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Review Article

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Computational Cybernetics of Glia-Neuron Cells Symbiosis versus Hopfield Recurrent Network: Do We Understand it? *

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Abstract

Science of artificial neural networks and relevant computing mechanisms since McCullock-Pitts artificial neuron [1] up via neurons and networks of Anderson (1972), Barto (1983), Grossberg (1967, 1976), *Hopfield* [2,3], Kohonen (1972) to Kasabov's evolving connectionist systems with spiking-neurons [4] have undergone developments beyond any conceivable predictions. The computational efficiency and functionality of all kinds of neural network implies stable operating steady-state equilibrium is fast established and guaranteed. In parallel, Neurophysiology has yielded many insights *Gayton-Hall* [5] converging to paradigm of systems biology. It appeared, on the crossroad of these findings with Hilbert's Thirteen problem and Kolmogorov's Superposition Representations in conjunction with Lyapunov foundations of stability and LaSalle invariance principle certain delicate subtle issues emerged *Siljak* [6] and *Sprecher* [7]. This re-thinking the foundations of neural networks via the quest for parallels between artificial and living neurons is believed to open a new horizon. This belief follows obtained results on cultured-neuron controllers and recurrent neural networks with time-varying delays. A closer look into how animal and/or human brain cells can be cultivated as a controlling brain for a mobile robot (physical body) such that can move around and interact with the world. In turn, a new kind of artificial intelligence may be created, which is emulated by stabilized complex highly non-linear complex neural network system.

Introduction

The idea of intelligent self-organizing system [8] has been put forward long ago by W Ross Ashby hence undergone tremendous evolution since. On the other hand, during the last few years there is taking place an unprecedented rapid development of computing software [9,10] for various technological applications largely based on cognition science and pattern recognition [11,12]. Even more so claims have been put forward by various software applications all designated as the real renaissance of Artificial Intelligence (AI) developments [10,13]. Recently deceased genius *Stephen W Hawking*, in his 2014 arXive article on conservation of information and estimation of time for black holes, argued that we are facing the century of complexity in the scientific studies and its mathematical capturing that grounded on physics composed energy, matter and information. Also, Hawking warned on considerable danger from abuse of AI information based technologies, which is imminent if the respective underlying human background be neglected. The main issues seem to involve interaction, interference, and interplay of energy, matter and information within complex networks and systems [15-18] such as the human brain is [19-22].

It is therefore that the complexity of human brain network systemic structure and integrity of harmonized and integrated functioning is getting an open question the knowledge quest on which seems a never-ending kind of story. Moreover, Hawking's warning emphasized how far reaching were the discoveries by

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David O Hebb (1949) on the learning organization of behaviour hence *John J Hopfield's* [3,23] dynamic artificial neural networks, physically founded on sound electronic foundations with rigorous mathematical proves via Lyapunov stability theory. The core heart of each of these discoveries was built up around the idea of recurrent network structure of neurons in the functionality of which human cortex retains centrality role hence the human intelligence mind does so too. Nonetheless, computational functionality of the recurrent artificial neural networks implies the operating steady-state equilibrium is reached fast and first.

Recently, *Forinto, et al*., [24] have proposed a rather innovative treatise of the fundamentals of brain network analysis approach. It appeared, the main issues evolve among the interference, interaction, and interplay of energy, matter and information within the complex networks such as the human brain appears to be. It has been generally adopted to view the healthy human nervous system for each of its life-physiology functions as a specific three-stage dynamic system with a certain internal, but outer acting, feedback with capacity of receiving stimuli (external and internal ones) and responding by relevant reaction as appropriate. Cybernetic computational model of the unit of neuron inevitably remain crucial hence new hybrid models of spiking neurons and artificial neural networks of *Kasabov* [25,26] and *Izhikevich* [27,28], *Izhikevich Edelman* [29] possessing for reaching performance effects have emerged. In those remarkable discoveries, however, the discovery of life science on glia- neuron-cell co-existence [29-33] in mutually supportive symbiosis has not been observed before the initial study [34,35] by these authors. This paper reports on the new follow up findings established.

