consciousness of a brain with merged memory (experiences) can be computed as a finite set, $\omega_G = \{\psi_{n,t} : n \in N, t \in Z^+\}$ and, $\omega_{Gn} = \cup_{t \in Z^+} \psi_{n,t}$. Hence, the distributed computational model of cognition and consciousness considers the memory embodied into ω_{Gn}.

However, this algebraic computational model can be shown to be coherent to the quantum mechanical model of conscious brain if one considers λ_n to be the real Eigen value $(\lambda_n \in Z \subset R)$ generated at a node $n \in N$ of G due to excitation. It can be shown that the computational model of consciousness has a basis in the quantum mechanical formalism incorporating quantum superposition under the influence of linear Hermitian.

Quantum mechanical convergence

In the unified modeling approach, the physical brain is considered to be a graph $G = (N, L)$ and the outputs of different nodes in G can have quantum superposition. Let a quantum state at time t of a functional node $n \in N$ be a *d*-dimensional $(d > 1)$ ket-vector represented as $|a_n\rangle$. The quantum states of the individual nodes are represented by, $\bar{u}_{nm} = (|a_n\rangle, |a_1\rangle, |a_2\rangle, \ldots, |a_m\rangle)^T$ which is a transpose matrix of Eigen-vectors. The set of all possible quantum states of G is $S(G|_t) = \{s_n = H_{m+1}\bar{u}_{nm} : \forall n \in N\}$ such that, $m = |f_n(.)|$ and, $H_{m+1} = (H_n, H_1, H_2, \ldots, H_m)$ is a row-matrix of Hermitian. Thus, the quantum state of G at time t is a ordered n-tuple $QS(G|_t) = <s_n : n = 1, 2, \ldots, |N|>$. The different superposition of quantum states s_n of a node n can be constructed considering uniqueness properties of Hermitian operator in G.

States of nodes with identical Hermitian

Let H_{m+1} be composed of identical linear Hermitian H and λ_x is an Eigen-value of a node $x \in N$ indicating, $H|a_x\rangle = \lambda_x|a_x\rangle$. Thus, the quantum state of node n at time t is represented as $s_n|_t = [\lambda_{\Sigma n} \bar{u}_{nm}]|_t$. Let there exists a permutation function $g(\lambda_{\Sigma n}) \in R_g$ with number of elements $B \leq (m+1)!$

where, $R_g = \cup_{j=1,..B} \{D_j\}$ and, the generated permutation is $D_j \in Z \subset R$. The condition governing B is that, $\exists \lambda_j \in \lambda_{\Sigma n}$ such that $\lambda_j < 0$ then, $B < (m+1)!$. Thus, the consciousness mappings are unique in the brain and, there exists a g^{-1} in the system resulting in $s_n|_t = [g^{-1}(D_j)\bar{u}_{nm}]|_t$. Thus, the quantum states in superposition at nodes and the consciousness mapping can be related as,

$$H\bar{u}_{nm} = g^{-1}(D_j)\bar{u}_{nm} \qquad (2)$$

States of nodes with non-identical Hermitian

Let the elements in linear Hermitian H_{m+1} are non-identical and, as a result, $s_n = (H_n, H_1, H_2, \ldots, H_m)\bar{u}_{nm}$. However, the transformation $H_x|a_x\rangle = \lambda_x|a_x\rangle$ can be modified as, $H_x|a_x\rangle = [\lambda_x/\lambda_1]\lambda_1|a_x\rangle$ considering ratio of real Eigen-values of two respective nodes. This results in $\lambda_1|a_x\rangle = H_{x1}|a_x\rangle$ where, Hermitian $H_{x1} = k_{1x}H_x$ and, $k_{1x} = [\lambda_1/\lambda_x]$. Hence, the quantum cross-superposition of states at node x due to m individual nodes can be computed as, $\lambda_1|a_x\rangle + \lambda_2|a_x\rangle + \ldots + \lambda_m|a_x\rangle = H_{x1}|a_x\rangle + H_{x2}|a_x\rangle + \ldots + H_{xm}|a_x\rangle$. This results in the following relation where, $(|a_x\rangle \mathbf{1}_m)$ is *m*-dimensional row-matrix $(|a_x\rangle, |a_x\rangle, |a_x\rangle, \ldots, |a_x\rangle)$,

$$(\lambda_1, \lambda_2, \ldots\ldots, \lambda_m)(|a_x\rangle \mathbf{1}_m)^T =$$
$$(H_{x1}, H_{x2}, \ldots, H_{xm})(|a_x\rangle \mathbf{1}_m)^T \qquad (3)$$

