Supplementary materials

1 Materials and methods

1.1 Intracranial stereo-EEG recordings

Intracranial stereo-EEG recordings possess both high spatial and temporal resolutions for measuring neural oscillations. A public multicenter EEG dataset is brought in for our research which is accessible from the following web links: https://mni-open-ieegatlas.research.mcgill.ca/ (Frauscher et al., 2018a; Frauscher et al., 2018b; Fonov et al., 2011). The intracranial Stereo-EEG activities are recorded as a preoperative assessment before epilepsy surgery at several hospitals. A total of 91 patients are enrolled to uncover the critical role of sleep in the previous study. All the patients signed the informed consent forms. Strict inclusion criteria are taken to get recordings of normal activity from non-lesion tissues which are assessed by Magnetic Resonance Imaging (MRI) (Frauscher et al., 2018a), while normal activities are chosen but inter-ictal and ictal neural activities are removed for further research.

The selected EEG signals is comprised of wakefulness and three individual sleep stages as follows: rapid eye movement (REM), non-rapid eye movement stage 2 (N2), and non-rapid eye movement stage 3 (N3). The sampling frequency for EEG signals is 200 Hz. A length of 60s sections is selected corresponding to individual wakefulness and sleep state. Then the stereo-EEG signals are gathered together that recorded from the same brain area according to the atlas location. Owing to its important role in the brain, SN, DMN and FPN is the target in this study. Particularly, SN is comprised of the anterior insula (AI) and anterior cingulate cortex (ACC), and DMN is constituted with the posterior cingulate cortex (PCC) and precuneus, while FPN contains the middle frontal gyrus (MFG) and supramarginal gyrus (SMG) in this work. Considering about recordings from SN, DMN, and FPN, a group of five patients are enrolled for a significance test.

The implanted electrodes contain subdural grids and stereo-EEG electrodes (Frauscher et al., 2018a; Frauscher et al., 2018b). All the 1468 implanted channels are distributed in 38 regions per hemisphere according to anatomical registration, where the ICBM152 template is applied for co-registration and anatomical localization in stereotaxic space (Frauscher et al., 2018a; Fonov et al., 2011). As there are multisite corresponds to one cortical region, it enables the network investigation on three spatial levels of brain areas. In the small spatial level, each cortex is taken as an individual network. As for the medial spatial level, SN, DMN and FPN are formed and for the large spatial level, SN, DMN and FPN are combined together for network analysis.

1.2 Dynamic functional connectivity extraction

Wakefulness and sleep involve large-scale information exchange (Dimitriadis et al., 2010). The integration and segregation of information exchanges can be investigated by way of neural synchrony. In detail, phase synchronization indicates functional connectivity effectively (Dimitriadis et al., 2010; Lachaux et al.,1999). Phase locking value (PLV) is efficient for solving volume conduction and zero-phase problem (Dimitriadis et al.,2010; Lachaux et al., 1999; Tang D

et al., 2020; Cao et al., 2022). Therefore, PLV is taken as the functional connectivity measurement in this study. As delta sub-band neural oscillations contain frequency components ranging from 1 to 4 Hz, a 2s non-overlapping sliding window is chosen to detect dynamic changes across the whole course. Later the value of PLV will be taken as the element of the functional brain network, where a weighted undirected network is produced and self-connections are set to be zero. Therefore, frequency-dependent connectivity networks are generated according to the implementation of sliding windows, as each slice represents functional connectivity of multisite stereo-EEG signals lasting 2s.

Comprehensively, the Butterworth filter is adopted to bandpass multichannel stereo-EEG signals into delta ((1–4) Hz), theta ((4–8) Hz), alpha ((8–13) Hz), beta ((13–30) Hz), and gamma band ((30–45) Hz) neural oscillations. Hilbert-Huang transform is deployed to capture instant phase from these band passed neural oscillations (Huang et al., 1998). Later, PLV (Dimitriadis et al., 2010; Lachaux et al., 1999; Tang D et al., 2020; Cao et al., 2022) is carried out on the correspondingly particular frequency to measure phase synchronization. As the electrical behavior is transient and instantaneous, a non-overlapping sliding window is implemented to track the gradual and rapid alterations in electrical activities. To sum up, time-varying functional connectivity networks are extracted by way of PLV and sliding window.

1.3 Network Control theory

Network control theory refers to navigating a complex system to the desired state by way of perturbation on its elements. Controllability is related with connectivity topology and network dynamics in the brain (Gu et al., 2015, 2017). In detail, it provides a mechanistic explanation for human cognition. Network controllability quantifies the possibility that navigating one network to the desired state through perturbation. Regular sleep restores the brain for cognition implementation. Under the sleep condition, the brain reacts very few to external stimulation, while the brain adjust its neural behaviors as quickly as possible under wakefulness condition. Various ensembled neural behaviors are modified through local or global neural activity. The distinction is critical for the health of the brain, and it is presumed that different controlling strategy exists between wakefulness and sleep. However, there is a lack of experimental evidence regarding of network control in wakefulness and sleep.

