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Using graph theoretical analysis of multi channel EEG to evaluate the neural efficiency hypothesis

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Abstract

Previous studies demonstrated that intelligence is significantly related to an impressive array of psychological, social, biological and genetic factors and that working memory (WM) can be considered as a general cognitive resource strongly related with a wide variety of higher order cognitive competencies and intelligence. Also, evaluating the WM of subjects might allow one to test the neural efficiency hypothesis (NEH). WM typically involves functional interactions between frontal and parietal cortices. We recorded EEG signals to study neuronal interactions during one WM test in individuals who had few years of formal education (LE) as compared to individuals with university degrees (UE). The two groups of individuals differed in the scores they obtained in psychological tests. To quantify the synchronization between EEG channels in several frequency bands, we evaluated the “synchronization likelihood” (SL), which takes into consideration nonlinear processes as well as linear ones. SL was then converted into graphs to estimate the distance from “small-world network” (SWN) organization, i.e., an optimally organized network that would give rise to the data. In comparison to LE subjects, those with university degrees exhibited less prominent SWN properties in most frequency bands during the WM task. This finding supports the NEH and suggests that the connections between brain areas of well-educated subjects engaged in WM tasks are not as well-organized in the sense of SWN.

Keywords: Neural efficiency; Graph theory; Small-world network; Synchronization likelihood; Working memory

Measurement of the brain’s glucose metabolism using positron emission tomography (PET) showed that cortical activation is more strongly focused and glucose consumption lower in more as compared to less intelligent individuals [9,10]. This observation has been explained by the neural efficient hypothesis (NEH), which predicts that lower and more focused cortical activation reflects higher neural efficiency. Thus, more intelligent subjects are expected to require less brain activation to accomplish a task and easier tasks are expected to produce lower brain activation in relation to difficult tasks. Additional studies using fMRI and EEG to evaluate local brain activation during cognitive tasks also supported this hypothesis [5,7,14,17–20,32] (see however ref. [18] for a discussion of studies failing to support the NEH).

Working memory (WM) can be considered as one general cognitive resource strongly related with a wide variety of higher order cognitive competencies and intelligence [4,7]. If WM underlies the mental abilities of normal individuals its study could allow one to evaluate the NEH. Here, we used a WM test such as the 2Back to check if persons that differ in their mental abilities (as shown by psychometric testing) due to the education they received (lower or higher) also differ in terms of neural organization at the network level. On the basis of the NEH, we hypothesized that brain activation is less intense when more educated individuals engage in cognitive tasks such as the 2Back WM test. This test is not particularly demanding so that less well-educated individuals do well albeit with longer reaction times and some failures. Our study is related to previous evaluations of the NEH in individuals with low or high intelligence. The latter term is used here in the sense of the empirical construct “g” (general intelligence) as discovered and described by

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Table 1
The psychological tests

	Low educated	High educated
WM: 2Back reaction time (ms)	1405.0 (610.1)	1043.2 (245.0)*
WM: 2Back error rates	4.4 (5.0)	0.0*
Digit span F	5.9 (1.2)	6.7 (1.2)*
Digit span B	4.5 (1.3)	5.9 (1.4)*
Digit symbol	51.6 (14.2)	63.0 (9.1)*
Stroop WCT	41.4 (8.2)	53.4 (11.4)*
Stroop Interference	−1.5 (5.8)	7.0 (8.6)*
Verbal IQ	110.6 (11.0)	129.9 (8.1)*

Mean scores (and S.D.) for psychological tests in both groups are presented. Asterisks indicate significant differences by Mann–Whitney test.

Spearman in 1904, and encompasses many individual cognitive abilities positively correlated with one another [4]. Additionally, g is significantly related to an impressive array of psychological, social, biological, and genetic factors [12]. Nevertheless, we decided to refer to the two groups of normal individuals we studied, as LE (those with few years of formal education) and UE (those with university degrees), respectively. Moreover, these two groups can be differentiated using classical psychometric tests as shown in Table 1.

