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A NETWORK THEORY VIEW ON THE THALAMO-CORTICAL LOOP

We used a network theory approach, based on the dynamic core hypothesis (DCH), to study the thalamo-cortical loop (TCL) and its subsets regarding their role in consciousness. We used the Collation of Connectivity Data on the *Macaque* Brain (CoCoMac) and calculated the degree distributions, transmission coefficients, connection density, clustering coefficients, path lengths, and modularity. Our results showed that the TCL and cortex exhibit exponential degree distributions, and the ratio of efferent/afferent connections in the thalamus is smaller than 1.0 This may support the notion that the connections received by the thalamus from the cortex play a key role in improving information processing in the conscious states. The average values of transmission coefficients for the cortex and TCL were found to be equal to 1.49 and 1.28, respectively. This indicates that: (i) the cortex is a system that mainly transmits information outward rather than receives it; (ii) the TCL is a cooperative system that performs this in a give-and-take manner; (iii) connections of the cortex are denser than those in the TCL, showing that the cortex might be advantageous for processing of complicated information during consciousness; (iv) both the TCL and cortex are small-world systems; (v) the scaled value of the characteristic path length in the TCL is smaller than that in the cortex, which implies a higher speed potential for information processing in the TCL than in the cortex; (vi) the scaled value of the clustering coefficient is nearly the same in the cortex and TCL, and (vii) the number of modules is 5 in the cortex and 6 in the TCL.

INTRODUCTION

One of the main problems in neuroscience is to find the neuronal correlate of consciousness (NCC). In order to deal with this problem, deep researches were carried out within the past two decades, and three main brain systems having the potential to produce consciousness have been proposed. (i) The thalamo-cortical loop (TCL) as a network containing interconnected cortical areas and thalamic nuclei (thalamo-cortico-thalamic connections). The widespread recursive interactions among neuronal populations in the TCL are suggested to be crucial for consciousness [1]. (ii) The cortex. It has been suggested that the actual NCC is exclusively the cortex. In particular, Crick and Koch [2] speculated that the actual NCC may be "only a small set of neurons,

especially those projecting from the back of the cortex to its frontal part". (iii) Thalamus. Although most previous studies debated on the first two possibilities, Ward [3] proposed the "thalamic dynamic core theory of conscious experience," which emphasized the role of the thalamus in producing primary consciousness. Moreover, one of the main hypotheses concerning consciousness is the dynamic core hypothesis (DCH).

According to the DCH, since conscious experiences are integrated and differentiated simultaneously, its neuronal correlates should also have these features at the structural level [4-6]. If a system is responsible for consciousness, it should have these attributes at the structural level in order to produce different integrated contents over time. One way to study the structural characteristics of complex networks is the network theory approach. Using the network theory provides an overview on the functions of networks based on their structures. Recently, network studies have been carried out on some brain systems. For example, Modha and Singh [7] studied network structural architecture of the macaque brain. Sporns and Zwi [8] focused on the cortex and studied its

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small-worldness. Also, Hagmann et al. [4] studied the human cerebral cortex and observed a correspondence between structural and functional connectivities based on the graph theory. Because of the suggested role of the TCL in consciousness, network studies would be advantageous. Scannell et al. [5] studied experimentally the cortico-thalamic system organization in the cat with a collation method and then analyzed its global features that are not apparent in the primary connection data.

In our research, we used the network theory approach to study the TCL and its subsets, i.e., cortex and thalamus, regarding their role in consciousness. For this purpose, we used the data on the macaque cortex and the TCL anatomical connections [7]. This information is presented in the Collation of Connectivity Data on the *Macaque* Brain (CoCoMac) database [6]. We calculated the degree distributions, transmission coefficients, connection density, small-worldness, and modularity in the TCL, cortex, and thalamus. We finally discussed the above-mentioned measures in order to uncover the role of these areas in consciousness.

METHODS

Dataset. The data used in our study are anatomical connections of TCL and cortex of the macaque. These data is a part of the network presented by Modha and Singh [7]. They constructed a macaque brain network from the CoCoMac neuro in formatic dataset [6, 9, 10]. Their network contained 383 regions of the cortex, thalamus, and basal ganglia. They used the connectivity information of the whole brain, while we focused on TCL and cortex connections in our study. For this purpose, we selected connections between the thalamus and cortex. This means that we selected the edges whose sources and destination nodes are loca-

lized in the thalamus or cortex. Based on the edge relations presented [7], we constructed a 340×340 binary connection matrix (Fig. 1). The nodes with indices from 1 to 73 represent thalamus regions, and nodes with indices from 74 to 340 represent cortex regions. In this figure, three sub-networks, i.e., thalamo-cortical, cortico-thalamic, and cortico-cortical (cortex), are shown.