Further this paper is written as follows. The next section presents some of the background scientific foundations for the present follow up study. In the third section, there is presented first brief but relevant discussion to outline the ideas behind the proposed novel model of a neuronal unit in recurrent Hopfield network; thus it leads to an innovated representation model of Hopfield network as well. The concluding remarks along with points research and the references follow hereafter recently has been discovered. It should be noted that glia- cells are electrically non-excitable [36] despite they accompany every neuron. In turn, the ANN community does not pay attention to glia-neuron symbiosis [14,16,29,37] let alone it does the AI community at large. It is a biological fact, neurons–the primary functional units that are electrically excitable–do get into close and crucial morphological as well as functional symbiotic relationship with glia-cells. In turn these occupy almost half the volume of the compound tissue with neurons.

On Certain Background Foundations

The just published most comprehensive exploration study by Ed S. Lein, Gabor Tamas and co-authors [38] has proven that glia-neuron-cell co-existence in symbiosis has not only vital but also far reaching on functionality of living neurons of human brain [39]. This fact has been discussed in SMC2016 paper by *Dimirovski*, et al., [19] at the same time argued it must be captured in the mathematical model of single artificial neuron (AN) in order to advance further computational power of artificial neural networks (ANN) along a road converging to living human neuronal network (LNN). This point appears rather crucial for the recurrent ANN aimed at mimicking human LNN.

Selected Points from Life Sciences

The life sciences based knowledge spectrum on recurrent neural networks delivered by Science of Neurophysiology [37] has yielded insights converging rather closer to the approach of Systems Biology Science [40]. Those considerably involved and non-transparent insights appear to fall on the crossroad of findings with Kolmogorov's representation superposition and Hilbert's Thirteen Problem hence yield emergence of certain rater delicate subtle issues as pointed out by *Sprecher* [7].

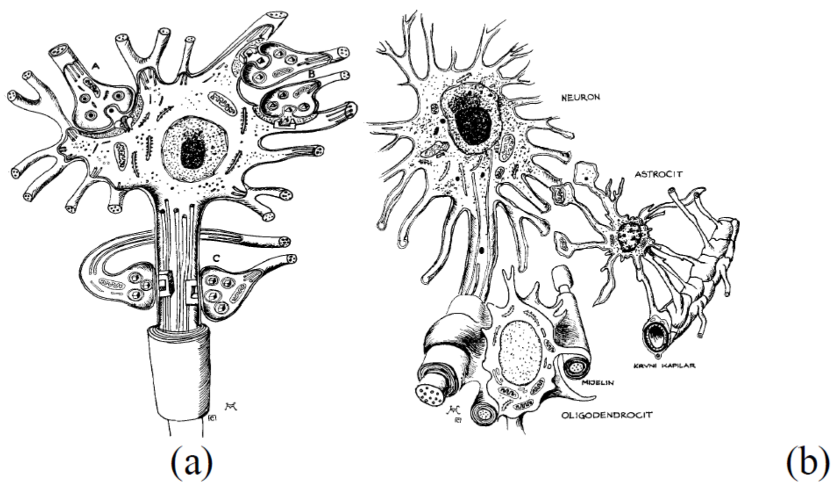

Figure 1: Schematic representation of living neuron physiology [22]: (a) on p.16, shoving synapses categories axon-somatic A, axon-dendritic B, and axon-axon C; and (b) on p. 26, showing symbiosis with glia-cell and blood vessels [19].

The present paper attempts to combine those two spectrum-ends in a cybernetic convolution by proposing an innovated electronic model of Hopfield recurrent ANNs based on the new model of the basic neuron unit employing the glia-neuron-cell symbiosis; see Figure 1. In particular the synaptogenesis in central neuronal system (CNS) [41,42] and the regulation of synaptic connectivity and communication [20,38,43] seem essentially dominated by this symbiosis. In [44], *Buffo* and *Rossi* [45] have shown clearly the origin lineage and function of cerebellar glia. Thus the closer examination neuron-glia symbiosis proposed in our SMC2017 paper [19] and investigation of its impact on revising the model of a single artificial neuron seems fully justified.