For the purposes of this study, we used graph theoretical analysis to estimate neural organization during WM. Graphs, as mathematically defined, are abstract representations of networks consisting of sets of vertices (nodes) linked by edges (connections). Their complexity due to their size and their architecture necessitates the use of mathematical tools for their study. Graphs are characterized by a cluster coefficient C and a characteristic path length L. The cluster coefficient is a measure of the local interconnectedness of the graph. Technically it is the likelihood that the neighbours of a vertex will be connected to each other, averaged over all vertices. The path length is an indicator of its overall connectedness. It is the mean shortest distance (expressed in number of edges) between pairs of vertices, once again averaged over the whole graph. "Small-world" networks, as explained below, are characterized by a high C and a low L.

The method derived from this theory, can be used to study both local and long distance functional connectivity in complex networks. Interest in using graph theory to study neural networks has risen rapidly in recent years [1,8,25,24,27,30]. It provides a unique window into the balance of local and distributed interactions occurring in the brain [3,6,8,33]. It has been used in several neuroscience studies, in animals and humans, such as in studies of anatomical connectivity, fMRI BOLD and EEG or MEG signals [15,21,27,29]. Most importantly, graph theory allows us to define what should be considered an optimal network. The notion of an optimal network is closely associated with the "small-world" phenomenon. The so-called "small-world" network architecture is distinguished from either ordered or random networks. Networks with 'small-world' architecture are characterised by a combination of strong local clustering and a short characteristic path length (an index of global integration). This means that although most of the connectivity is local, the network remains highly integrated due to a small number of long distance connections. This has been proposed as a sign of optimal organization during specific functions [3,24].

To apply graph theoretical analysis to multi channel EEG data, we first estimated the synchronization likelihood (SL) to determine the scalp-wide pattern of functional connectivity. SL is a measure sensitive to both linear and nonlinear synchronization between signals, hence giving more accurate information about functional interactions [28]. This measure was then used to construct and evaluate the graph parameters. Because they are known to differ in terms of functional significance and their relation to each other [2,11,23,31], patterns of functional connectivity were determined with SL in different frequency bands of the EEG.

The 20 normal volunteers that were relatively less well-educated went to school for 11.3 years on the average. Fourteen of them were male and 6 female, while 17 were right-handed, 3 left-handed, and their average age was 31.9 years. The 20 volunteers with university degree were 27.4 years old, on the average and spent an average of 18.3 years in school. Fifteen were male and 5 female, 19 were right-handed and 1 left-handed. All evaluated individuals had unremarkable developmental histories and no relatives with psychotic illness. Additionally, they were examined with the Mini International Neuropsychiatric Interview to exclude major psychiatric disease. Prior to EEG recording, participants undertook the 1Back-, 2Back- and 3Back WM tests using Greek letters. The 1Back WM test is not really a WM test. We used it to help subjects familiarize themselves with the testing procedure. The 3Back WM test was very difficult for the less well-educated subjects who failed in it from the start and was thus discontinued. Thus, only the 2Back WM test was used in our study while recording EEG. Each test consisted of 18 trials 12 of which were correct (using only 6 letters of the alphabet called targets), while the remaining were false (foils). Besides the 2Back WM test (reaction time and error rates), both groups were psychometrically evaluated by one of the authors (E. Pachou) with the Digit span F and B, Digit symbol, Stroop and Verbal IQ tests. Written informed consent was obtained after complete description of the study to the subjects.

The EEG signals in both groups were recorded from 28 cap electrodes, according to the 10/20 international system, referred to linked A1 + A2 electrodes. We analysed epochs of 8 s at rest, i.e., while the individual had the eyes fixed on a small point on the screen of a laptop 80 cm in front of them and then during a 2Back working memory test using capital Greek letters (which differed from the letters used in the screening stage). Participants viewed letters that were consecutively presented to them and were required to press a button with their index finger whenever a current letter was the same as the letter presented two letters before. The hand they used in their responses was counterbalanced across subjects. In order to control for possible errors, only EEG data acquired during correct task completion were further analysed.

The synchronization likelihood between all pairs of electrodes was calculated after digital, zero-phase filtering to distinguish the traditional EEG frequency bands (theta, 4–8 Hz; alpha1, 8–10 Hz; alpha2, 10–13 Hz; beta, 13–30 Hz; gamma1, 30–45 Hz; gamma2, 45–90 Hz). Graph theoretical analysis was based on the full 28 × 28 matrix of all possible (378) pair-wise combinations of electrodes. Computation of the SL and the two graph theoretical measures (cluster coefficient *C*, and characteristic path length *L*) were estimated off-line with the DIGEEGXP software written by one of the authors (C.J. Stam).