Network Analysis. In this paper, we used Matlab 7.8 for calculations of the degree distribution and transmission coefficient. The remaining analyses were done using Brain Connectivity Toolbox (BCT) [11].

Degree Distribution. The degree of a node k is the number of its connections with other nodes:

$$k_i = \sum_j a_{ij}, \tag{1}$$

when link (i,j) exists, $a_{ij} = 1$; otherwise, $a_{ij} = 0$.

The degree distribution is the probability distribution of these degrees over the whole network. Cumulative degree distribution is the fraction of nodes with degrees greater than or equal to k. For a directed network, in-degree and out-degree are defined as the number of edges coming into/out of a vertex in a directed graph.

Transmission Coefficient. In order to locally characterize inputs and outputs of a specific brain area (which is represented by a node in the brain graph), we use a simple measure known as the "transmission coefficient." Based on the definition, it is the relative number of efferents to afferents (in the graph theory known as out-degree and in-degree) [12].

For a given area (node)i, the transmission index (T_i) is

$$T_i = \frac{\sum_{j=1}^{e_i} A_{i,\varepsilon_i(j)}}{\sum_{j=1}^{e_i} A_{i,\varepsilon_i(j)} + \sum_{k=1}^{a_i} A_{\alpha_i(k),i}}, \tag{2}$$
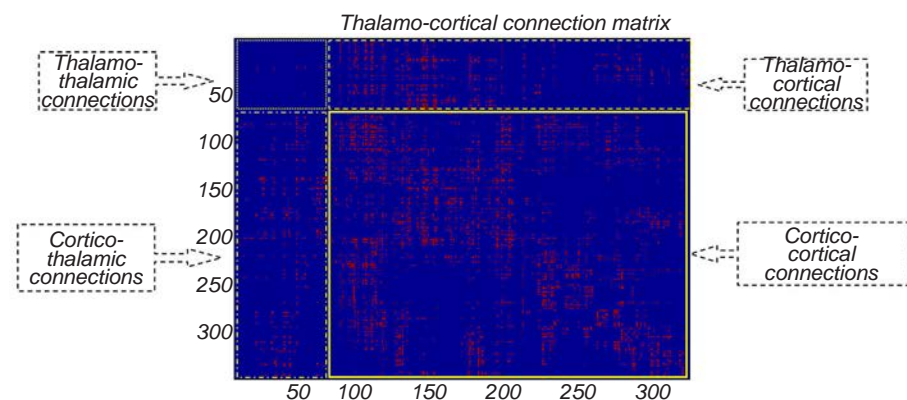

F i g. 1. Connectivity matrix of the thalamo-cortical loop (TCL). Sub-networks of the TCL are shown.

Р и с. 1. Матриця зв'язності в таламо-кортикальній петлі.

where

$A_{i,j} = 1$ when connection from area i to area j exists, and $A_{i,j} = 0$ when connection from area i to area j is absent, e_i and a_i are efferent and afferent connections; ε_i and α_i are indices for information on efferents and afferents, respectively; $T_i > 0.5$ means that the area i has more efferents than afferents; for $T_i < 0.5$, the situation is opposite [13].

Modularity. The modules in a network are its divisions into non-overlapping groups of nodes so that the number of within-group edges is maximized, and at the same time the number of between-group edges is minimized.

