

Distributed Computation using Evolutionary Consciousness : An Approach

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Abstract

The modeling of biological phenomena and its adaptations to distributed computing are promising research areas. The computational modeling of neurobiological phenomena, such as cognition and consciousness, has potential for applications into bio-inspired distributed computing. The functioning of neurological structures is inherently distributed in nature having a closer match to distributed computing. This paper proposes a mathematical model of state of consciousness by following the functional neurophysiology as well as elements of distributed computing. The scopes of evolution of consciousness and memory are incorporated into the model. The nodal classifications and formation of structural hierarchy in distributed computing nodes by incorporating elements of cognitive model are investigated. Evaluation of the model is made by numerical simulation considering different choice functions. The results illustrate that, model of consciousness can be adapted to bio-inspired distributed computing structures and the gradual evolution of consciousness is deterministic under fair excitations from environment.

Keywords: Cognition, consciousness, bio-inspired computing, distributed computing, fuzzy logic.

1. Introduction

There are two different approaches to understand and model cognitive functions and consciousness. The host biological systems are composed of complex network of neurons and other specialized neuro-anatomical structures. The consciousness is a neurobiological phenomenon of a living being. At the physical layer of consciousness, a biological system interacts with the environment through the sensors and it processes the input signals in brain to generate output. However, the modular cerebral network of brain often processes the inputs in the unconscious state [7]. Often, the conscious and abstract thinking happens at the global workspace (GW) level [2, 7]. It is observed that, the individual neurons in neuro-network implement computational mechanisms to achieve cognitive functions [26, 27, 29, 33]. As a result, the computational modeling of cognitive functions such as, learning, intentionality and consciousness based on neuro-network are conceived [28, 29, 31]. The computational models of machine consciousness as well as artificial cognitive functions are proposed following artificial neural network and probabilistic reasoning employing Bayesian and hidden Markov models [30, 32, 34, 35, 36, 37]. Researchers have proposed that, neurobiological and physiological attributes

are not the absolute parameters to explain consciousness. There exists a computational and information theoretic model to explain abstract thinking and consciousness. In general, the attributes of defining consciousness are vague and incomplete, which have resulted in incompleteness of computational models of consciousness [8]. The main reason is that, the models aim at human-centric consciousness definitions rather than trying to create a functional model of consciousness following neurobiological phenomena 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 [1]. The cognitive functions of brain generating consciousness are inherently a distributed computing mechanism, because the information processing happens at different locations in brain due to an input [7]. This paper argues that, a brain can be viewed as a distributed computing machine comprised of nodes (representing parts of a brain) connected by network. This paper proposes a novel bio-inspired distributed computational model employing states of consciousness. The model is composed of functional algebraic structures, where the nodes coordinate and implement information processing in distributed fashion

generating conscious output or expression. Moreover, the nodes have memory and they evolve by storing information.

1.1. Motivation

The modeling of cognitive neuro-functions and their integration into computing platforms have given rise of machine intelligence having closer approximation to biological systems [2, 5, 7, 8]. There can be a wide array of applications of such systems in the domains of artificial intelligence, humanoid robotics, self-adaptive distributed computing and, intelligent human-computer interactions. Existing models of cognition and consciousness focus on human cognitive capabilities, which are vaguely defined [8]. On the contrary, the experimental data suggest that higher cognition capabilities differ from human to other species while basics remain the same and, a neuronal structure can be modeled by a tree-structure of computation [1, 14]. The basic form of consciousness due to environmental excitations is fundamental to living species of any order. Moreover, the state of consciousness is evolutionary in nature, where the state of consciousness is variable and it evolves towards a deterministic final state depending upon environmental inputs and memory. Interestingly, the predictive coding model of neocortex exposes the existence of elements of distributed computing structures into the neocortical computation [12]. The majority of existing models of cognition follow concepts of artificial neural network, which are complex and cannot explain generalized notion of consciousness and evolution [7, 8]. The reductionism in information processing to understand consciousness is not an effective approach [25]. Hence, it is required that a more fundamental approach should be made to model state of consciousness of any species based on physiological neuronal functions.

This paper proposes a novel computational model of deterministic consciousness following the functional attributes of neurobiological phenomena. The proposed model combines the distributed computing concepts to the functional attributes of neurobiology to understand the state of deterministic consciousness. The concepts of evolution and memory are incorporated into the model to understand the dynamics of state of deterministic consciousness. This paper explains how the model of consciousness states can be integrated into the distributed computing domain to establish bio-inspired distributed computing systems. It is illustrated that, distributed computing structures can adapt model of deterministic consciousness. The experimental evaluations are conducted through numerical computation aiming to quantify deterministic consciousness and to follow its

dynamics. The proposed model and the results illustrate that, consciousness can be possibly quantified and the dynamical states can be traced if appropriate choice functions are selected matching neurobiological phenomena. The main contributions of this paper are:

- Construction of a generalized computational model of consciousness by combining the functional neurophysiology and elements of distributed computing.
- Incorporation of concepts of memory as well as evolution of deterministic consciousness based on environmental excitations.
- Integration of basic model of deterministic consciousness into the bio-inspired distributed computing structures.

The rest of the paper is organized as follows. Section 2 describes related work. Section 3 explains the construction of mathematical model of consciousness. Section 4 describes a set of analytical properties of the model and the adapted distributed computing structures. Sections 5 and 6 describe experimental evaluation and comparative studies, respectively. Section 7 concludes the paper.

2. Related Work

The physiological level of understanding of cognitive capabilities involves neuronal structures and signal transductions. The neural correlation models are proposed by researchers to explain the development of consciousness in brain [2, 11, 13]. The mind-brain relationship and the structural analysis are derived through experimentation involving EEG, fMRI and, PET [1, 2]. The idealized functional structure of brain is proposed for understanding of consciousness [2]. According to the study, the cerebral hemisphere is activated by diffusion of signal/information from thalamus and ascending arousal system, which are critical to generate consciousness [21]. However, the physiological understanding of brain structures cannot explain the cognitive capabilities and consciousness in complete form. It has been proposed that neurological cognitive actions can be explained by following computational models such as, finite state automation as well as push-down stack [1, 9, 10]. Following this approach, a single neuron is modeled as a tree-shaped computing structure [1]. The tree-model tries to map the physiological structure and functions of neurons into the computational structure. At the functional level, the predictive coding model of neocortex is proposed [12, 14]. The predictive coding model is a generalized

model and incorporates elements of distributed computation. The predictive coding model of neocortex is different from the traditional bottom-up neocortical computation model. In the bottom-up neocortical model, the two distributed neuronal nodes perform cognitive actions considering chained unidirectional information flow. It is observed that, at the algorithmic levels, the cognitive functions become computationally intractable although living species perform such functions without delay [15]. The reason is that, the living organisms often employ heuristics and greedy algorithmic models in problem solving.

The expression of intension is a cognitive function having neurological mechanisms. Researchers have proposed models to predict intention based on pattern matching and sequence analysis [5]. The simulation theory is proposed by researchers to explain intention prediction [18]. According to simulation theory, cross-simulation and cross-observation between two subjects can be performed making one subject aware of intension of another by using own state of cognition and consciousness. However, this model is based on empiricism.