The SL matrix was converted into a graph by choosing a threshold *T* and allowing the presence of an edge between two electrodes when their SL weight was greater than *T*. Otherwise that edge was set to zero. Hence the matrix of SL strengths between all pairs of electrodes was converted into a binary or unweighted graph. The next step was to characterize this graph in terms of its cluster coefficient *C* and its characteristic path length *L*. A formal description of the SL, the clustering coefficient and path length are given in ref. [29].

A sparsely connected graph is expected, on average, to have a lower clustering coefficient and longer path length than a densely connected one with the same topology. When *C* and *L* are evaluated as a function of threshold *T* for both groups, the results can be influenced by group differences in the mean strength of synchronization and the average number of edges in the graphs. To control for this effect we repeated the analysis, computing *C* and *L* as a function of degree *K*, which is the average number of edges per vertex. This is achieved by selecting the threshold that generates the desired number of edges, which will then be the same in all subjects. In this way any remaining differences in *C* and *L* between the groups reflect pure differences in graph organization. We calculated the *C*, *L* as well as the ratios *C*/*C*-s and *L*/*L*-s where *C*-s and *L*-s denote the values of *C* and *L* for appropriate ordered and random reference graphs, for $K = 4$, 5 or 6 [29]. Random graphs were generated from the experimentally obtained graphs by a constrained shuffle of the vertices, keeping both the number of vertices and the degree distribution constant. The random graphs with preserved degree distribution were obtained with the procedure described by Sporns and Zwi [26].