The modularity Q can be defined as a cost function:

Q = (fraction of the edges within communities) – – (expected fraction of such edges)   (3)

where a community is assumed to be groups of nodes in a network that are more densely connected internally than with the rest of the nodes. For a directed network, the equivalent of Eq. (3) is

$$Q = \frac{1}{m} \sum_{ij} \left[A_{ij} - \frac{k_i^{in} k_j^{out}}{m} \right] \delta_{c_i, c_j}, \qquad (4)$$

where m is the total number of edges in the network, which will have an edge from vertex j to vertex i with the probability $(k_i^{in} \cdot k_j^{out})/m$; k_i^{in} and k_j^{out} are the in- and out-degrees of the vertices, respectively; A_{ij} represents the connectivity between i and j and will be equal to 1 if there is an edge from i to j and equal to zero otherwise, c_i is the label of the community to which vertex i is assigned, and δ_{ij} is the Kronecker delta symbol. Then, a search algorithm is needed in order to find the optimum division of the network into communities, $\{c_i\}$. The optimization process is based on a Q cost function; the best division makes the Q maximum. In our study, we used the Brain Connectivity Toolbox (BCT) for calculation of modularity [11]. In this toolbox, determination of optimized module structures is based on the Newman optimization method [14].

Small-Worldness. When studying complex networks, one of the most interesting phenomena is "small-worldness", introduced by Watts and Strogatz [15]. Small-world networks have two main key features, a high "clustering coefficient" (similar to that in regular networks) and a low "characteristic path length" (similar to that in random networks). These two attributes provide small-world networks with some benefits in processing and transmission of information [16].

Based on the definition, the node clustering coefficient $\gamma (v)$ is the ratio of existing connections among the β_v neighbors and the maximal possible number of such connections $(\beta_v^2 - \beta_v)$. The clustering coefficient γ of the graph is the average of all node clustering coefficients [17].

An ordered sequence of distinct edges, which links a source vertex j to a target vertex i, is called a "path." The number of distinct directed edges in the path is defined as the "path length." The average length of the shortest paths is defined as the "characteristic path length" (λ) of a graph.

In a spectrum of networks, ranging from totally disordered to totally regular, random and lattice networks are the two extreme topologies. For evaluating the randomness or regularity of a given network, it is more informative to compare λ and γ of that network with their corresponding values in the two extreme topologies, i.e., random and lattice networks. Hence, scaled values of λ and γ for a given network of unknown topology are calculated as

$$\lambda_{scl} = (\lambda_{network} - \lambda_{random})/(\lambda_{lattice} - \lambda_{random}), (5)$$

$$\gamma_{scl} = (\gamma_{network} - \gamma_{random})/(\gamma_{lattice} - \gamma_{random}), (6)$$

where λ_{scl} and γ_{scl} will be between 0 and 1 in networks that are neither entirely random nor lattice.

We used the BCT for calculating of the clustering coefficient and path length [11].

RESULTS

The above-mentioned network measures and statistics were calculated for the macaque TCL data. Figure 2 shows the cumulative degree distribution in the TCL and cortex. During calculation of this measure, we did not take into consideration the direction of the edges. It is apparent from the Fig. 2 that the patterns of the degree distribution are nearly the same for the TCL and cortex. In order to consider the edge directions, in-degree and out-degree distributions of the TCL were calculated and are shown in Fig. 3. As mentioned before, nodes with indices 1 to 73 correspond to the thalamus regions, and the remainder ones correspond to the cortex regions. It can be observed that the out-degrees for the thalamus regions are lower than the average value over the whole TCL. Figure 4 shows distribution of transmission coefficient, which is the
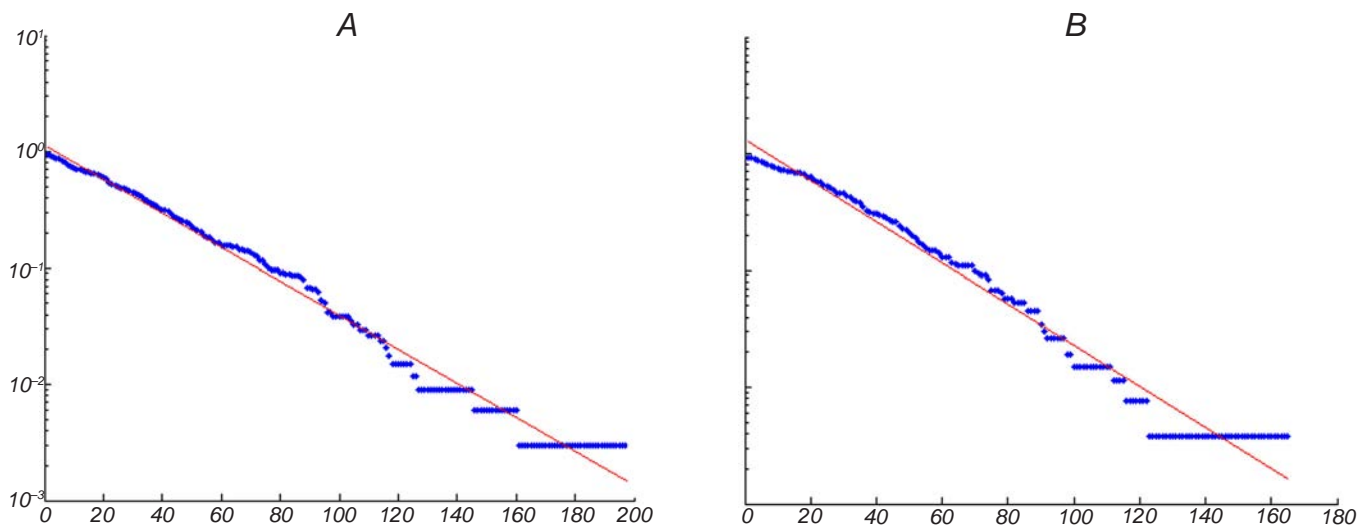
F i g. 2. Cumulative degree distributions for the TCL and cortex (A and B, respectively).