The achievement of successful cognition depends on the interactions among distinct brain areas. Control and network theories offer the opportunity to capture underlying brain dynamics based on structural and functional network connectivity (Medaglia et al., 2017; Gu et al., 2015, 2017). Network controllability refers to the adaptive control from one state to another targeted state in a complex system (Gu et al., 2015; Karrer et al., 2020). At first, it focuses on the structural brain network derived from diffusion-weighted imaging, which demonstrates microstructures of white matter (Gu et al., 2015). Network dynamics are determined by interconnected units. In neuroscience, a trajectory is delineated as a temporal path across various states, while a state is interpreted as the temporal magnitude of neural activity. By way of the regulation on a single node, the brain network transits from one condition to another. In general, controllability portends the possibility of network manipulation over the desired orbit for favored states (Gu et al., 2015, Karrer et al., 2020).

1.4 Network controllability metrics

In the aspect of network controllability, three kinds of metrics are provided including average controllability, modal controllability, and boundary controllability (Gu et al., 2015). The network controllability quantifies the required energy for state control that achieves successful state transition after perturbation. Average controllability favors densely connected brain areas including DMN (Gu et al., 2015). Stimulating the default mode network induces great changes in large-scale brain dynamics because of dense structural connections (Muldoon et al., 2016). In other words, one node or subgraph spreads control energy to other components and changes the global state (Jeganathan et al., 2018). On the contrary, modal controllability measures the theoretical capability of a single node for driving the brain into hard-to-reach states. Boundary controllability quantifies the ability to integrate and segregate communities of the brain. Since the brain is composed of more than ten billion neurons, the complex network technique considers the total brain as a graph G=(V, E), which contains edge sets E and node sets V. The nodes denote distinct recording sites, while the edges represent their interaction measurements. In this work, control can be considered as the alteration of neural firings in the brain, which emerges as interactions among separate regions. As PLV is taken to calculate band-limited phase synchrony, the weighted brain matrix of G is defined as A=[aij], where self-loops are removed and each network is denoted as a separate 'state' value. This time-evolving state represents network evolution. Average and modal controllability are the main metrics in this work.

In graph theory, a network is denoted by the graph $\boldsymbol{G}=(V, E)$, where V and E stand for edge and node sets. For the associated matrix, its element a_{ij} denotes the weight between node$(i,j)\in E$, where the weighted matrix of $\boldsymbol{G}$ is a matrix $\boldsymbol{A}=[a_{ij}]\in R^{N\times N}$, and $a_{ij}=0$ if node i equals j. As linear discrete system is proved to have statistically similar controllability to a continuous-time system via Gramian, it is adopted for state transition investigation in the brain system (Gu et al., 2015). After the extraction of the functional brain network, the dynamics of neural processes are defined as follows (Honey et al., 2009; Gu et al., 2015) as a discrete-time system:

$$x(t+1)=Ax(t)+B_{\kappa}U_{\kappa}(t)$$

where $x{:}R_{>0}\rightarrow R_N$ delegates network states over time, $\boldsymbol{A}$ represents the weighted associated matrix, and B_{κ} stands for control point κ, while $U_{\kappa}{:}R_{\geq 0}\rightarrow R_N$ determines control strategy, where $\kappa=\{\kappa_1 \ldots \mathrm{k_m}\}$ and $B_{\kappa}=(e_{\kappa_1}\cdots e_{\kappa_m})$, where e_i represents the i-th canonical vector. The dynamics of neural processes are represented as functional connectivity networks in this paper. As for node sets κ, network controllability is equivalent to invertible Gramian controllability w_{κ} as follows in control theory:

$$w_{\kappa}=\sum_{\tau=0}^{\infty}A^{\tau}B_{\kappa}\,B_{\kappa}^{T}A^{\tau}$$

$$K=\{\kappa_1, \kappa_2 \ldots \quad \kappa_m\}$$

$$B_{\kappa}=(e_{\kappa_1}\cdots e_{\kappa_m})$$

The input matrix B_κ assigns the control points and κ stands for the controls point sets. U_κ:$R_{\geq 0}$→R_N delegates control tactics. As an example, one node is chosen at one time in order to simplify the calculation process. Later, average controllability is taken as the main metric as it counts the average input energy over all possible states in a limited set of control nodes (Kalman et al., 1963; Lee et al., 2016; Shaker et al., 2013; Gu et al., 2015), here Trace (w_κ) is taken as the route to quantify average controllability. Meanwhile, modal controllability is produced from the eigenvector, and all modes are taken into consideration in this scaled measure (Chari et al., 2022). If one sliding window is taken as a slice, the multi-slice connectivity matrix stands for network evolution under wakefulness and sleep condition. Then the node's states are combined into a vector to reflect state transition (Gu et al., 2015).