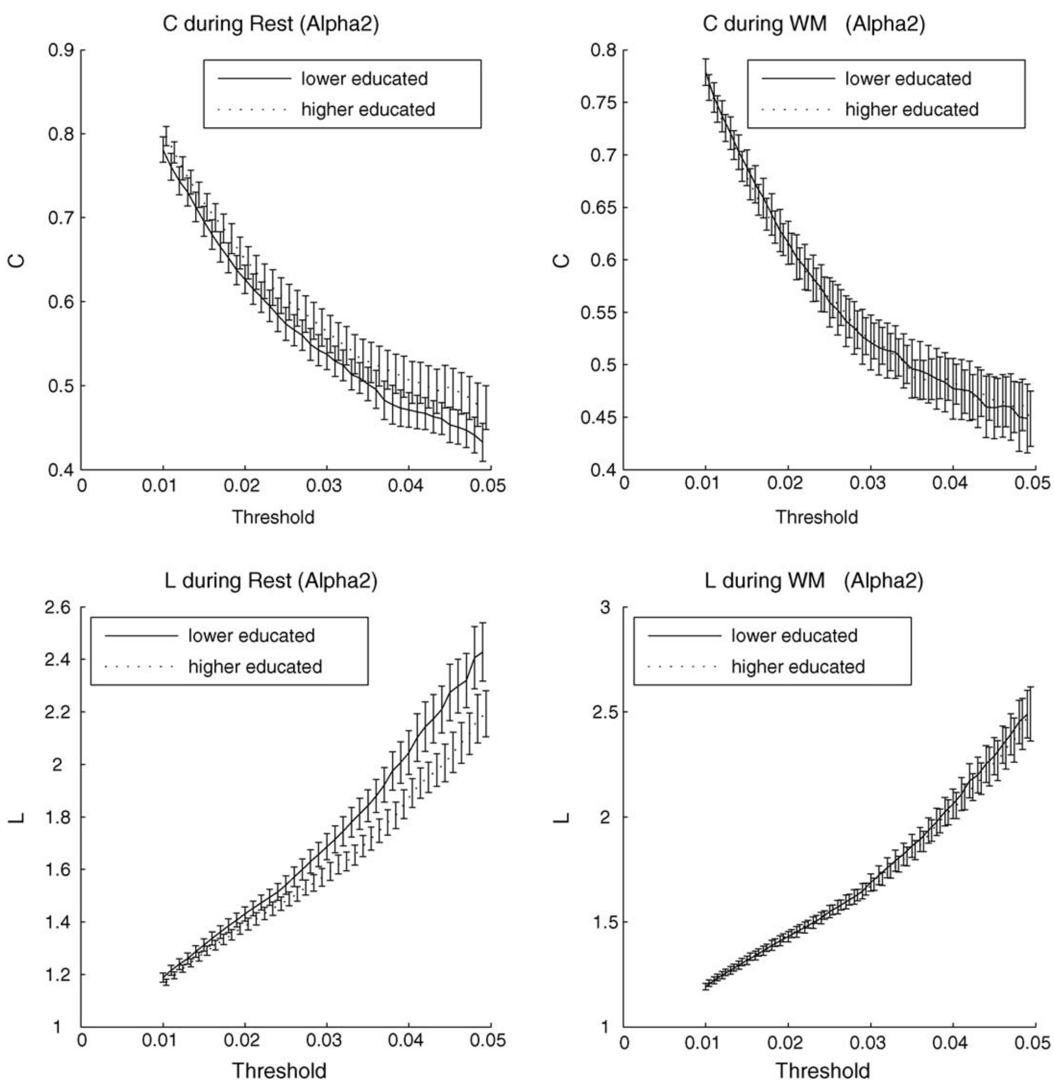

Fig. 1. Mean *C* and *L* of the alpha2 band. Mean cluster coefficient *C* and characteristic path length *L* of alpha2 EEG frequency band at rest and during WM for different values of threshold (0.01–0.05). The bars indicate the standard error of mean. Increasing the values of threshold, decrease the values of *C*, due to the fact that more and more edges are lost (providing that $SL < T$). In contrast, increasing the values of threshold, the average path length increases due to the fact that more and more edges drop out. For intermediate and higher values of thresholds, the cluster coefficient at rest and during WM is lower in the lower educated subjects. For the path length, the values of lower educated are higher at rest for intermediate and higher values of threshold. There are not statistical differences.

For statistical analysis we compared the SL values of the different EEG bands as well as the graph parameters (C, L, C/C-s and L/L-s) using t-tests and the neuropsychological results were compared using the Mann–Whitney test.

The results of the psychometric evaluations of both groups are presented in Table 1. Significant differences were found between both groups indicative of lower overall cognitive performances in the LE group. Not shown are the results of the 1Back "WM test" where both groups were equally successful.

The mean values of SL in all EEG bands showed no statistically significant differences between the groups. The results of the mean cluster coefficient C and the characteristic path length L both as a function of threshold for alpha2 band at rest and during WM are shown in Fig. 1. Between-group differences (lower C and higher L for less well-educated individuals) were observed in the alpha2 band for C and L and were more prominent for higher thresholds and at rest but did not reach statistical significance. Similar minor differences were also detected for the other bands (not shown) at rest and/or during the working memory test.

To control for the potential influence of subtle (non-statistical) differences in mean SL between the groups, additional results were obtained using constant K values of 4, 5 or 6. Recall, that undertaking the analysis for fixed node degree K instead of fixed threshold T, and constructing appropriate reference graphs, preserving the "degree of distribution", we normalize the networks and correct for the influence of any differences in the mean level of SL between the groups. Hence we focus on the ratio of C and L derived from the observed EEG data to matching values derived from the reference random networks (C-s and L-s): C/C-s and L/L-s. C/C-s and L/L-s values close to 1 are indicative of random networks. Simultaneous values of C/C-s and L/L-s significantly greater than 1 are indicative of ordered networks. Small-world network organization is evident when values of C/C-s are significantly greater than 1, close to 2 whilst values of L/L-s are near the value of "1".

The most striking findings in this study are at $K = 5$, as presented in Fig. 2. We see large differences between C/C-s and L/L-s during WM in the less well-educated group and for theta, alpha1, alpha2, beta and the gamma1 band. In the same frequency bands, differences between C/C-s and L/L-s were less prominent in individuals with university degrees but the graphs obtained from them also display the SWN pattern (L/L-s close to one and C/C-s close to 2). To render the difference between groups more clear we subtracted the L/L-s from the C/C-s separately for each group. The resulting values were statistically significant for theta, alpha1, alpha2, beta and gamma1 bands. This implies that the SWN organization during a WM task is lower in more educated subjects as compared to less well-educated ones, across almost all of the frequency bands examined. At rest the values show similar patterns in both groups and the comparison of the differences showed no statistical differences.