Physiological schematic of human neuron, as depicted in Figure 1, can be found in neuroscience literature where glia's internal structure [20-22] is also involved. Though, the impact of glia on neuronal synapses [38,41,46] only recently has been discovered. It should be noted that glia cells are electrically non-excitable [21] despite they accompany every neuron. In turn, the ANN community does not pay attention to glia-neuron symbiosis [14,16,29,37] let alone it does the AI community at large. It is a biological fact, neurons–the primary functional units that are electrically excitable–do get into close and crucial morphological as well as functional symbiotic relationship with glia-cells. In turn these occupy almost half the volume of the compound tissue with neurons.

Complexity [47] of neuronal tissue organization exhibits remarkable features [19,34,48] much more than that in a circuit implementation of RANN [5,29]. It is at the very 'heart' of the basic neuron where neuron-cells and glia-cells are interconnected via numerous mountain-spoors dendrites, and where inter-cell space is astonishingly reduced to a– possibly systemic–set of too narrow channels (Figure 2).

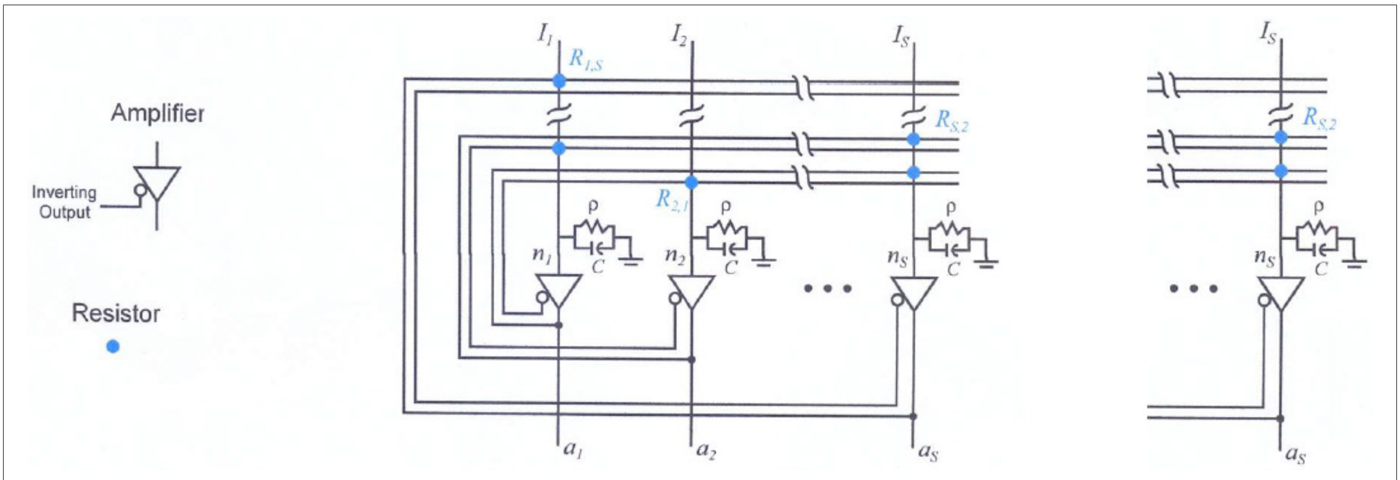

Figure 2: Schematic of originally envisaged Hopfield networks based on Analogue Electronics (a) as depicted in [17]; Fig. 21-3 (2a) in there and a scan of its last segment (b); both global and local feedback loops are readily inferred emphasizing the recurrent dynamic features of Hopfield's network system.

For these make a viable structure in which both cells accomplish their different as well as their specific functionality tasks. The comprehensive roles of this coupled complexity [10,19] is believed, to have been overlooked in more or less in all models of a neuron, in spite of its paramount importance understanding of the cybernetics of this complexity neuron- glia cells symbiosis appeals to revisit the modeling problem of the basic and primary unit of all neural networks.

For scientific reasons, first of all, we ought to refer to human central nervous system (CNS) where the neuron-glia symbiosis plays the crucial roles in human developmental life from the embryonic till the aging epochs [41]. It is not only for progressive daily functions and well-being. Though some of biochemical and molecular-biology mysteries of neuron- glia cells symbiosis only recently have been understood and uncovered; see works [4,10,11,20,21,29,30-32,36,49,50].