Р и с. 2. Накопичені розподіли рівнів для таламо-кортикальної петлі та кори.
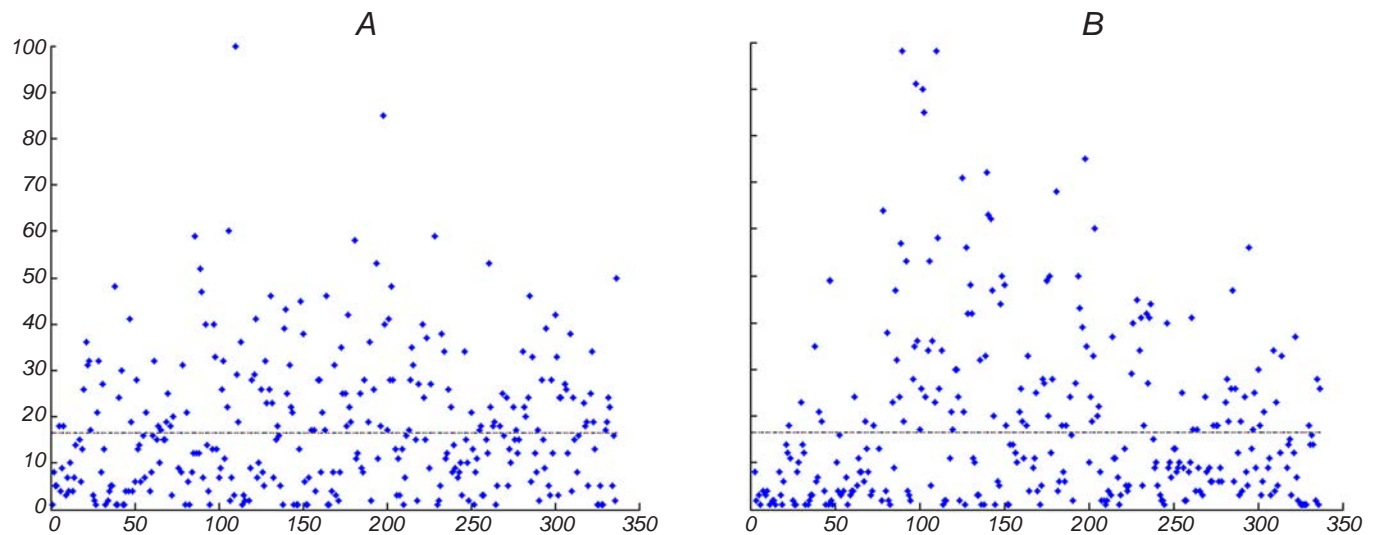

F i g. 3. In-degree and out-degree distributions for the TCL and cortex (A and B, respectively).

Р и с. 3. Розподіли внутрішніх та зовнішніх рівнів для таламо-кортикальної петлі та кори.

ratio of out-degree to in-degree links. From this figure, it can be seen that transmission coefficients for most thalamic regions are smaller than 1. Figure 5 shows results of comparison among the connection densities in the TCL, cortex, and thalamus. It is obvious from this figure that the connections in the cortex are denser than those in both TCL and thalamus.