In general, the existing models of cognitive functions and consciousness can be broadly classified into six categories [2, 4, 6], namely: (1) global-workspace model, (2) information integration model, (3) internal self-model, (4) higher-level representation theory, (5) theory of attention mechanisms and, (6) virtual machine formalism. The global-workspace model considers interconnection of distributed cerebral networks and its activation for certain duration of time. The consciousness model based on artificial neural network (ANN) is proposed following global-workspace concept representing abstract thinking [7]. On the other hand, the cognition capability of abstract thinking is modeled by Central-Representation architecture along with monitor system [16]. The CLARION system is a knowledge-based cognitive architectural model, which employs representational-difference approach along with distributed neural systems [38]. However, these models are complex, computationally expensive and do not consider evolutionary consciousness [2, 7, 8]. The global-workspace model is further refined into a self-model considering neurobiological functionalisms [23]. In a different approach to explain cognition and consciousness, an artificial machine oriented concept is proposed named as virtual machine (VM) model. The VM model of consciousness considers two levels such as, a physical (host) framework and a conceptual virtual machine executing on top of host [22]. The virtual machine formalism is further classified into two groups, namely: VM functionalism and phenomenal VM. Effectively, the

VM model resembles to the finite state machine in computing paradigm. The main drawback of the VM model of consciousness is that, the model cannot specify some of the intermediate states of consciousness of living beings and has a rigid structure.

The realization of consciousness following machine model is proposed using symbolic tracking and information processing based on reduced set [24]. However, others have provided evidences towards a contradictory view, where reductionism in symbolic tracker effectively degrades quality of consciousness model [25]. It is illustrated that, neurological phenomena of consciousness and experiences are not instantaneous neuronal activities and, the retention (memory) has a role into it [3]. Furthermore, the expression of experiences has a computational basis, which can be modeled by mathematical frameworks [17, 19, 20].

3. Computational Modeling

It is necessary to transform the neuro-physiological structures as well as functions into the computational structures prior to construct a concrete model in order to understand the dynamics of deterministic consciousness and cognition. From the physiological as well as anatomical point of view, different sections of a brain are responsible to process different excitations from environment. The neuro-computational modeling and experimentations have revealed that, the information processing in brain is inherently distributed in nature [1, 7, 38, 39, 40, 41]. However, there is a mechanism of coherency and coordination among the neuronal sections to produce a conscious output. In view of computation, a brain can be modeled as a tightly-coupled distributed computing system, where specialized neuronal sections are represented as the nodes connected to each other through neuro-network. In this paper, a map of the brain-model in view of distributed computing structures is formulated and the computational model of state of consciousness is constructed following functional neurophysiology. The computational structure of brain is illustrated in Fig. 1.



Fig. 1. Schematic representation of computational brain.

According to Fig. 1, the functional neurophysiology of brain can be mapped into the graph model of distributed computing. The nodes in the graph accept inputs from the environment and produces conscious outputs. It is important to note that, not all nodes in the graph accept inputs from environment directly. The functions of the nodes are classified into different sets and, the outputs generated to the environment by the graph are coherent as well as conscious. The nodal structure of the computational model is illustrated in Fig. 2. In following subsection, a mathematical model of the consciousness of a computational brain is constructed.

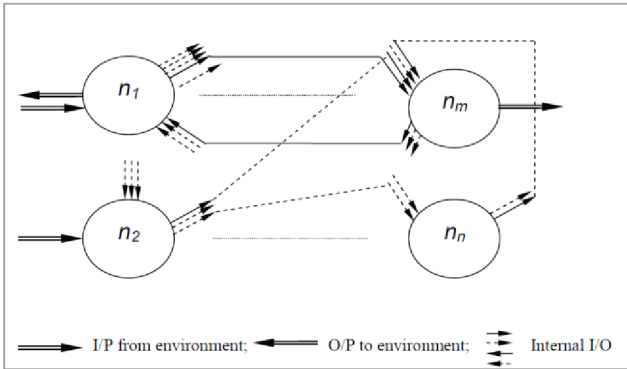


Fig. 2. Internal computational structures of nodes.

3.1. Model of consciousness and state dynamics

Definition of symbols:

- G : a simple graph
- $P(.)$: power set
- $\langle e \rangle$: environmental input row vector
- $\delta(.)$: excitation function
- ω_G : time-ordered set of output of G
- X_E : random environment variable
- i_{en} : input to a node n from environment
- λ_n : temporary local excitation at node n
- $\mu_n(.)$: fuzzy membership function of node n
- ω_{G^*} : previous set of output of G to environment
- ω_{Gn} : previous set of output of n to environment
- O_n : set of output channels of node n
- $f_n(.)$: selector function for signal propagation
- $\gamma_t(.)$: transmission function at time t at any node
- I_m : inter-node signal generated by n due to excitation
- $g(.)$: output generation function
- β_n : conscious output generated at node n
- $\sigma(.)$: transformation function at node n

Let, the set of random environmental sensory input to a conscious brain be given by $I_E = \{X_E \langle e \rangle, \omega_{G^*}\}$ where, $X_E : \langle e \rangle, \omega_{G^*} \rightarrow R$ and $i_{en} \in I_E$. Let, $S \subset Z$ be a set of excitation states in $G = (N, L_G)$, where N is a set of nodes representing regions in a brain controlling individual functionalities of a living body and $L_G \subset N^2$. Suppose, $I_{\beta n}$ is a set of all inter-node input signals coming to $n \in N$ from other nodes (excluding environment) and, the entire set of inputs to a node n is given by, $I_{cn} = (I_{cn} \subset I_E) \cup I_{\beta n}$. It is evident that set I_{cn} contains every possible input to a node in brain inclusive of excitations from the environment. The normal operation of a brain having consciousness is dependent upon two parameters: (1) all the nodes in $G = (N, L_G)$ are operational and, (2) inter-node signal propagation is normal. The state of consciousness can be dynamically varying over time and the dynamic state of consciousness can have two bounds, a maxima (v) and a minima (u), where $(u, v \in Z)$. The boundary state of consciousness $u < 0$ of a node $n \in N$ is considered if the function of node is impaired due to some physical or environmental conditions. It is evident that, a person having normal state of consciousness produces output to environment due to an excitatory input to n by utilizing a subset of nodes $N_e \subset N \setminus \{n\}$ together with the node $n \in N$. Hence, the dynamic selections of N_e depending upon the types of environmental excitations and the inter-node information transactions to produce conscious output are two important steps to consider. Let, $\forall n \in N, f_n(.)$ be a selection function at n depending upon the different types of excitations from environment. It dynamically determines the subset of nodes required to produce a conscious output due to a particular input either from environment or excitation from other nodes in a brain having normal state of consciousness.

The excitation function due to an input to a node in brain having normal state of consciousness is defined as, $\delta : I_{cn} \rightarrow S$ such that, $\delta(\delta^{-1}) = 1$. There exists a k such that, $\delta(i_x) = ki_x$ and, $k = 1$ if $i_x \in I_{\beta n}$, otherwise, $0 < k < \max(S)$. The output of a node as well as the set of nodes (i.e. brain) due to an excitation is such that, $\omega_{G^*}, \omega_{Gn} \subset \omega_G$ and, $\omega_{G^*} \cap \omega_{Gn} \neq \phi$. Thus, for the entire brain represented by G , $\omega_G = \cup_{n=1, |N|} \omega_{Gn}$. The inter-node excitation (information) transactions are controlled by a function $\gamma_t(.)$. Suppose, at time t , $N_e = f_n(.)$. Hence, the dynamics of state of consciousness of a node $n \in N$ can be governed by a triplet function represented as follows ($\forall h \in N_e, \lambda_n \in [-u, v], \mu_n(.) \in [0, 1]$ and, $Y \subset P(O_n)$ of node n):

$$\begin{aligned} \lambda_n &= \sigma(\mu_n(\delta(I_{cn})), \omega_{Gn}) \\ f_n &: (\delta(I_{cn}), \lambda_n) \rightarrow Y \\ \gamma_t &: (I_n, h) \rightarrow \{0, 1\} \end{aligned} \tag{1}$$

This indicates that, the natural dynamics of consciousness states at any time t are dependent upon the execution of communication function $\gamma_f(\cdot)$. In addition, the level of inter-node excitation (I_{cn}) generated in node n at time t is equally important for inter-node coordination in generating conscious decisions. This is important to note that, $\exists i_n \in I_{cn}$ such that $j \in f_n(\cdot)$ then, $n \in f_j(\cdot)$ for the corresponding I_{β_j} . However, it is not necessary to restrict the dynamics of consciousness states by imposing condition as, $f_n(\cdot) = f_j(\cdot)$ for an input from environment.