Differing patterns of functional integration were found for the theta, alpha1, alpha2, beta and gamma1 EEG frequency bands in both groups. During WM, the activity of these bands showed higher values of C and low values of L compared to (random) reference graphs during WM in lower educated individuals.

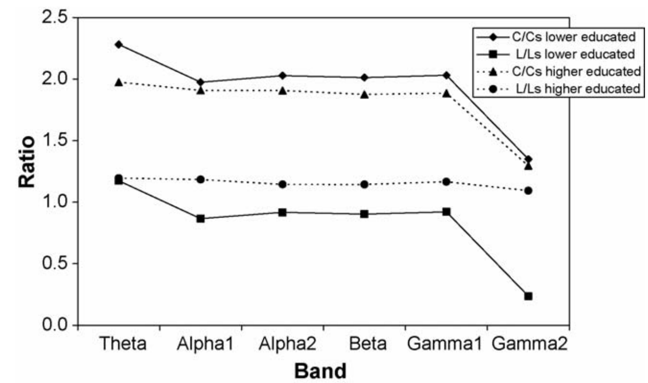

Fig. 2. Ratios of C/C-s and L/L-s during WM in both groups. The C/C-s and L/L-s during WM with $K = 5$ for both groups are represented. For theta, alpha1, alpha2, beta and gamma1 frequency bands, the individuals of both groups show L/L-s low values (near the value of 1) and C/C-s high values (near the value of 2). These differences are more prominent for the group of lower educated individuals. To render the difference between groups more clear we subtracted the L/L-s from the C/C-s separately for each group and the bands: theta, alpha1, alpha2, beta and gamma1. The resulting values were statistically significant (the SWN organization during a WM task is lower in more educated subjects as compared to less well-educated ones, across almost all of the frequency bands examined).

This "small-world" pattern is not as clearly present in relatively well-educated individuals and the differences between the two groups are significant (C/C-s minus L/L-s differ significantly for the mentioned bands). These findings suggest that the brain of better-educated individuals is less prominently organized along small-world network lines than that of less-educated subjects when both try to perform a working memory task.

The SW organization has some optimal properties. WM has limited capacity and exhibit linear or quadratic trends in brain activation [7,13,16]. The 2Back WM test we used is the simplest N-Back WM test and it is under these capacities as shown by the clinical findings. The LE group shows an optimal SW organization in contrast to the UE group where the more efficient WM is expressed by less prominent organized SW networks. Under WM load, less local activation was found in high-performing in relation to low-performing individuals in fMRI [22] as well as less local activation using EEG signals and ERD of the alpha band [7]. Our results agree with these findings estimating the coordinated activity of the neuronal assemblies. Coordination of activity between different neural assemblies is required to achieve a complex cognitive task or complete a perceptual process. Theoretical and empirical findings suggest that the behavior of neuronal assemblies may vary depending on the size of the neuronal populations involved and the strength of the interactions between the neurons that comprise them [31]. These are expressed in part by diverse changes in different EEG frequency bands. The higher SWN organization of individuals, who are less well-educated and are characterized by lower cognitive abilities, suggests that they need to optimize their neuronal organization to perform well in demanding cognitive tasks relying on WM.

WM is related to many cognitive abilities including intelligence [4] and it has been used to study the NEH [7]. Nevertheless, WM is one distinct cognitive function and our findings are to interpret as directly related to that cognitive function. We used one simple WM task which summons long-range cross-talk and this cross-talk typically is associated with SWN properties. The result is that the UE group responds more efficiently with less neuronal networks activation in this simple task. More WM load would result in more prominent neuronal SW organization.

Small-world networks have been described in a variety of natural and social systems [26]. They reflect a high degree of local clustering and a small number of long-range connections. Small-world networks have been shown to efficiently transfer information whilst simultaneously maintaining a local "working group" of neurons. That is, they satisfy the apparently competing needs for functional integration and functional segregation [27]. Small-world functional connectivity has been previously described in several frequency bands of MEG signals recorded from healthy, resting individuals and is indicative of their optimal functional organization [27]. Of particular interest is that the same author found that the *C* and *L* parameters evaluated from the beta band – the frequency most affected – of patients suffering from Alzheimer disease are modified in a manner indicative of the loss of complexity of the neural networks of such patients [29]. Studies such as this and the present one suggest that the method we employed could supply interesting insights into the organization of neuronal networks.

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