In Table 1, results of small-worldness analysis are presented for TCL and cortex networks, as well as their corresponding random and lattice networks. Random and lattice networks have the same nodes and edges with the original networks. The normalized difference

(difference of two variables divided by the larger one) is 0.01. As is seen, the difference between clustering coefficients in the TCL and cortex is smaller. The scaled characteristic path lengths measure is lower for the TCL than for the cortex (their normalized difference is 0.28).

Results of modularity analysis are presented in Table 2. The number of modules is 6 for TCL and 5 for the cortex. The normalization difference between modularity indices of these two is 0.061.
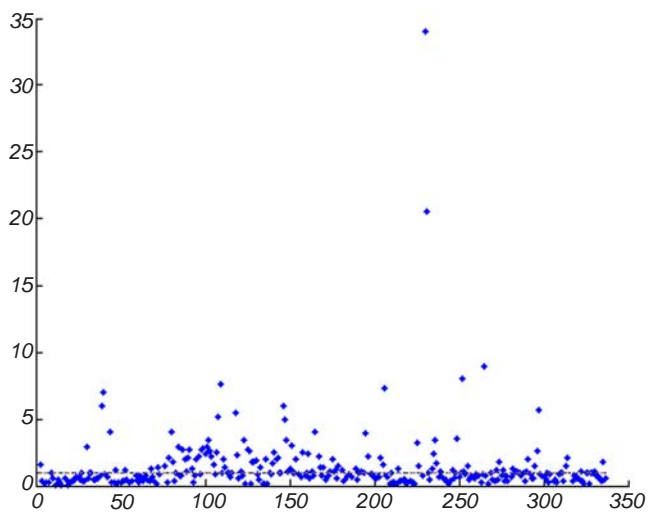
F i g. 4. Distribution of the transmission coefficients in the TCL.

Р и с. 4. Розподіл коефіцієнтів передачі для таламо-кортикальної петлі.

DISCUSSION

The majority of works showed that higher brain functions rely on the activity of large populations of neurons in TCL distributed networks [18, 19]. In our study, we used graph theory methods to study the TCL, cortex, and thalamus in order to investigate their roles in consciousness in the sense of DCH.

In general, our results show that: (i) The TCL and cortex exhibit exponential-degree distributions (see Fig. 2). The patterns of degree distribution for the TCL and cortex are the same. This result is in accordance with the data of Modha and Singh [7]; in their work, they studied whole brain networks. Hagmann et al. [4] calculated the degree distribution of the human cortex, which exhibited a normal-like distribution. It seems that the type of data, the method of data acquisition, and the resolution of the data may affect the results
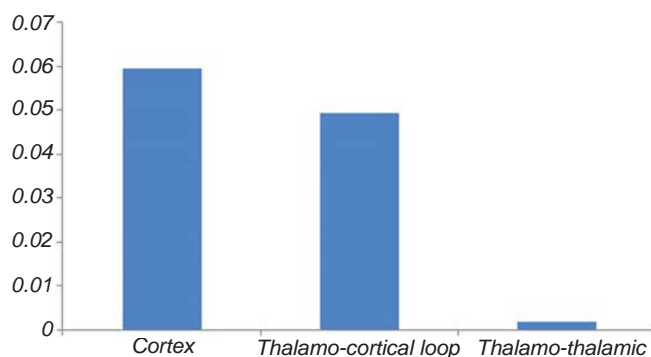

F i g. 5. Connection densities in the cortex, TCL and thalamus.

Р и с. 5. Щільності зв'язків у корі таламо-кортикальній петлі та таламусі.

and cause such differences. It should be noted that the Modha and Singh matrix used in our study is redundant (i.e., it includes overlapping regions that are difficult to interpret correctly within the framework of a single connectivity matrix). Moreover, it was extracted from the CoCoMac using an oversimplified technique that ignored contradictory statements in the database [20, 21].

