American Journal of Engineering Research (AJER) **2022**
American Journal of Engineering Research (AJER)
e-ISSN: 2320-0847 p-ISSN : 2320-0936
Volume-11, Issue-11, pp-08-10
www.ajer.org
Research Paper Open Access

Realistic Neural Networks

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Abstract
After several decades of Research and Development there is still not much Science behind Realistic Neural Networks (RNN) and the Artificial Intelligence (AI) dependent on this Science. This short paper points out these deficiencies and proposes an easy way to at least bring in some Science from Biological Intelligence (BI) as documented in the author's Statistical Mechanics of Neocortical Interactions (SMNI).
This paper proposes a relatively simple modification to Neural Networks (NN) to create more Realistic Neural Networks (RNN) and the Artificial Intelligence (AI) dependent on this Science. This work is based on the author's work and publications in Statistical Mechanics of Neocortical Interactions (SMNI), which has been in a series of 40+ papers since circa 1970, e.g., (Ingber, 2018).
Keywords: *statistical mechanics; neocortex; artifical intelligence*

Date of Submission: 26-10-2022 Date of acceptance: 06-11-2022

I. Background: Statistical Mechanics of Neocortical Interactions (SMNI)

Since 1981, SMNI scales synaptic interactions, from neuronal firings, to minicolumns-macrocolumns of firings, up to regional macroscopic sites (Ingber, 1981; Ingber, 1982; Ingber, 1983; Ingber, 1984; Ingber, 1985; Ingber, 1994).

SMNI has experimental data from neocortical interactions: properties of short-term memory (STM) (Ingber, 2012), including capacity in auditory 7 ± 2 and visual 4 ± 2 neocortex (Ericsson & Chase, 1982; Zhang & Simon, 1985), duration, stability, recency rule of primacy versus recency, Hick's law (Hick, 1952; Jensen, 1987; Ingber, 1999), macrocolumnar interactions including rotation of mental images (Ingber, 1982; Ingber, 1983; Ingber, 1984; Ingber, 1985; Ingber, 1994). SMNI is scales neuronal interactions across neocortical regions fitting EEG data (Ingber, 1997b; Ingber, 1997a; Ingber, 2012).1 depicts this model (Ingber, 1983).
Fig.

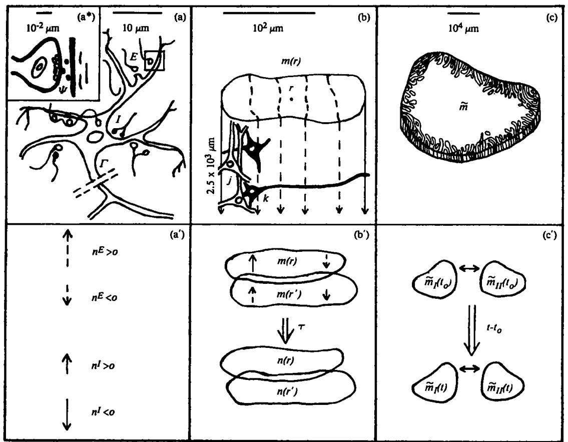

Figure 1 illustrates three SMNI biophysical scales: (a)-(a*)-(a') microscopic neurons; (b)-(b') mesocolumnar domains; (c)-(c') macroscopic regions.

(a*): synaptic inter-neuronal interactions, scaled up to mesocolumns, phenomenologically described by the mean and variance of a distribution Ψ (a): intraneuronal transmissions phenomenologically described by the mean and

variance of Γ (a'): collective mesocolumnar- averaged inhibitory (I) and excitatory (E) neuronal firings M
(b) : vertical organization of minicolumns including their horizontal layers, yielding a physiological entity, the mesocolumn (b'): overlapping mesocolumns at locations r and r' from times t and $t+\tau$, τ on the order of 10 msec
(c) : macroscopic regions of neocortex arising from many mesocolumnar domains (c'): regions coupled by long−ranged interactions

Permission to reuse granted by Physical Review A (Ingber, 1983).

Note that nonlinearities in the denominator of F^G are quite important to properly describe STM. Since 2012, quantum effects from tripartite synaptic interactions (neuron-astrocyte-neuron) have been added yielding synaptic interactions dependent on products of time and h.