1.5 Dynamical neural process evaluation via network controllability

The dynamical neural process is delegated as the connectivity matrix derived from multisite recordings in the brain areas, including AI, ACC, MFG, PCC, Precuneus, and SMG, which constitute DMN, SN and FPN later. For each brain network, their nodes correspond with individual recording sites, and their edges represent phase synchronizations between them. For all these different network scales, a nonoverlapping 2 s windowed PLV is taken on band passed EEG oscillations to produce dynamic functional connectivity. Then network controllability metrics are implemented on these brain networks. The proposed framework is illustrated in Fig. 2. analysis of variance (ANOVA) and false discovery rate (FDR) are combined for the significance test (p<0.001).

Intracranial stereo-EEG recordings detect temporal continuity in the brain that ranges from multi-spatial scales. In detail, three spatial levels of network connectivity are considered contemporaneously. For the first level, small networks come from stereo-EEG recordings on AI, ACC, MFG, SMG, PCC, and precuneus separately. For the second level, medium correlation matrices are generated from SN (comprised of AI and ACC), DMN (contains precuneus and PCC), and FPN (incorporates MFG and SMG). For the third level, SN, FPN, and DMN are gathered together as a big network. Here small, medium, and big refer to the spatial coverage of brain areas.

Network connectivity reflects interactions among various neuron populations, while EEG gathers the postsynaptic potential together and reflects cognitive conditions objectively. At first, intracranial stereo-EEG signals are recorded by multisite stereo-electrodes for prior surgical evaluation in epilepsy patients, and normal neural activities are selected corresponding to wakefulness and sleep condition. Later, stereo-EEG signals are assembled from multiple subjects. In this study, the stereo-EEG signals come from 5 patients covering AI, ACC, MFG, SMG, PCC, and precuneus. Then bandpass filtering and Hilbert transform are implemented on windowed stereo-EEG signals to extract the transient connectivity network. Finally, average network controllability is carried out to depict the character of brain networks corresponding to individual frequency components.

Table S1 ANOVA test of Modal controllability in EEG networks

	ACC	AI	MFG	PCC	Precuneus	SMG
N2	1	$8.40 \times 10^{-4} *$	1	$5.40 \times 10^{-4} *$	$3.3 \times 10^{-4} *$	0.0188
N3	0.2502	$4.70 \times 10^{-5} *$	1	$5.40 \times 10^{-4} *$	0.0282	0.0632
REM	0.4633	0.0012*	1	$4.3 \times 10^{-5} *$	$2.1 \times 10^{-5} *$	0.9902
Wake	0.2179	0.5357	1	0.002*	0.0016*	0.9521

ANOVA: analysis of variance; N2: non-rapid eye movement stage 2; N3: non-rapid eye movement stage 3; REM: rapid eye movement; ACC: anterior cingulate cortex; AI: anterior insula; MFG: middle frontal gyrus; PCC: posterior cingulate cortex; SMG: supramarginal gyrus.

Table S2 ANOVA test of correlation between modal controllability and average controllability

	ACC	AI	MFG	PCC	Precuneus	SMG
N2	0.5715	0.9775	1	0.8534	0.99	0.9997
N3	$1.49 \times 10^{-4} *$	0.9955	0.0262	0.8356	0.9844	0.999
REM	0.5595	0.8602	0.0212	0.9737	0.9891	0.9675
Wake	$7.24 \times 10^{-5} *$	0.0027*	$3.33 \times 10^{-4} *$	0.0021*	0.0274	0.0195

ANOVA: analysis of variance; N2: non-rapid eye movement stage 2; N3: non-rapid eye movement stage 3; REM: rapid eye movement; ACC: anterior cingulate cortex; AI: anterior insula; MFG: middle frontal gyrus; PCC: posterior cingulate cortex; SMG: supramarginal gyrus.

Table S3 ANOVA test of average controllability metrics in five sub-band EEG networks

	ACC	AI	MFG	PCC	Precuneus	SMG
N2	$1.68 \times 10^{-6} *$	$5.43 \times 10^{-8} *$	0.0821	$4.80 \times 10^{-9} *$	$8.49 \times 10^{-4} *$	$4.26 \times 10^{-5} *$
N3	$5.21 \times 10^{-5} *$	$1.0 \times 10^{-7} *$	$1.14 \times 10^{-6} *$	$7.21 \times 10^{-7} *$	$3.13 \times 10^{-6} *$	$4.37 \times 10^{-5} *$
REM	$7.88 \times 10^{-7} *$	$1.50 \times 10^{-7} *$	0.3076	$2.10 \times 10^{-10} *$	0.0022*	0.0211
Wake	0.0014*	0.2739	$2.58 \times 10^{-4} *$	$3.58 \times 10^{-13} *$	$2.15 \times 10^{-4} *$	$1.28 \times 10^{-4} *$

ANOVA: analysis of variance; N2: non-rapid eye movement stage 2; N3: non-rapid eye movement stage 3; REM: rapid eye movement; ACC: anterior cingulate cortex; AI: anterior insula; MFG: middle frontal gyrus; PCC: posterior cingulate cortex; SMG: supramarginal gyrus.