However, at node $n \in N$ in graph, $\lambda_{\Sigma n}\bar{u}_{nm} = (H_{xn}, H_{x1}, H_{x2}, \ldots, H_{xm})\bar{u}_{nm}$ considering the m+1 functional nodes under excitation having superimposed quantum states. Thus, the relationship between superimposed quantum states and consciousness at nodes under non-identical Hermitian can be formulated as,

$$(H_{xn}, H_{x1}, H_{x2}, \ldots, H_{xm})\bar{u}_{nm} = g^{-1}(D_j)\bar{u}_{nm} \qquad (4)$$

The Eqs. (2) and (4) indicate that an invertible g(.) leads to the unification of quantum mechanical basis and the algebraic functional models of consciousness, which leads to the following lemma.

Lemma: Let λ_D be a degenerate Eigen-value in G. If there exists $N_\lambda \subset N$ such that, $\forall n \in N_\lambda$, $H_n|a_n\rangle = \lambda_D|a_n\rangle$ then, an oriented consciousness is maintained by N_λ in G.

Proof: Let there exists $N_\lambda \subset N$ such that, $|N_\lambda| \geq 0$. If the linear Hermitian operators are non-identical then, $\forall n \in N_\lambda$, $H_n|a_n\rangle = \lambda_D|a_n\rangle$ and, $\forall x \in N\backslash N_\lambda$, $H_x|a_x\rangle = \lambda_x|a_x\rangle$. However, in case of identical operators, $\forall x \in N\backslash N_\lambda$, $H|a_x\rangle = \lambda|a_x\rangle$ and, $\forall n \in N_\lambda$, $H|a_n\rangle = \lambda_D|a_n\rangle$. In both the cases, the relative orientation in states of consciousness (θ) is represented as, $\theta = (|N| - |N_\lambda| + 2)/(|N|+1)$ by considering nodes in N_λ as a singular permutable element (having internal permutations) and *autapse*. The surface-map of orientation due to degenerate Eigen-values is illustrated in Fig. 2.
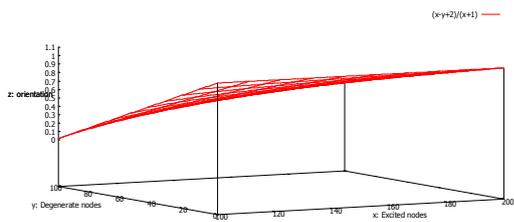

Figure 2. Characteristic surface-map of orientation.

However, if the condition $|N_\lambda| < |N|$ is relaxed in G indicating the existence of permanent degenerate Eigen-values of nodes in G then, g(.) generates the skew given by, $\rho = (||(|N| - |N_\lambda|)|| + 2)!/(|N|+1)!$. The surface-map of skew dynamics due to permanent degeneracy is illustrated in Fig. 3. It is observable that, the skew-zone is aggregated by the nodes having degenerate Eigen-values in G providing specific orientation.
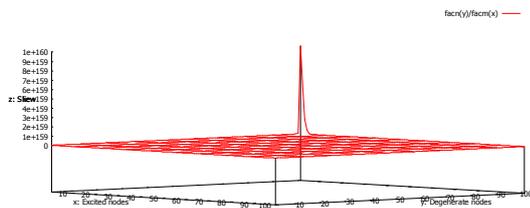

Figure 3. Surface-map of skew dynamics in G (100 nodes).

Hence, the oriented consciousness is maintained by N_λ in G due to the existence of degeneracy in neural network.

Computation of neural network dynamics

The dynamics of deterministic consciousness are stable neurophysiologic and cognitive processes in nature. Evidently, the dynamics of consciousness are not Boolean expressions covering environmental inputs and variables. In addition, the dynamics of neurological functions do not exhibit rapid excitation and overshoot in neural network. On the contrary, the internalization of environmental excitation in a node as well as inter-nodal neuro-signals transductions can be modeled by employing fuzzy functions rather than functions on crisp sets. Thus, the following fuzzy membership function is constructed to model a smooth and continuous surface of evolution of consciousness,

$$\mu_n(\delta(x)) = \begin{cases} 0.5(1 + \delta(x)^2) \text{ if } x \in I_{\alpha n}, \delta(x) = kx \\ \\ 0, \text{ otherwise} \end{cases}$$

$$(5)$$

The surface map of the unconstrained fuzzy excitation function within the limit for the corresponding varying input vectors $[-1, 1]$ and variable gain (k) is illustrated in Fig. 4. In order to maintain fuzzy set in $[0, 1]$, the gain can be set to unity signifying unamplified excitation internalization.
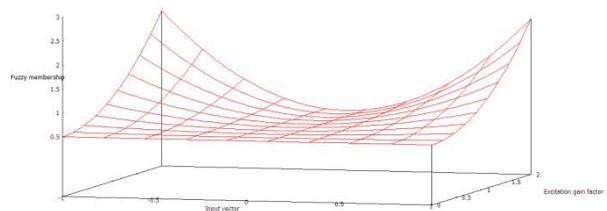

Figure 4. Fuzzy excitation function for $-1 \leq I_{\alpha n} \leq 1$ and
$0 < k < 2$.