II. Key Equations for RNN

The key equations proposed here to use in RNN are derived from columnar interactions:
The Lagrangian is the exponential argument of a conditional short-time probability distribution. In this Lagrangian there is an expression in terms of F^G that can be applied to RNN nodes. Note the presence of tanh which is present in many RNN models. The Lagrangian L is proposed to be used at RNN nodes. See (Ingber, 2018) and References therein for more details on the derivation.
This research also points to functional forms that can produce more accurate neural networks, thereby enhancing Artifical Intelligence (AI) by better mapping information from Biological Intelligence into AI, e.g., neuron-astrocyte-neuron tripartite interactions (Ingber, 2022b). Another important aspect of AI research should promote instilling affective understanding into AI systems, to better control "unintended consequences" of AI; this will require tests for AI systems (Ingber, 2022a).

The Ito prepoint representation (instead of the Feynman midpoint representation) defines the Lagrangian L

$$L = \sum_{G,G'} (2N)^{-1}(\dot{M}^G - g^G) g_{GG'} (\dot{M}^{G'} - g^{G'})/(2N\tau) - V' \tag{1}$$

where

$$g^G = -\tau^{-1}(M^G + N^G \tanh F^G)$$

$$g^{GG'} = (g_{GG'})^{-1} = \delta^{G'}_G \tau^{-1} N^G \mathrm{sech}^2 F^G$$

$$g = \det(g_{GG'}) \tag{2}$$

The threshold factor F^G is derived as

$$F^G = \sum_{G'} \frac{\nu^G + \nu^{\ddagger E'}}{\left((\pi/2)[(v^G_{G'})^2 + (\phi^G_{G'})^2](\delta^G + \delta^{\ddagger E'}) \right)^{1/2}} \tag{3}$$

where

$$\nu^G = V^G - a^G_{G'} v^G_{G'} N^{G'} - \frac{1}{2} A^G_{G'} v^G_{G'} M^{G'}, \quad \nu^{\ddagger E'} = -a^{\ddagger E}_{E'} v^E_{E'} N^{\ddagger E'} - \frac{1}{2} A^{\ddagger E}_{E'} v^E_{E'} M^{\ddagger E'}$$

$$\delta^G = a^G_{G'} N^{G'} + \frac{1}{2} A^G_{G'} M^{G'}, \quad \delta^{\ddagger E'} = a^{\ddagger E}_{E'} N^{\ddagger E'} + \frac{1}{2} A^{\ddagger E}_{E'} M^{\ddagger E'}$$

For this context with realistic experimental paramters, the system lies in a parabolic trough, which can be taken advantage using

$$a_{G'}^{G} = \frac{1}{2} A_{G'}^{G} + B_{G'}^{G} \, , \, a_{E'}^{\ddagger E} = \frac{1}{2} A_{E'}^{\ddagger E} + B_{E'}^{\ddagger E} \tag{4}$$

where $A_{G'}^{G}$ is the columnar-averaged direct synaptic efficacy, $B_{G'}^{G}$ is the columnar-averaged background-noise contribution to synaptic efficacy. The "‡" parameters arise from regional interactions across many macrocolumns.

Experimental evidence supports shifts in background synaptic activity under selective attention (Mountcastle *et al*, 1981; Briggs *et al*, 2013). The numerator of F^G has terms with $M^{E'}$, $M^{I'}$ and $M^{\ddagger E'}$. The "Centering Mechanism" creates a maximum number of minima to the physical firing M^G-space, due to the minima of the new numerator in a parabolic trough defined by

$$A_E^E M^E - A_I^E M^I = 0 \tag{5}$$

about which nonlinearities develop multiple minima. When this condition is applied, STM phenomena are calculated in agreement with experimental data.

III. Conclusion

Key equations for AI/RNN to include more realistic BI are given in this paper. It is essential to recognizethat STM survives within a sea of noise, so using all nonlinear features above is essential.

CONFLICTS OF INTEREST

The author states that there are no conflicts of interest.

AUTHOR CONTRIBUTIONS

The author has written the entire manuscript.

FUNDING

The author declares that all work on this paper has been done without external funding.

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Lester Ingber. "Realistic Neural Networks."*American Journal of Engineering Research (AJER),* vol. 11(11), 2022, pp. 08-10.