3.2. Generating conscious output

Suppose at time t , a certain excitation has entered into a node $n \in N$ of graph G . Thus, at time $t+a$, ($a > 0$), the row vector representing a state of consciousness is given by, ($m = |f_n(\cdot)|$),

$$\lambda_{\Sigma_n} |_{t+a} = (\lambda_n, \lambda_1, \lambda_2, \dots, \lambda_m) \quad (2)$$

The output due to excitation is generated at time $t+b$, ($b > a$), from a conscious brain and, it is computed by a function $\beta_n |_{t+b} = g(\lambda_{\Sigma_n} |_{t+a})$ depending upon $\lambda_{\Sigma_n} |_{t+a}$ such that,

$$g : \lambda_{\Sigma_n} \rightarrow R \quad (3)$$

It is possible to limit the range of $g(\cdot)$ in a way so that at any time, $\beta_n |_t \in [-r, r]$, $r \in Z^+$.

3.3. Evolution of state of consciousness

The evolution of state of consciousness at time t is highly dependent upon the experiences during $0 < t-1 < t$. Let, an ordered pair $\psi_{n,t+i} = \langle I_{cn} |_t, \beta_n |_{t+i} \rangle$ represents experience in n for $i > 0$. Thus, the consciousness of a brain with merged experiences can be computed as a finite set, $\omega_G = \{\psi_{n,t} : n \in N, t \in Z^+\}$ and, $\omega_{G_n} = \cup_{t \in Z^+} \psi_{n,t}$. Interestingly, this completely fits into the model of state of consciousness and the respective dynamics.

3.4. Deterministic state of consciousness

Suppose in a biological system, all parts (i.e. nodes) of a brain are functional without physical impairment indicating $\forall t, \gamma_f(\cdot) = 1$. The computed value of $\beta_n |_t$ for different cases can occur in three ways as follows (considering $|u|=|v|=1$), (I) $\beta_n |_t \in \{-1, 0, 1\}$, (II) $\beta_n |_t \in (-1, 0)$ and, (III) $\beta_n |_t \in (0, 1)$. An output $\beta_n |_t = 1$ indicates that, a deterministic positive conscious decision is made; $\beta_n |_t = -1$ indicates that, a deterministic negative conscious

decision is made and, $\beta_n |_t = 0$ indicates neutrality in conscious decision at time t .

The intermediate values of $\beta_n |_t$ indicate indeterminism in conscious decision either with positive-bias or with negative-bias depending upon respective signs. It is important to note that, more than one value of $\beta_n |_t$ can never occur simultaneously at any single point of time. Hence, if an output is generated following case (I), then it is a deterministic state of consciousness at that point of time. On the other hand, the occurrences of case (II) or case (III) at output indicate indeterministic state of consciousness in decision.

4. Analytical Properties

In this section, a set of analytical properties of the proposed algebraic model is determined in order to gain insight to the functional dynamics.

4.1. Composition of $f_n(\cdot)$ and $\gamma_f(\cdot)$

The distributed nodes in the system determine consciousness through inter-nodal coordination as well as information transactions. Let, a functional composition is being denoted by $\gamma_f \circ f_n$ between the selector function and the transmission function at any node in G . If $\forall n \in N, \gamma_f \circ f_n = 1$, then the graph G will produce deterministic consciousness every time.

However, if $\exists n^* \in N$, such that $\gamma_{t-1} \circ f_{n^*} = 0$, then G will fail to produce deterministic consciousness at t . Evidently, the functional composition $\gamma_f \circ f_n$ is not a commutative composition.

4.2. Cardinality variation

Suppose, $m = |f_n(\cdot)|$ for some excitation at t to a node n in G . Now, if it is assumed that $\forall n \in N, \gamma_f \circ f_n = 1$, then $|\lambda_{\Sigma_n} |_{t+a}| = m + 1$, $a > 0$. Thus in general, $|\lambda_{\Sigma_n} |_{t+a}| = |f_n(\cdot)|_t + 1$ iff $\gamma_f \circ f_n = 1$.

4.3 Distributed global consensus

The regions of neuronal networks in brain compute and propagate signals from source region to destination region through a series of neuronal firings. The regions of brain can be segmented based on specific excitations and functions by employing fMRI technology [42]. The globally consistent conscious output is made by a distributed consensus by different regions in brain in coherence. The information propagation and formation of

regions are illustrated in Fig. 3. The coordination and consensus in local regions in brain are established through burst synchronization with theta frequency [43]. However, the coherence at global cortical level is achieved due to lateral inhibition.

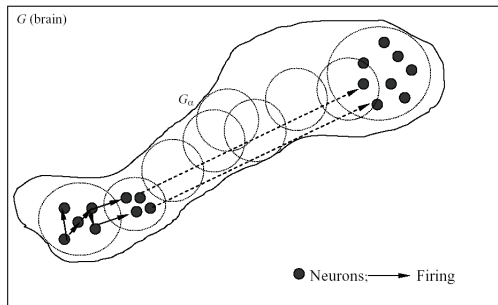


Fig. 3. Schematic diagram illustrating information propagation.

Let, $\Delta_j = G_j(N_j, L_{G_j})$ be a sub-graph of G representing a localized region and, for $I_{\alpha m}$, $G_\alpha = \cup_{j=1, F} \Delta_j$. The regional consensus is defined as a potential given by, $\epsilon^{\Delta_j} = (1/|N_j|) \int_{\Delta_j} d\beta_n, n \in N_j$. The distributed global consensus about a conscious output due to an excitation is computed by a distributed consensus algorithm in different regions of brain represented by $D(G_\alpha, \epsilon^{\Delta_j} : 1 \leq j \leq F)$. An example of simplified definition of generating global consensus about consciousness is, $D(\cdot) = \epsilon^{\Delta F} - \max(\epsilon^{\Delta_j} : 1 \leq j \leq F-1)$.

4.4. Effect of delay distribution

The neuronal interconnection between two neurons can be modeled as a channel for signal (message) propagation. In biological systems, a neurological signal between two nodes (neurons) either propagates with a delay of transmission, otherwise it decays over short time (i.e. signal is blocked in channel). A channel function in G is defined as, $C: I_{n_t} \rightarrow I_{\beta n}$ and thus, $(i_b \in I_{\beta n}) = C(i_a \in I_{n_t})$ where, $0 \leq C(\cdot) \leq \max(S)$ and, $(n_a, n_b) \in L_G$. The delay-density distribution of the channel is represented as $d_C(t)$ such that, the strength of signal after propagation is $i_b|_{t=\tau} = i_a|_{t=0} \int_{0,\tau} d_C(t) dt$ where, the signal propagation delay is τ . This indicates that, a neuro-signal or message may be propagated unchanged or may be attenuated (blocked) depending on the delay-density distribution of a channel between two nodes.