It is well known, interconnected neurons, via respective axon-dendrite synapses, constantly emit/receive chemically transmitted electrical signals thereby performing complex brain activities according to the processing of those signals, carrying biochemically encoded information Glia cells play crucial role in formation of synapses [44]. Furthermore, it was found, the glia-derived cholesterol is crucial for enhancing the CNS synapto-genesis [5], which largely governs most of mind functions and thus aspects of computational cybernetics [19]. As shown in [38], certain category of ions are transmitting signal to glia-cells, which likely then in turn enhance activities of the associated neuron-g ia cells. As shown in [45], there exists considerable ion-origin lineage enabling differentiation of glia-cells. It reflects on millennia natural evolution based, biological pattern recognition 'computation'.

Brief Overview of Authors Previous Findings

Several recent investigation studies by these authors, albeit one departed from the stability problem of recurrent artificial neural network [19,35] while the other form creating complex biological controller of cultivated rat brain on appropriate electronic circuit [50-52], ultimately have led to the common conclusion that currently mathematical models of a basic neuron unit have neglected the symbiotic co-existence of glia-cell and neuron-cell within the neuronal body. On the other hand, the Hopfield recurrent artificial network [2,3,46] is well-known to mimic human brain recurrent neuronal system considerably better than any other neuromorphic electronic system (Maed, 1990) based artificial neural network. However, nonetheless the unit artificial neuron that has been used in so far still does not account for and observe the essential life-supporting glia-neuron symbiosis [24,34].

Most recently these authors have embarked on exploration those findings and transcended them into novel ideas in ANN. There upon, they have made certain original innovation of the long existing computational neural networks such as multi-layer perceptron, involving models that capture glia's impulse phenomena within neuron-glia cells interactions. In classical literature [37] and recent fundamental articles [20,30,38,40,44,45] the symbiotic coexistence of neuronal cells and the associated glia cells has been pointed out to be rather crucial. But only a few have studied deeply [21,31,36,49] in the context of the ANN. In *Zhao, et al.,* [10] have observed the importance of neuron-glia symbiosis and have managed to develop a kind of extreme learning machine implementing soft computing decision-making for autonomous UAV missions.

Known Facts to Observe

A brief scanning of the selected references readily reveals the state of the art of both the feed-forward artificial neural networks (FANN) and the recurrent (RANN) ones [46,47,53]. The former have been well scientifically grounded via Kolmogorov's functional superposition theory of functions (see Sprecher, 2017, for a comprehensive study). Yet, the same cannot be said for the latter albeit Hopfield and his followers [2,3,46,] as well as Kasabov and his school [25,26] have indeed achieved remarkable progresses in this direction.

Nonetheless these both represent supervisory-controlled self-stabilizing and feedback reference-tracking network, systems that may contain hidden thousands and millions local feedbacks just as the human brain. Thus, naturally more than just one unique asymptotically stable operating equilibrium state do exist. In conjunction with Izhikievich's question [28] in his 2004 article (for full details of deeper scientific knowledge the references therein [28]) at this point. It is instrumental to revisit and carefully examine a brief, but illustrated, outline of what is pertinent to neuron [19]. These facts again support the innovated model as proposed in Figure 3 below.