According to neurophysiologic firing of neurons, the excitation transductions between neurons require crossing the potential threshold at synapses. The coordinated neuro-signal processing and expression of consciousness are gradual phenomena. The transformation function at a node avoiding over amplification and instability in consciousness is chosen as ($x = \mu_n(.)$ and, $y = avg(\omega_{Gn})$),

$$\sigma(x, y) = y(1+xy)^{0.5} \qquad (6)$$

The surface map of transformation function is illustrated in Fig. 5, where z-axis represents $\sigma(.)$ values.
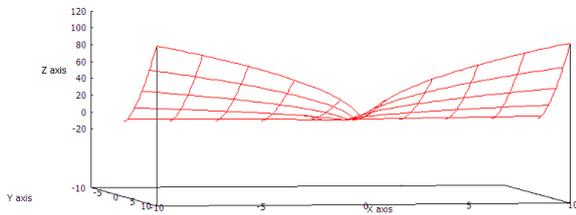

Figure 5. Surface map of transformation function, $\sigma(x, y)$.

The surface map illustrates that, the origin of dynamics is centered at zero with a small region of relatively rapid evolution (having steep slope) and, later the growth is gradual (having lower slope) in both positive and negative orientations.

Composition and expansion

The nodes in the neural network of brain coordinate by inter-nodal signal (message) transactions to carry-out cognitive functions and to express consciousness. Thus, there exists a functional composition denoted by $\gamma_t \text{of}_n$ at a node n in graph such that, brain can generate deterministic consciousness if $\forall n \in N$, $\gamma_t \text{of}_n = 1$; otherwise, impaired output would be observable due to lack of coordination (partitioning). Evidently, the functional composition $\gamma_t \text{of}_n$ is not a commutative composition. Suppose, $m = |f_n(.)|$ for an excitation at t to a node n in G. If it is assumed that $\forall n \in N$, $\gamma_t \text{of}_n = 1$, then $|\lambda_{\Sigma n}|_{t+a}| = m + 1$, $a > 0$. This leads to the fact that, $|\lambda_{\Sigma n}|_{t+a}| = |f_n(.)|_t| + 1$ iff $\gamma_t \text{of}_n = 1$.

Quantum mechanical analysis

In order to analyze the quantum mechanical properties of the system generating states of consciousness, a simplified definition of $g(.)$ is considered in order to reduce complexity. The analysis is formulated in two classes considering linear Hermitian having different uniqueness properties.

Case I: H is an identical linear Hermitian in G.

Let $\lambda_n = (m+1)g(\lambda_{\Sigma n}) - \sum_{i = 1,m} \lambda_i$ considering computation of output $g(.)$ as global function. Thus, the quantum transformation $H|a_n\rangle = ((m+1)g(\lambda_{\Sigma n}) - \sum_{i = 1,m} \lambda_i)|a_n\rangle$. Furthermore, $((m+1)g(\lambda_{\Sigma n}) - (\lambda_n + \sum_{i = 1,m} \lambda_i) + \lambda_n)|a_n\rangle = \lambda_n|a_n\rangle$. This leads to following Equation where, $\lambda_{nm} = \lambda_n + \sum_{i = 1,m} \lambda_i$,

$$(m+1)g(\lambda_{\Sigma n})|a_n\rangle = \lambda_{nm}|a_n\rangle \qquad (7)$$

Hence, there exists a Hermitian H_{nm} such that, $H_{nm}|a_n\rangle = \lambda_{nm}|a_n\rangle$. However, $k_{xn} = \lambda_x/\lambda_n$ is a ratio of Eigen-values and, $\lambda_x|a_n\rangle = k_{xn}(H|a_n\rangle)$. This leads to the following Equation,

$$(m+1)g(\lambda_{\Sigma n})|a_n\rangle =$$
$$(1, k_{1n}, k_{2n}, ..., k_{mn})(H|a_n\rangle \mathbf{1}_m)^T \qquad (8)$$

Hence, $H_{nm}|a_n\rangle = (1, k_{1n}, k_{2n}, ..., k_{mn})(H|a_n\rangle \mathbf{1}_m)^T$.