4.5. Computing structures and nodal classifications

Evidently, the brain is a complex neuro-network having functions resembling elements of distributed computing. Thus, the bio-inspired adaptive distributed computing structures can be formulated by incorporating

computational model of consciousness into the graph-model of distributed computing. Following the distributed computational model of consciousness, the bio-inspired adaptive distributed computing structures can be constructed into two forms such as, structural forms and nodal classification forms. In the structural forms, the computation can be subdivided into two levels such as, Level I and Level II as illustrated in Fig. 4. The nodes in Level I are capable of carrying out computation and performing I/O to environment (i.e. users), whereas the nodes in Level II are capable of performing computation only (i.e. backend nodes). In the nodal classification forms, nodes can be portioned into various classes depending on their respective functions.

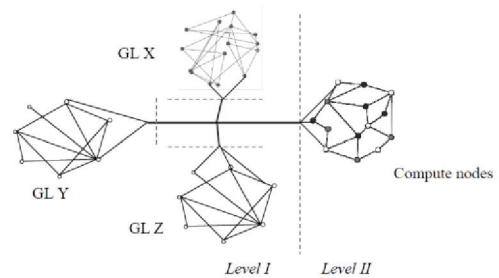


Fig. 4. Bio-inspired Distributed Computing Structures.

The nodes in Level I can be subdivided into three groups based upon their I/O capabilities to the environment. The GL X nodes are capable of accepting inputs from environment without providing any direct output, GL Y nodes are capable of delivering outputs to environment but cannot accept any input and, GL Z nodes provide bidirectional I/O to/from environment. The nodes in Level II are the computational nodes having interconnection to nodes in Level I through the network topology. It is not necessary for the network topology to follow a complete-graph model.

5. Experimental Evaluation

The evaluation of dynamics of state of consciousness has three components namely, state of deterministic consciousness, state of indeterminism and, the evolution of state of consciousness. The distributed computational model of consciousness is evaluated by discrete numerical computation and simulation. The numerical simulation of the model is implemented considering different choice functions in order to understand the performance. The set of experiments are classified into two broad groups: (a) nodal dynamics of state of consciousness without transformation of excitation and, (b) multi-nodal dynamics of state of consciousness with transformed excitation.

Furthermore, the experiments are carried out following two different combinations of inputs and memory capacities. In one case, the input vectors to the system are always deterministic (i.e. $\{-1, 0, 1\}$). In another case, the input vectors are made combinatorial in the range $[-1, 1]$. The input vectors are chosen with uniform randomness. On the other hand, a system can have memory (partial or complete) or it may not have any memory at all (i. e. zero memory system). The dynamics of a memory-less system and a system with memory would be different because of the effects of memory on the evolution of state of deterministic consciousness.

5.1. The choice functions

The experiments are carried out utilizing different choice functions and their compositions so that, the state of dynamics of deterministic consciousness can be evaluated from base level to the gradually evolved state. In nature, the dynamics of deterministic consciousness appear to be stable. In order to reduce rapid excitation and to reduce overshoot/undershoot of the system, a smooth fuzzy function is chosen. The definition of fuzzy membership function is as follows,

$$\mu_n(\delta(x)) = \begin{cases} 0.5(1 + \delta(x)^2) & \text{if } x \in I_{cn} \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

The surface map of the unconstrained function for the varying gain within the limit for the corresponding varying input vectors is illustrated in Fig. 5.

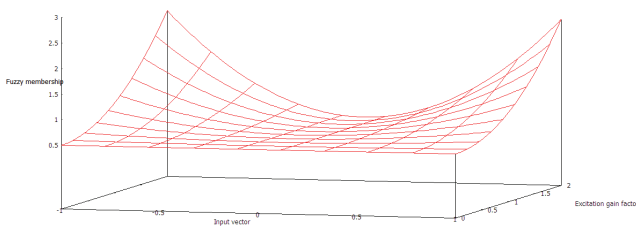


Fig. 5. Dynamics of fuzzy function for $-1 \leq I_{cn} \leq 1$ and $0 < k < 2$.

The characteristic variation of fuzzy function (y-axis) for unit gain (i.e. linear mapping of excitation) for the corresponding varying input vector (x-axis) is illustrated in Fig. 6. According to natural observations, the evolution of state of consciousness is gradual. In order to understand the gradual evolution dynamics of state of deterministic

consciousness, a moderate transformation function is chosen.

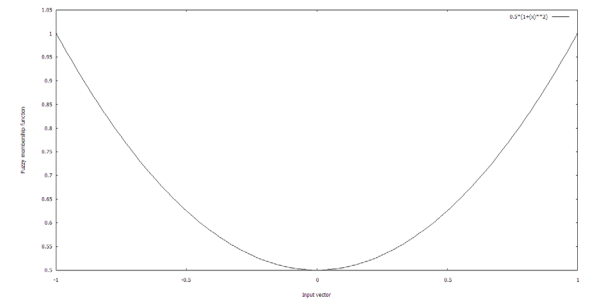


Fig. 6. Characteristics of fuzzy membership function at $k = 1$.

An over amplified transformation function is avoided to eliminate instability in conscious behaviour. The transformation function at a node is chosen as, $\sigma(x, y) = y(1+xy)^{0.5}$, where $x = \mu_n(\cdot)$, $y = avg(\omega_{Gn})$. The dynamics of transformation function is illustrated as a surface map in Fig. 7.

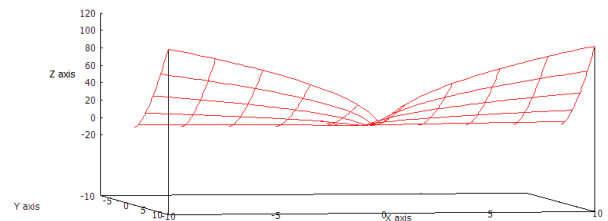


Fig. 7. Dynamics of transformation function, $\sigma(x, y)$.

Furthermore, the transformation is constrained within the limits as, $x \in [0, 1]$ and, the corresponding memory vector $y \in [-1, 1]$. The characteristic map of constrained surface of the transformation function is illustrated in Fig. 8.

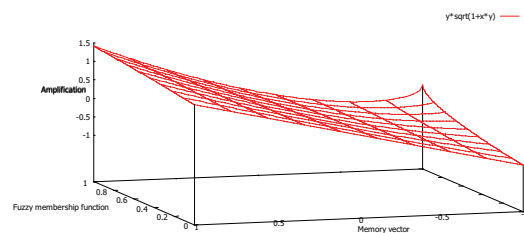


Fig. 8. Characteristic map of constrained $\sigma(x, y)$.

It is observable from Fig. 8 that, the high and uneven surface of amplification is avoided in the constrained transformation function, which would correlate to the gradual evolution of the deterministic state of

consciousness in a system. The channel delay-density distribution function is modeled as a product of exponential decay and trigonometric wave-deviation in narrow phase-range ($d_C(x) = -2e^{-x} \cos x$), where x is delay-density variable. The characteristic map of channel delay-density distribution function between two nodes is illustrated in Fig. 9. This indicates that, immediately after generation of a message by a node, the channel tries to carry the message at maximum potential to the destination node and the message decays over time if the integral delay increases in the channel. A full-cycle delay of signal propagation will lead to complete decay of the corresponding signal within the channel.