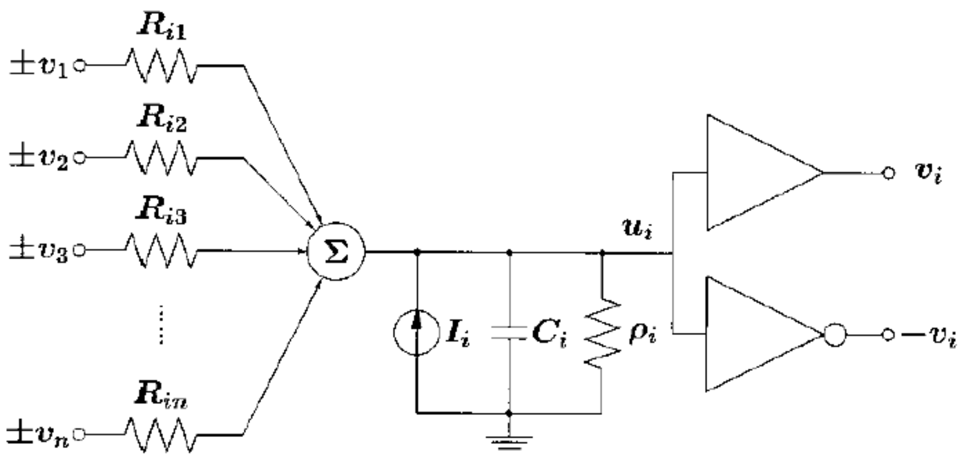

Figure 3: Novel representation model the neuron unit in Hopfield networks based on the investigations of these authors; in both cases the local feedback due to glia-neuron cell symbiosis is depicted by means of a varying resistor symbol in order to represent all the foreseen cases discussed above using either source models, of Khallil [54] or of *Jang, et al.* [55].

Guidance to Modify AN Model in Hopfield Networks

In order to present our understanding of neuron-glia symbiosis and its resulting impact on mutual functionality at neuronal level some facts on Hopfield networks [3,23] their outstanding computational cybernetics need to be recalled. In doing so, we shall make use of the Ch. 21 in the famous monograph [46] by Hagen and his collaborators; see Figure 2.

Figure 2A schematic of originally envisaged Hopfield networks based on Analogue Electronics (a) as depicted in [46]; Figure [3,45] (2a) in there and a scan of its last segment (b); both global and local feedback loops are readily inferred emphasizing the recurrent dynamic features of Hopfield's network system.

It is well known in his pioneering research *John J Hopfield* [3,13] had used analogue electronic-electrical units employing amplifiers as perceived in 1980-ties. In his fundamental article [3] he had pointed out: "Any physical system whose dynamics in phase-space is dominated by a substantial number of locally stable states to which it is attracted can therefore be regarded as a general content-addressable memory. The physical systems will be potentially useful memory if, in addition, any prescribed set of states can be readily made the stable set of the system." This was the departure point in the previous studies [40,35] and [50-51] by these authors (Figure 3).

Remark 1: It should be noted, formally, the authors have used different schematic drawings of analogue electronic amplifier in Figures 2-5. We followed strictly Hopfield's original conceptualization [23].

Thus, Khallil [54] has pointed out presence of both inverting and non-inverting outputs along with resistors and capacitors, as depicted in Figure 5. The pattern of chosen interconnections then allowed to derive the mathematical representation from Kirchhoff's Current Law. This law elementary unit level obeys linear superposition but enhances nonlinear overall dynamics on the entire neural network due to possible potentially induced amplifier operating in saturation mode, i.e. the typically used sigmoid $v_i = f\left(net_i\right)$ [21,23].

Somewhat slightly modified schematic is found in Section 11.17 in Figure 11.15 of famous monograph by *Jang, Sun and Mizutani* [55] in order to emphasize the dynamics of Hopfield recurrent network; see Figure 4 below Focused attention to the glia-neuron cell symbiosis yields discovery at the neuron level local feedbacks shall improve considerably the overall operating capacity of this network by self-stabilizing operating equilibria [6,19,48] induced shown in [56,57]. Nonetheless, on the grounds of the biological co-operative neuron-glia co benefit notice a nonlinear-function based feedback is needed too. In turn the proposed novel model appears as in Figure 5 which depicts both variants by making of electronic schematics above: (a) innovated Khalil's model in Figure 3; (b) innovated Jang's model in Figure 4.