Case II: Nodes in G with non-identical Hermetian.

The quantum superposition of states due to excitation of $n \in N$ is given by, $(\lambda_n, \lambda_1, \lambda_2,..., \lambda_m)\bar{u}_{nm} = H_n|a_n\rangle + H_1|a_1\rangle + ...+ H_m|a_m\rangle$. However, $\lambda_1|a_n\rangle = k_{1n}H_n|a_n\rangle$ and, $H_n|a_n\rangle = ((m+1)g(\lambda_{\Sigma n}) - (\lambda_n + \sum_{i = 1,m} \lambda_i) + \lambda_n)|a_n\rangle$. Thus, the quantum superposition at n with respect to node 1 can be derived as $(\lambda_n, \lambda_1, \lambda_2,..., \lambda_m)\bar{u}_{nm} = ([1/k_{1n}]H_{n1}, [1/k_{11}]H_{11}, [1/k_{12}]H_{21}, ..., [1/k_{1m}]H_{m1})\bar{u}_{nm}$. Furthermore, $k_{11} = 1$ and, $H_{11} = H_1$. Considering the Hermitian row-matrix $([1/k_{1n}]H_{n1}, [1/k_{11}]H_{11}, [1/k_{12}]H_{21}, ..., [1/k_{1m}]H_{m1}) = H_{nm}$ the following relation can be concluded,

$$g^{-1}(D_j)\bar{u}_{nm} = H_{nm}\bar{u}_{nm} \qquad (9)$$

Message propagation in channels

Following the graph model of distributed computation, the neuronal interconnections or signal-pathways between two neurons (i.e. nodes in graph) can be modeled as a set of channels. According to neurophysiology, the inter-nodal signal propagation in channels is a slow process based on potential barrier at physical substrate. Let, $\exists n_a, n_b \in N$ such that, $(n_a, n_b) \in L$. A channel function in G between two nodes is defined as, $C: I_{nt} \to I_{\beta n}$ such that, $(i_b \in I_{\beta n}) = C(i_a \in I_{nt})$ where, $I_{\beta n}$ is a set of all inter-node input signals coming to $n \in$

N from other nodes (excluding environment). The potential barrier of the channel is strictly bounded as, $0 \leq C(.) \leq \max(S)$. Let the delay-density distribution of the channel be $d_C(t)$ such that, $-\max(S) \leq d_C(.) \leq \max(S)$. If the propagation delay of a signal is τ then, $i_b\big|_\tau = i_a\big|_{t=0} \int_{0,\tau} d_C(t)dt$. Thus, either a neuro-signal (or a message) propagates without modification in a channel, or it is attenuated (depending upon delay-density distribution of the channel). Hence, the channel delay-density distribution function is modeled as a product of exponential decay in a narrow phase-range represented as,

$$d_C(t) = d/dt[e^{-t}(\cos t - \sin t)] \tag{10}$$

The channel delay-density distribution affects the evolution of deterministic positive consciousness due to the possibility of information attenuation or alternation within the channels. The surface map of channel dynamics (z-axis) for varying input (y-axis) and, the delay-density distribution (x-axis) is illustrated in Fig. 6.
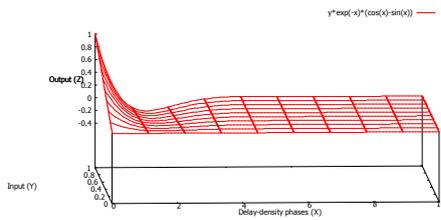

Figure 6. Dynamics of information transformation within channel.

According to Fig. 6, the density distribution model closely resembles the firing of neurons in physical substrate of brain. There is a minor phase-shift of origin to right of the initial triggers in biological neurons (initial slope of neuron firing is ignored). Finally, following the model proposed by Penrose and other researchers, it can be said that the triggering and the quantum mechanical behavior of microtubules within the biological neurons are the responsible factors for determining neuro-coordination and expressions of consciousness (Hameroff, 1996; Beck, 1992; Beck, 2001; Hagan, 2002).

Conclusion

The brain is a complex neurological device having similarities to distributed computational structures expressing cognition. A distributed computational model of consciousness can be constructed as triplet function where, localized computations are carried out at specialized locations on graph model having communication channels. The computational model has a basis in the quantum models of cognitive functions of brain. The unified model supports the expression of consciousness as distributed computation at nodes having quantum superposition of final states. Appropriate choice functions can be computed having closer approximation to neurodynamics in order to explain consciousness and to design bio-inspired fault-tolerant distributed computing systems in future.

Bagchi S., Quantum phenomena in computational model

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