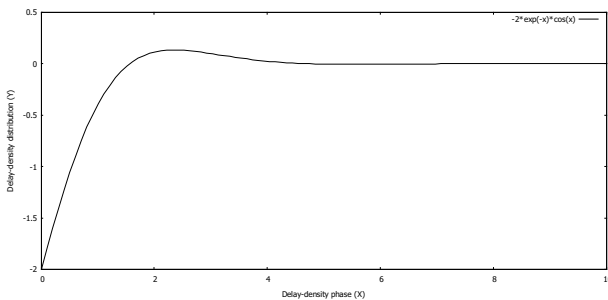


Fig. 9. Delay-density distribution between nodes.

The inter-nodal channel delay-density distribution has an effect on the evolution of deterministic positive consciousness due to the information transformation within the channel. In the experimental setup, the following condition is maintained to reduce complexity of computation, $\lim_{\tau \rightarrow 0^+} \int_{0, \tau} d_C(t) dt \approx 1$ considering delay-density as a time-variable following neuronal firing model.

5.2. Consciousness without memory

In this section, a memory-less system is considered, where the state of deterministic consciousness is instantaneous irrespective of dynamics of input vectors. The instantaneous state of deterministic consciousness is computed following continuous averaging method. Thus, in this experiment the parameters are chosen as, $u = v = r = 1$ and, $g(\lambda_{\Sigma n}) = (\lambda_n + \sum_{j=1, m} \lambda_j) / (m + 1)$. The indeterminism in the consciousness is evaluated by computing relative distance between a state of deterministic consciousness (positive or neutral or negative) and the computed output.

The input vectors are varied into two classes such as, (C1): deterministic input vectors (excitations are in $\{-1, 0, 1\}$) and, (C2): combinatorial (or fair) input vectors (where excitations are chosen in $[-1, 1]$ randomly). The comparative study of degree of variations of indeterminism

and the corresponding deterministic consciousness are illustrated in Figs. 10-15, where the input vector size is monotonically increased for both classes of input vectors.

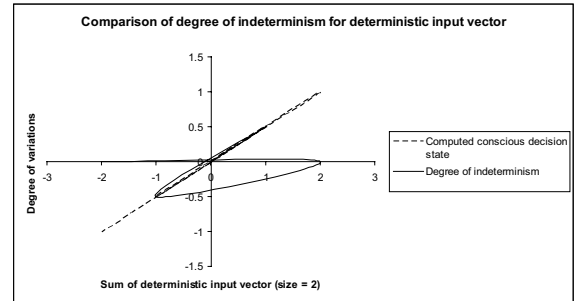


Fig. 10. Variation of state of consciousness in C1 (size = 2).

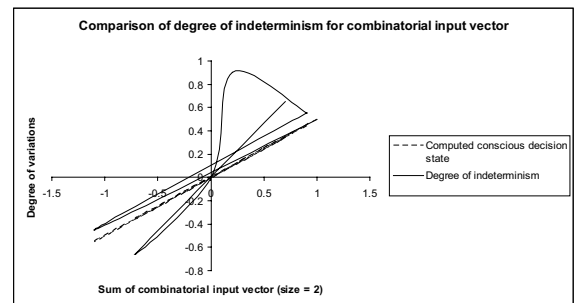


Fig. 11. Variation of state of consciousness in C2 (size = 2).

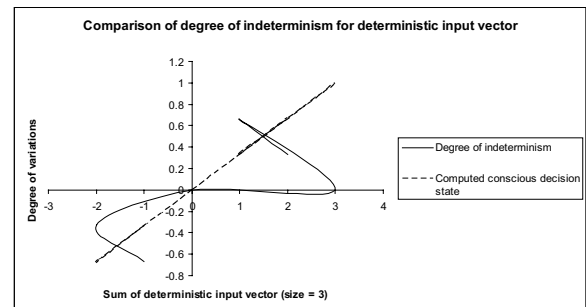


Fig. 12. Variation of state of consciousness in C1 (size = 3).

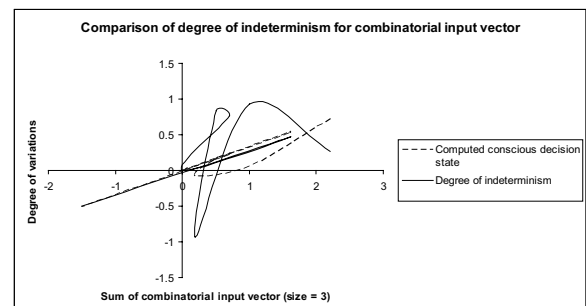


Fig. 13. Variation of state of consciousness in C2 (size = 3).

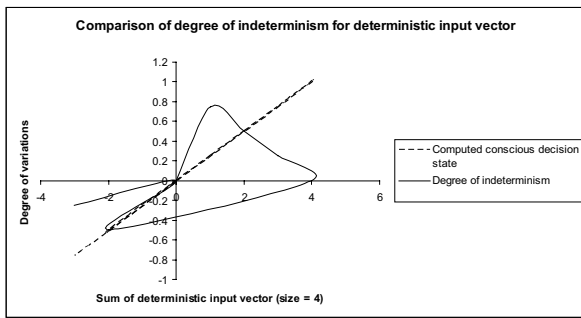


Fig. 14. Variation of state of consciousness in C1 (size = 4).

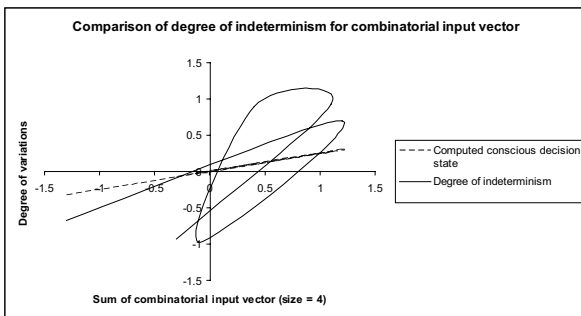


Fig. 15. Variation of state of consciousness in C2 (size = 4).

It is observable that, the conscious decision states are bounded in a relatively small linear domain in comparison to indeterminism. The dynamics of consciousness appears to be closer to linearity in majority cases (not all cases). However, the indeterminism in consciousness is highly non-linear and unpredictable (i.e. chaotic in nature). In addition, the chaotic variations of indeterminism in consciousness tend to increase with the increasing size of combinatorial input vector class (C2). The patterns of variations of deterministic consciousness appear to be unaffected to a high degree for the increasing size of input vectors of both classes. This is consistent with nature because, the system has zero memory in it and, the evolution of state of consciousness is stateless.

5.3. Consciousness with memory

In this section, memory is incorporated into the system and, the dynamics of state of deterministic consciousness as well as indeterminism are evaluated.

The characteristic surface map of interplay of deterministic consciousness, indeterminism and memory size is illustrated in Fig. 16. It is observable from Fig. 16 that, on the negative consciousness surface, the indeterminism tends to increase minimally with the increasing memory size.

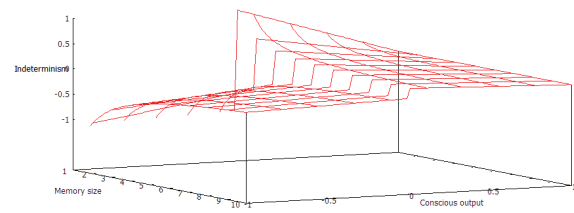


Fig. 16. Dynamics of consciousness and indeterminism with memory size.

