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Mathematical remarks on the computational study of perilesional plasticity in cerebral cortex

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Lesionectomy in eloquent cerebral cortex was practiced recently and has shown beneficial clinical effects (1). The idea of an underlying electrophysiological property for improvements observed after lesionectomy in eloquent areas was proposed using the capacity of artificial networks (2, 3). It has been demonstrated that artificial neural networks can be used for the modeling of injured cerebral networks and also as a modeling to estimate the response to treatments aimed at neural connections (3).

The modeling of neural function with artificial neural networks had two mathematical novelties in the field of neuroscience (3). First, the use of absolute nodal weights instead of real values made it possible to detect significant differences that were also consistent with the differences noted in the results of computational analyses. As it is shown in table 1, as compared to the similar table with absolute values in the original article (3), using real values results in similar means and wide standard deviations and hence abolishes significance of observed differences (3). Relative importance of input values on the production of desired outputs is provided by the Neural-Power software. It is also possible to check relative importance of input values by comparing their nodal weights (Table 2). The difference between relative impact of functional and disturbing signals is also significant when absolute values are analyzed. This also shows higher influence of functional signal in the network. The relative impact of functional signal decreases and that of disturbing signal increases in synchronous group. This is consistent with general theory of counter-plastic behavior of eloquent area cortical lesions (Table 2).

Second remark was the use of an index referred to as Rate of Change (ROC) in the second investigation. This notation is described as,

Table 1. Comparison of real values of nodal weights between random and synchronous groups derived from artificial neural network modeling as a comparison to absolute values in original article.

	Synchronous group (n=50) (Mean±SD)	Random group (n=50) (Mean±SD)	P-value
Input layer(n=100)			
Functional node	0.21 ±1.33	-0.062±1.67	0.20
Disturbing node	0.042±0.54	-0.029±0.46	0.313
Hidden layer(n=50)			
Hidden node 1	0.29±0.85	0.05±0.81	0.146
Hidden node 2	-0.032±0.758	-0.113±0.832	0.61
Bias node1(n=100)	.102±.598	-.013±.4942	0.13
Bias node2(n=50)	-.022±.253	-.049±.306	0.63

Table 2. relative impact of input variables analyzed with real and absolute nodal weights.

Relative impact	Functional signal	Disturbing signal	P-value
Absolute nodal values			
Synchronous network	1.061±0.827	0.454±0.298	<0.001
Random network	1.395±0.9116	0.365±0.277	<0.001
Real nodal values			
Synchronous network	0.210±1.333	0.042±0.543	0.24
Random network	-0.062±1.671	-0.029±0.459	0.85
Software developed relative importance			
Synchronous network	69.243±12.499	30.756±12.50	<0.001
Random network	78.02±11.31	21.97±11.31	<0.001

$$ROC = \frac{\Delta(Wt)}{\mathrm{Wt}} \quad \text{(Eq. 1)}$$

Where Wt refers to the nodal weight that is changing with every iteration analogous to time (t). Defining ROC as a differential equation and solving for "Wt" gives,

$$\int ROC \times d(t) = \int \frac{d(Wt)}{Wt} d(t) \quad \text{(Eq. 2)}$$

$$ROC \times t = \ln(Wt) + C \quad \text{(Eq.3)}$$

$$Wt = A \times e^{ROC \times (t)} \quad \text{(Eq. 4)}$$

$$Wt_{inf} = A \times e^{ROC} \quad \text{(Eq. 3)}$$

Where Wt_{inf} indicates nodal weight with infinitismus idea and lowest limit of time that is defined as a single iteration of calculation (t=1).

The parameters "ROC" and "A" can be estimated from calculations of two consecutive iterations of artificial neural network which itself can be used according to equation 4 to estimate the nodal weight of the same node in the next iteration. In order to study the response of each single node in the course of reorganization estimation units are defined: each estimation unit consists of three nodal weights corresponding to three consecutive iterations of a single node, of which 2 first weights overlap with previous estimation unit. The absolute deviation of formula-estimated "Wt" from software-calculated "Wt" for the third iteration can then be used and graphed as an indicator for fluency of network training and capability of learning in different settings of modeled real cortical networks and the efficacy of different ablative or reconnecting surgical and non-surgical techniques (Biofeedback, magnetic cortical stimulation, drug therapy) and as a means to study nodal microstate in course of clinical recovery.

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