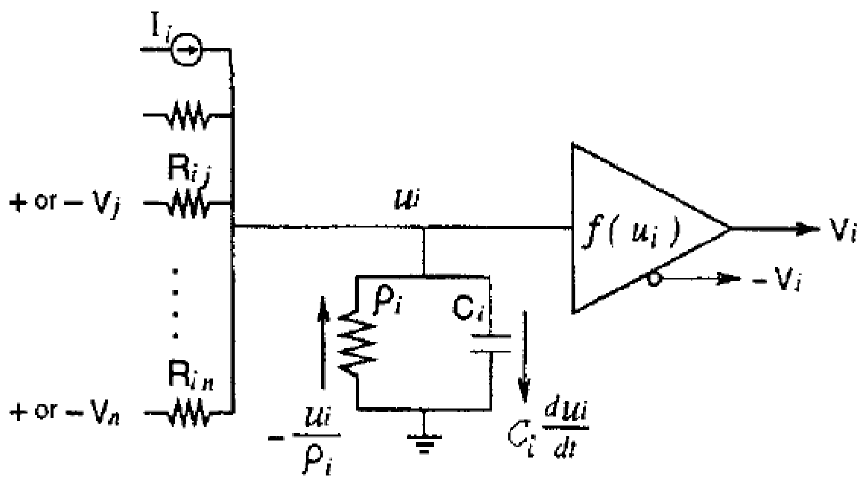

Figure 4: Schematic representation of the neuron unit in Hopfield networks based on physical electronics (a) as depicted in [55], Fig. 11.15 in Sec. 11.7.3.

Moreover, we believe, this nonlinear static feedback can be further extended by using self-stabilizing nonlinear systems in order to capture both the settled operating neuron-glia cells interactions and the switched ones between learning and non-learning phases. It is therefore the innovated electronic schematic for artificial neurons proposed as depicted in Figure 3 below.

It is apparent now that writing the respective equations down, based on Kirchoff's current law, is not that difficult task. Source equations of circuit in Figure 3 without feedback due to Khallil [54] are available in, while those of circuit in Figure 4 due *Jang, et al.,* [55] are available in. In here, it is adopted to approximate mathematically the unit glia neuron using the circuit in Figure 3(a). Then, it remains in the next step only current term through the feedback resistor is to be included as well. Proportional feedback employing constant resistor *RFBji* is naturally the simplest and straightforward one. However, we have in mind various feasible feedback paths hence we use slightly modified symbols for variables and parameters:

$$\frac{1}{R_{FBji}\left(R_{ij}\right)} v_{ji}\left(t\right) = C_i \frac{du_i(t)}{dt} + T_{ij} u_i\left(t\right) - \sum_{k=1}^{n} \frac{v_k}{R_{ik}} - I_i\left(t\right), \qquad (1)$$

$$T_{ji} = 1/\left(\rho_i^{-1} + \sum_{k=1}^{n} R_{ik}^{-1}\right),\ and\ R_{ji} = T_{ji}^{-1} \quad (2)$$

$$R_{FBji} = const, or\ R_{FBji} = N_{FBji}\left(t, v_j\right) \quad (3)$$

are subject to design synthesis [34,40]; voltages are carrier of processed information signals. If output is taken from the inverting amplifies then signs would be opposite. It should be noted however, the issue of the varying resistor feedback is an open issue yet to be explored and design synthesis of function $N_{FBji}\left(t, v_j\right)$ solved. Considerably many relevant variants may be conceived apparently, and one of those is to emulate adaptive control of switched nonlinear systems by *Sun, et al.,* [47]. Of course, this is one of the future research endeavors by those interested to pursue further this line of exploration [35,50].

At this point it should be emphasized that the proposed innovated model has been found [34,35] to comply consistently with the requirement for stable operating equilibrium of recurrent artificial neural networks possessing billions of local feedbacks with time-varying delays, which may involve time-delays, as proved in [56,57]. It is thus believed this novel representation model may well yield new prospect for further innovative improvements and wider of applications. In addition, considerable empirical evidence in Biological Neuroscience has been established suggesting that sections of human living recurrent neuronal network, while performing specific reasoning tasks, get coupled [27,46,58,59] into certain optimizing mean field game-like cooperation or non-cooperation. Thus, one possible modelling extension may be foreseen along the lines of mean-field game and optimal control theory [15,18,39].