However, the inherent indeterminism in positive consciousness is relatively higher than the surface of negative consciousness. Interestingly, the indeterminism in consciousness tends to decrease rapidly on the surface of positive consciousness when the memory in the system is increased to a large extent, which is consistent to the nature. In the next step, the comparative study of dynamics of deterministic consciousness is carried out separately considering C1 and C2 input classes. In the case of evaluating a system with memory, the input vector classes are further subdivided into three types such as, (1) fair input vectors (where input values can vary randomly in $[-1, 1]$), (2) positively-biased input vectors (where input values can vary randomly in $[0, 1]$) and, (3) negatively-biased input vectors (where input values can vary randomly in $[-1, 0]$).

5.3.1. System with memory and C1 inputs

In this experiment, the system with memory is considered and class C1 input vectors are chosen with fair, positively-biased and negatively-biased values. Accordingly, the experiments are conducted in three categories and the comparative studies of the indeterminism as well as the state of deterministic consciousness are illustrated in Figs. 17 - 19. It is observable that, the dynamics of state of consciousness and indeterminism in a system with memory is relatively symmetric as compared to the memory-less system.

On the other hand, the response of a system with memory with fair C1 input is relatively more symmetric than the response of the system with biased input vectors. In case of responses of a system with memory with biased input vectors, the states of deterministic consciousness and indeterminism converge to singular value on several occasions and next, diverge afterwards with increasing size of the vectors (appears to be chaotic). In case of fair input vector, the responses of a system having memory tend to converge initially within a limited size of input vector. However, the distances between deterministic

consciousness and indeterminism diverge when the vector size is further increased (residual indeterminism is enhanced).

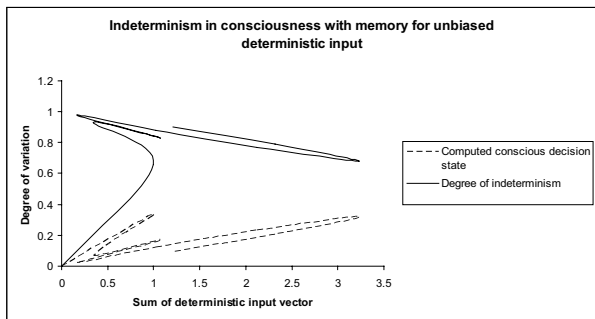


Fig. 17. Variation of state of consciousness in system with memory (fair C1).

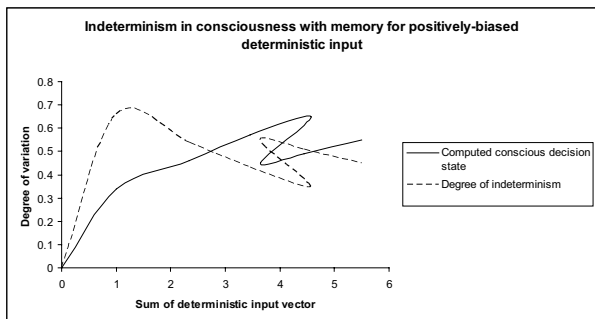


Fig. 18. Variation of state of consciousness in system with memory (+biased C1).

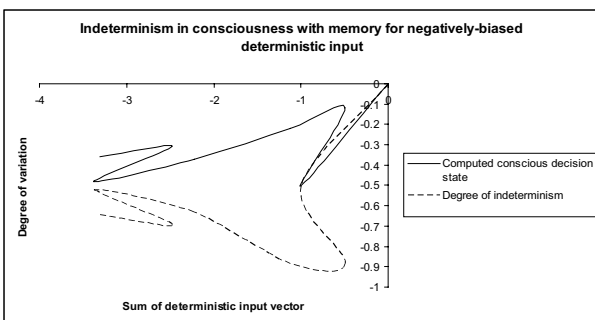


Fig. 19. Variation of state of consciousness in system with memory (-biased C1).

5.3.2. System with memory and C2 inputs

In this experiment, the state of consciousness of a system having memory is evaluated for C2 class input vector along with fairness as well as \pm biasness. The responses of the system are illustrated in Figs. 20-22. It is observable that, symmetric response patterns in consciousness are broken when a system with memory is excited with fair C2 class input vectors. In such case, the deterministic

consciousness tends to be bounded within a narrow domain, whereas indeterminism appears to be chaotic.

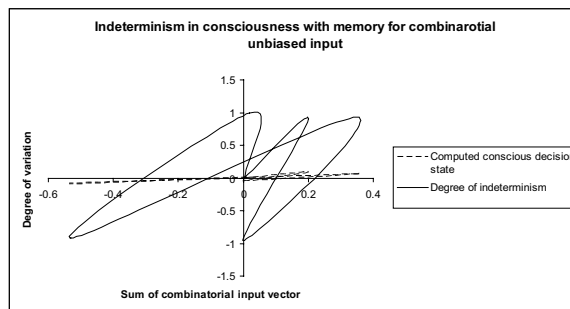


Fig. 20. Variation of state of consciousness in system with memory (fair C2).

However, the states of consciousness and indeterminism of a system having memory under positively-biased C2 class input vectors converge at the lower end of vector size (i.e. low inherent memory). Later, the bifurcation effect takes place in the state of consciousness as well as indeterminism and, the system tends to achieve symmetry for higher order of positively-biased C2 class vectors.

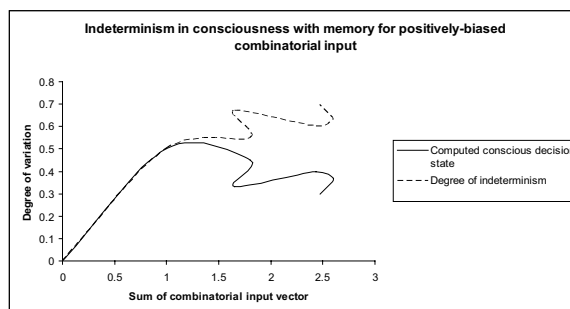


Fig. 21. Variation of state of consciousness in system with memory (+biased C2).

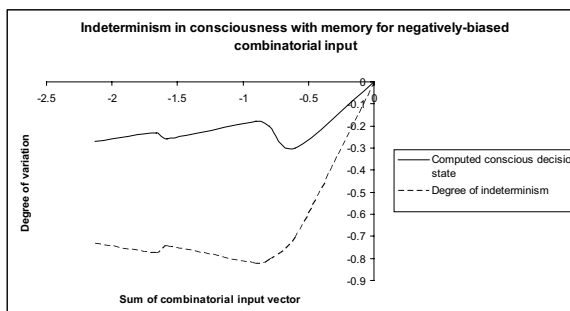


Fig. 22. Variation of state of consciousness in system with memory (-biased C2).

On the contrary, the state of consciousness and indeterminism in a system having memory under

negatively-biased inputs diverge from an early stage (at lower vector size). The relative distance between indeterminism and the state of consciousness is relatively larger in case of negatively-biased input vectors than the other cases.

5.4. Consciousness with transformation

In this section, the experiments are carried out in a system with memory and, the non-linear transformation function is employed to the excitation. The dynamics of state of consciousness is computed for C2 class input vectors with fair and biased categories. The initial point of evolution of the state of consciousness of the system is considered to have median value. A relatively low amplification factor of excitation is considered to estimate natural dynamics.

5.4.1. Transformation with partial memory

On the first stage, the response of the system with partial memory is computed. In the case of partial memory, the system can store the previous state of consciousness indicating, $y|_{t+1} = avg(\beta_n|_t)$. However, the system cannot store the elements of previous set of input vectors throughout lifetime.