References

Cao J, Zhao Y, Shan X, Wei HL, Guo Y, Chen L, Erkoyuncu JA, Sarrigiannis PG. Brain functional and effective connectivity based on electroencephalography recordings: A review. Hum Brain Mapp. 2022 Feb 1;43(2):860-879. doi: 10.1002/hbm.25683.

Chari A., Seunarine K. K., He X., et al., 2022. Drug-resistant focal epilepsy in children is associated with increased modal controllability of the whole brain and epileptogenic regions. Commun Biol., 5(1):394. doi: 10.1038/s42003-022-03342-8.

Dimitriadis S. I., Laskaris N. A., Tsirka V., et al., 2010. Tracking brain dynamics via time-dependent network analysis. J Neurosci Methods., 193(1):145-55. doi: 10.1016/j.jneumeth.2010.08.027.

Fonov V., Evans A. C., Botteron K., et al., 2010. Brain Development Cooperative Group. Unbiased average age-appropriate atlases for pediatric studies. Neuroimage., 54(1):313-27. doi: 10.1016/j.neuroimage.2010.07.033.

Frauscher B., von Ellenrieder N., Zelmann R., et al., 2018(a). Atlas of the normal intracranial electroencephalogram: neurophysiological awake activity in different cortical areas. Brain., 141(4):1130-1144. doi: 10.1093/brain/awy035.

Frauscher B., von Ellenrieder N., Zelmann R., et al., 2018(b). High-Frequency Oscillations in the Normal Human Brain. Ann Neurol., 84(3):374-385. doi: 10.1002/ana.25304.

Gu S., Betzel R. F., Mattar M. G., et al., 2017. Optimal trajectories of brain state transitions. Neuroimage., 148:305-317. doi: 10.1016/j.neuroimage.2017.01.003.

Honey C. J., Sporns O., Cammoun L., et al., 2009. Predicting human resting-state functional connectivity from structural connectivity. Proc Natl Acad Sci U S A., 106(6):2035-40. doi: 10.1073/pnas.0811168106.

Huang Norden E., et al., 1998. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. Proc. R. Soc. Lond. A. 454:903-995. doi: 10.21105/joss.02977.

Jeganathan J., Perry A., Bassett D. S., et al., 2018. Fronto-limbic dysconnectivity leads to impaired brain network controllability in young people with bipolar disorder and those at high genetic risk. Neuroimage Clin., 19:71-81. doi: 10.1016/j.nicl.2018.03.032.

Kalman, R. E., Ho, Y. C., Narendra, S. K., 1963. Controllability of linear dynamical systems. Contrib. Differ. Equat. 1, 189–213. doi:10.2478/bpasts-2013-0031.

Karrer T. M., Kim J. Z., Stiso J., et al., 2020. A practical guide to methodological considerations in the controllability of structural brain networks. J Neural Eng., 17(2):026031. doi: 10.1088/1741-2552/ab6e8b.

Lachaux J. P., Rodriguez E., Martinerie J., et al., 1999. Measuring phase synchrony in brain signals. Hum Brain Mapp., 8(4):194-208. doi: 10.1002/(sici)1097-0193(1999)8:4<194::aid-hbm4>3.0.co;2-c.

Lee H, Park Y. Degree of controllability for linear unstable systems. Journal of Vibration and Control. 2016. 22(7):1928-1934. doi:10.1177/1077546314545101

Medaglia J. D., Pasqualetti F., Hamilton R. H., et al., 2017. Brain and cognitive reserve: Translation via network control theory. Neurosci Biobehav Rev., 75:53-64. doi: 10.1016/j.neubiorev.2017.01.016.

Muldoon S. F., Pasqualetti F., Gu S., et al., 2016. Stimulation-Based Control of Dynamic Brain Networks. PLoS Comput Biol., 12(9):e1005076. doi: 10.1371/journal.pcbi.1005076.

Shaker H. R., Tahavori M., 2013. Optimal sensor and actuator location for unstable systems. Journal of Vibration and Control., 19(12):1915-1920. doi:10.1177/1077546312451302

Tang D., Du W., Shekhtman L., et al., 2020. Predictability of real temporal networks. Natl Sci Rev., 7(5):929-937. doi: 10.1093/nsr/nwaa015.