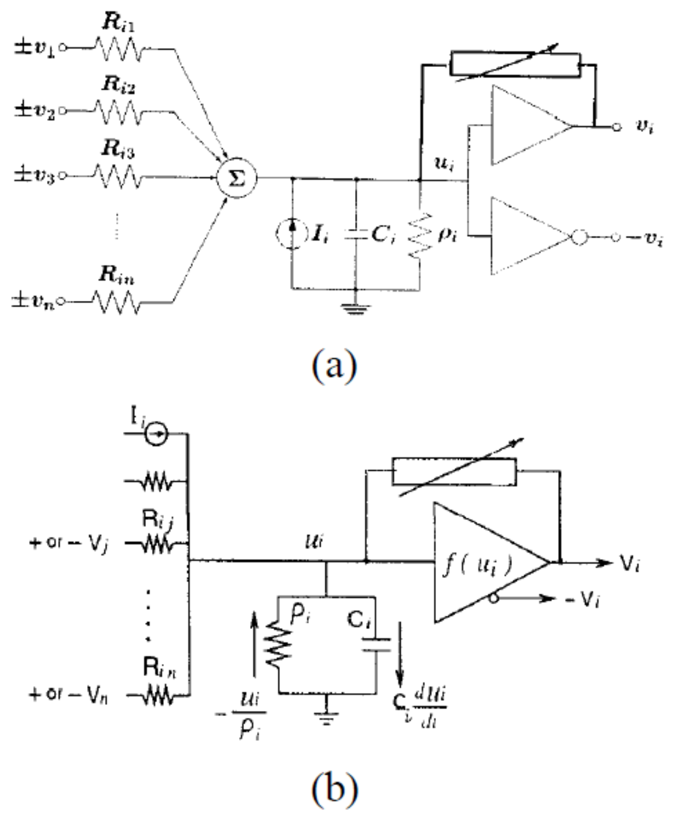

Figure 5: Schematic representation of the neuron unit in Hopfield networks based on physical electronics (a) as depicted in [54], Figure 1.3 in Sec. 1.2.5, where its essentially nonlinear dynamics is emphasized by its input-output characteristic of amplifiers and Khallil's comprehensive Lyapunov stability analysis in Sec. 9.5.

An Enquiry: Neural Intelligence Versus Biology

Comparison Looks Back on Artificial and Living Neurons Versus Human Neuronal System

Science of neural networks, since the artificial neuron of *McCullock and Pitts* [1] via *Hopfield's neurons* [3] to *Hagen and co-authors* [46] neural designs to Kasabov spiking-nerurons and 'neucube' evolving connectionist systems by *Kasabov* [25,26] to hybrid spiking models of neurons by *Izhikevich* [4,28] have undergone developments beyond any predictions put forward in due course. Even the most recent works by Hagen and co-authors, they begin rightly their book with this very first sentence: "As your read these words you are using a complex biological neural network. You have a highly interconnected set of some 1011 neurons to facilitate reading, breathing, motion and thinking. Each of your biological neurons, a rich assembly of tissue and chemistry, has the complexity, if not the speed of microprocessor. Some of your neural structure was with you at birth. Other parts have been established by experience." ending the quotation. Apparently there is no any other indication for further step to approach and possibly meet the other side of complex neural networks spectrum, the computational one.

Living Neurons Versus Recurrent Artificial Neuron Nets

These authors have not found even an indication for any further step into the other side of complex neural networks the spectrum, human living neuronal networks, to which recurrent artificial neural networks should imitate. Yet, on the other side of this spectrum Science of Neurophysiology [5] has yielded insights, which are converging closer and closer to the approach via the novel science of Systems Biology. Though, it is true that those rather involved issues on the crossroad of the current findings with Kolmogorov's representation superposition and Hilbert's Thirteen Problem. Furthermore, as thoroughly discussed by *David A Sprecher* [53] in monograph [22], it appeared [27] these crossroad findings to yield emergence of certain rather delicate subtle issues, which are yet to be explored [6,12,22,58,59].

Concluding Remarks

An innovated model of the neuron unit has been derived on the grounds of the recent discoveries of essential indispensable glia-neuron-cell co-existence symbiosis in human neurons. It has been obtained following Hopfield's ideas envisaging the unit neuron as well as recurrent neural network on the grounds of analogue electronics model [23,30]. The new feature in the proposed model is the emulation of glia-neuron-cell symbiosis in terms of local feedback path, which may be static proportional one or time-varying and even varying as if controlled switching of nonlinear systems.

Though intelligent systems ought to emulate biological intelligence [48] as close as possible and so do artificial neural networks [12,34,42]. The underlying issues of the varying feedback are an open task yet to be explored since design synthesis of function $N_{FBji}\left(t,v_j\right)$ solved. This is a topic of future research endeavors along the lines of exploration as in works [35,50].

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