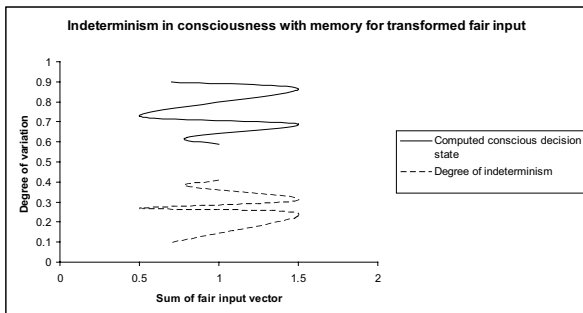


Fig. 23. Variation consciousness in system with transformed excitation (fair C2).

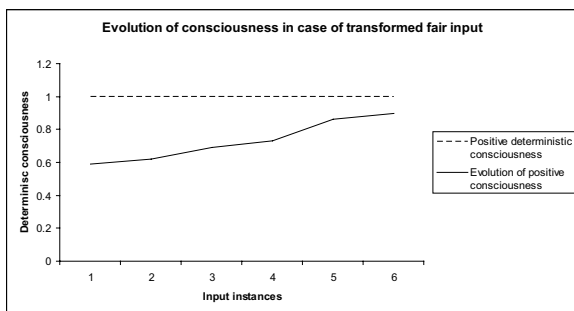


Fig. 24. Evolution of consciousness in system with transformed excitation (fair C2).

Thus, the initial values are set as, $y|_0 = 0.5$ and, $k = 1$. The inter-nodal signal transaction values are computed as, $I_{nt} = 0.5(\delta I_{cn}) + \lambda_n$ to eliminate over-excitation of transmission. The variations of state of consciousness and corresponding degree of indeterminism for fair C2 class input vectors in a system having partial memory are illustrated in Fig. 23. It can be observed that in the system having partial memory, transformation and fair C2 inputs exhibit symmetry in response. In this case, the state of consciousness is gradually evolved towards positive determinism as illustrated in Fig. 24. It is evident from Fig. 23 and Fig. 24 that, the indeterminism never reaches to zero and state of positive deterministic consciousness never reaches to unity.

However, if the input vectors are positively-biased, then the state of consciousness and degree of indeterminism of the system having partial memory tend to diverge as the input vector size in memory is monotonically increased. This effect is illustrated in Fig. 25. The evolution of consciousness, in this case, follows a steady and slow monotonic increasing path as depicted in Fig. 26.

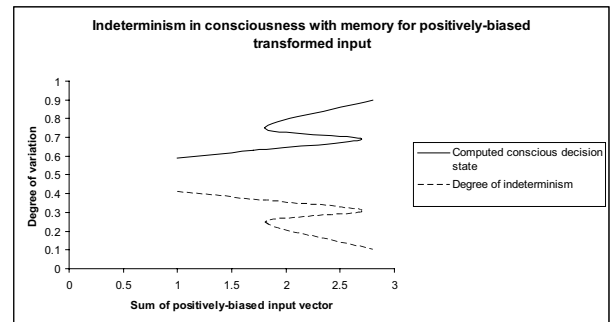


Fig. 25. Variation consciousness in system with transformed excitation (+biased C2).

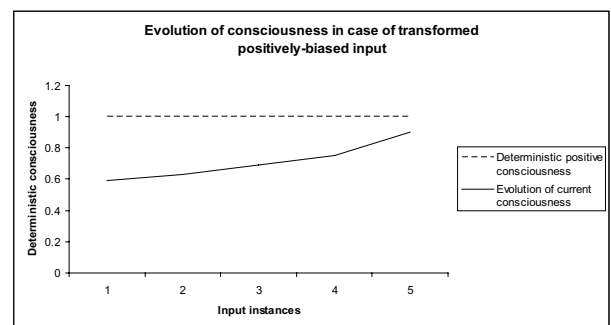


Fig. 26. Evolution of consciousness in system with transformed excitation (+biased C2).

In case of negatively-biased C2 class input vectors, a system having partial memory under transformed excitation exhibits fairly simple divergence patterns when

the vector size is monotonically increased. This is illustrated in Fig. 27. It is observable that, with the increasing negatively-biased inputs to the system, the degree of indeterminism tends to converge to the sum of inputs. On the other hand, the relative distances between the state of deterministic consciousness and degree of indeterminism in the system steadily increase as the sizes of input vectors are monotonically increased with negative bias.

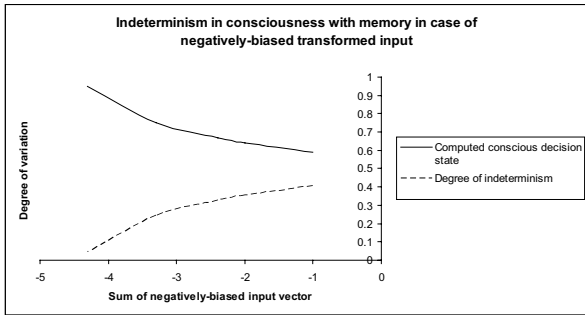


Fig. 27. Variation consciousness in system with transformed excitation (-biased C2).

The dynamics of evolution of state of consciousness of the system is illustrated in Fig. 28. It is evident that, the evolution of state of consciousness in a system having partial memory under negatively-biased input vectors along with transformed excitation is gradual in nature.

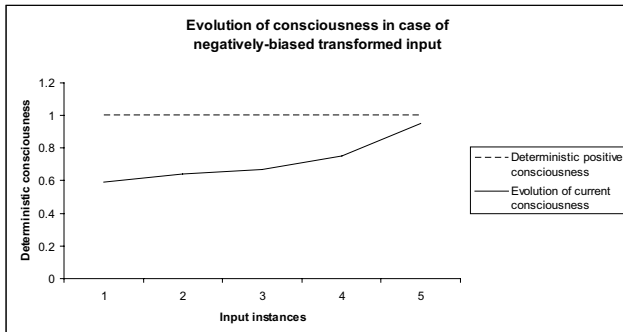


Fig. 28. Evolution of consciousness in system with transformed excitation (-biased C2).

5.4.2. Transformation with $\psi_{n,t+i}$

In the next case, the evolution of deterministic consciousness of a system having complete memory is computed. In the case of complete memory, the system can store the elements of previous state of consciousness as well as the history of input vectors indicating, $y|_t = avg(\beta_n|_{t-1})$ and, $I_{cn} = \sum_{j=0, t} I_{cn}|_j$. The initial values are set as, $y|_0 = 0.5$ and, $k = 1$. The inter-nodal signal transaction

values are computed as, $I_{nt} = 0.5(\delta I_{cn}) + \lambda_n$ to eliminate over-excitation of transmission. It is important to note that, the sizes and values of input vectors in all cases of experimentation in this section are kept exactly same as with experimentations with a system having partial memory. This would help to compare the dynamics of consciousness with respect to variations of memory capacity of a system.

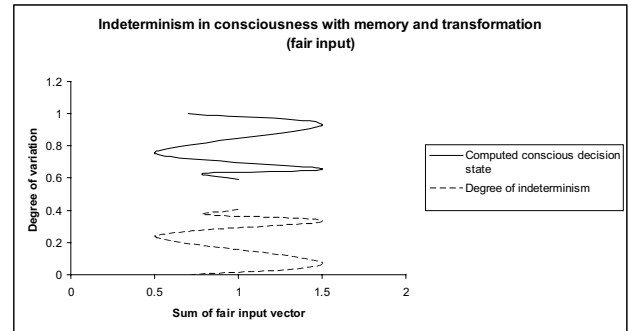


Fig. 29. Consciousness in complete memory system (transformed excitation, fair C2).