(ii) The out-degrees of thalamus regions are smaller than the out-degree average over the TCL. This shows that the thalamus sends a smaller number of connections compared with other parts of the network (see Fig. 3). On the other hand, Fig. 4 shows that the ratio of efferent to afferent connections in the thalamus (thalamo-thalamic network) is less than 1 (with average 0.72), which indicates that afferent connections are more numerous than efferent ones. It seems that the reciprocal connections received by the thalamus from the cortex play a key role in improving information processing in the dynamic core, which will produce conscious states. The average values of transmission coefficients for the cortex and TCL are 1.49 and 1.28, respectively. This explains the cortex

Table 1. Small-world properties of the macaque TCL and cortex

Т а б л и ц я 1. Властивості модусу „дай-та-бери" в таламо-кортикальній петлі та корі макака

Region	Characteristic path length (λ)	Clustering coefficient (γ)
Cortex:		
Original network	2.53	0.34
Lattice	11.51	0.71
Random	2.3	0.06
TCL:		
Original network	2.57	0.33
Lattice	13.87	0.71
Random	2.37	0.049

Table 2. Modularity analysis of the TCL and cortex

Т а б л и ц я 2. Аналіз модульності таламо-кортикальної петлі та кори

Region	Number of modules	Modularity (Q)
Macaque cortex	5	0.363
Macaque TCL	6	0.341

as a system which, on average, transmits information outward rather than receives it and interprets the TCL as a cooperative system that functions in a give-and-take manner.

(iii) Connections in the cortex are denser than those in the TCL.This suggests that the cortex might be advantageous for processing of complicated information in the state of consciousness (see Fig.5). Both the TCL and cortex are small-world (see Table 1). Previous studies in humans, macaques, and cats have demonstrated the small-worldness of the cortex, but no study has evaluated this property in the TCL [5]. Since cortical and TCL networks have different sizes, we computed the scaled values of these two measures according to the corresponding random and regular networks for comparing their clustering coefficients and path lengths. The scaled clustering coefficients are nearly the same in the cortex and TCL (see Table 1).We found that scaled value of the characteristic path length in the TCL is smaller than that in the cortex (see Table 1), which may result from a higher speed of information processing in the TCL than in the cortex. The number of modules is 5 in the cortex and 6 in the TCL. This supports the notion of specialization of the TCL for performing particular information processing in consciousness according to the DCH.

Based on the results of our study, we suggest that TCL is the most appropriate candidate in studying the neural correlates of consciousness. While it has the capability of high-speed information processing, its sub-networks have interesting attributes. Intracortical (cortico-cortical) connections transmit information out more readily than receive it; the thalamus receives reciprocal cortical connections that extend the information processing in the dynamic core of consciousness. As a future prospect, it might be emphasized that using the network theory approach may be the key to uncover the functional role of the brain during cognitive behaviors, like consciousness [22].

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ЗАСТОСУВАННЯ ТЕОРІЇ МЕРЕЖ ПРИ АНАЛІЗІ ТАЛАМО-КОРТИКАЛЬНОЇ ПЕТЛІ

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Р е з ю м е

Ми проаналізували організацію таламо-кортикальної петлі (ТКП) і її компонентів, враховуючи її роль у забезпеченні свідомості, з використанням підходу, заснованого на теорії мереж і гіпотезі динамічного ядра. Ми використали базу даних про зв'язки в мозку макака (CoCoMac), розрахували розподіли рівнів і значення коефіцієнтів передачі, щільності зв'язків, коефіцієнтів кластеризації, довжини зв'язків і модальності. Отримані результати показали, що розподіли рівнів для ТКП і кори є експоненціальними, а відношення кількостей еферентних та аферентних зв'язків у таламусі є меншим одиниці. Це підтверджує положення про те, що зв'язки, одержані корою від таламуса, відіграють ключову роль в оптимізації обробки інформації в станах наявності свідомості. Середні значення коефіцієнтів передачі для кори і ТКП дорівнювали 1.49 і 1.28 відповідно. Згідно з цим, по-перше, кора є системою, котра в більшій мірі передає інформацію, ніж отримує її; по-друге, ТКП є кооперативною системою, яка виконує це в модусі „дай-та-бери"; по-третє, зв'язки в корі є щільнішими, ніж у ТКП, що свідчить про провідну роль кори в обробці складної інформації в стані свідомості; по-четверте, і ТКП, і кора є small-world-системами; по-п'яте, скалярне значення довжини зв'язків у ТКП є меншим, ніж у корі, що вказує на потенційно більш високу швидкість обробки інформації в ТКП, ніж у корі; по-шосте, скалярні значення коефіцієнта кластеризації в ТКП і корі є приблизно однаковими, і, по-сьоме, кількості модулів у корі і ТКП відповідають п'яти і шести.

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