The evolution of positive deterministic consciousness in a system having complete memory along with fair input is illustrated in Fig. 29. It is evident that, when input vector size is monotonically increased, the system achieves deterministic consciousness rapidly and the degree of indeterminism reduces to zero. However, if the input vector is made positively-biased, then the state of positive deterministic consciousness fails to reach unity as illustrated in Fig. 30.

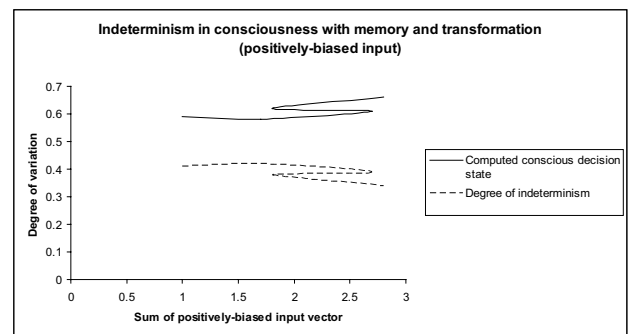


Fig. 30. Consciousness in complete memory system (transformed excitation, +biased C2).

The similar effect is observable in Fig. 31, when the input vector is made negatively-biased. In both the cases (with \pm biased inputs), a system having complete memory fails to achieve positive deterministic consciousness. Thus, the system having complete memory along with fair excitations can successfully evolve to the positive

deterministic consciousness state, which is consistent to nature. In other cases, the residual degree of indeterminism remains in the system to varying degrees.

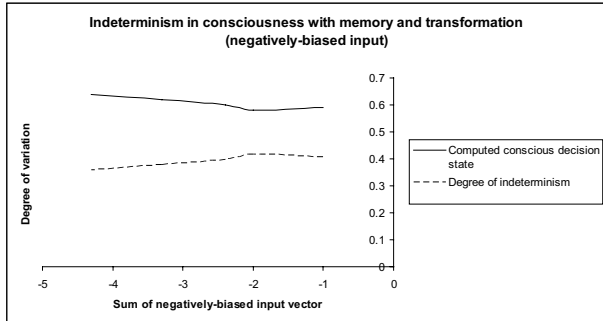


Fig. 31. Consciousness in complete memory system (transformed excitation, -biased C2).

6. Comparative Analysis

In this section, a detailed comparison of evolution of positive consciousness between a partial-memory system and a complete-memory system is explained considering same types and values of input vectors. The comparative study in case of fair inputs is illustrated in Fig. 32. It is evident that, a system having complete memory achieves positive deterministic consciousness, whereas a residue of indeterminism remains in a system having partial memory. On the contrary, the enhancement of memory to full extent by incorporating $\psi_{n,t+i}$ in a system would not help to achieve positive deterministic consciousness if the inputs to the system are biased as illustrated in Fig. 33 and Fig. 34. In these cases, the biased inputs negate the effects of gained experiences (y values) in a system irrespective of memory capacities.

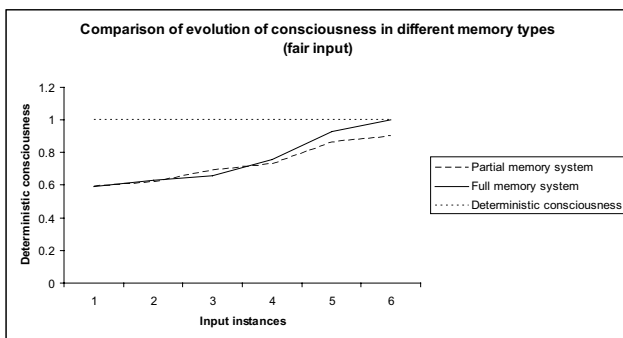


Fig. 32. Comparison of deterministic consciousness with memory (fair input).

The conjugated effects of memory capacity and the biasness of excitations to a system are observable in Fig. 35.

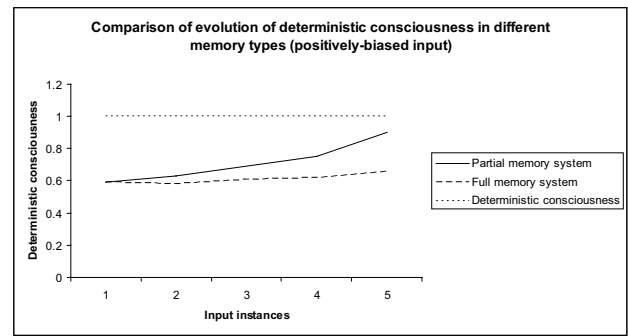


Fig. 33. Comparison of deterministic consciousness with memory (+biased input).

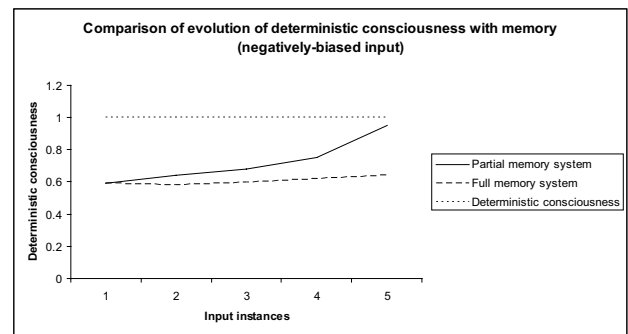


Fig. 34. Comparison of deterministic consciousness with memory (-biased input).

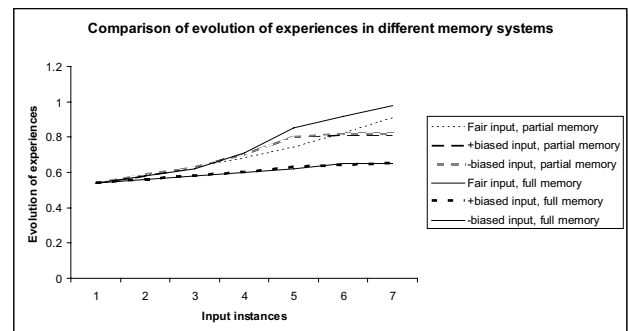


Fig. 35. Comparison of evolution of experiences in different memory and input.

A system having complete memory, transformation and fair inputs gains experiences from environmental excitations and thus, it reaches to the state of positive deterministic consciousness. The other systems with different memory capacities and transformation fail to integrate experiences from environmental excitations under different input conditions (biases), which negatively affect the evolution of state of positive consciousness in the systems. However, a system having partial memory fails to achieve positive deterministic consciousness with fair inputs, because partial memory containing reduced

information retards the evolution of experiences in such system.

7. Conclusion

The state of consciousness is an important neuro-cognitive function of brain having similarities to the elements of distributed computing. Thus, the computational model of consciousness can be constructed in view of distributed computing structures. Furthermore, the traditional distributed computing models can be transformed into bio-inspired adaptive distributed computing structures by incorporating the computational model of consciousness. In this paper, a computational model of state of deterministic consciousness is constructed by following the functional neurophysiology and elements of distributed computing. The constructed model follows the graph-theoretic view of the neurophysiology of brain having complex network structures. The proposed distributed computational model incorporates dynamics of neuro-signal propagation and fuzzy internalization of input excitations in the complex network of nodes. The delay-density variations and its effects on message propagations in the network are modeled following the dynamics of signals in the neuro-network of brain. It is illustrated that, the distributed computational model of deterministic consciousness incorporates memory and properties of evolutionary dynamics. Experimental results illustrate that, fair environmental excitations and nodal memory can realize the state of positive deterministic consciousness. Furthermore, a bio-inspired adaptive distributed computing structure is constructed by incorporating the computational model of consciousness resulting in nodal classifications at different levels.

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