Dense array EEG in Analyzing Functional Brain Connectivity

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Weizhong He（Jack）
贺威忠
MagstimEGI

fieldtrip

Sensor-level ERF, TFR and connectivity analyses

Introduction

In this tutorial, we will provide an overview of several sensor-level analyses to help you get started working with FieldTrip. We will work on a dataset((Schoffelen, Poort, Oostenveld, & Fries (2011) Selective Movement Preparation Is Subserved by Selective Increases in Corticomuscular Gamma-Band Coherence. J Neurosci. 31(18):6750-6758)) collected during an experiment where subjects were instructed to fixate on a screen. Each trial started with the presentation of a cue pointing either rightward or leftward. This cue indicated which hand the subject had to use for the trial's response. Next, the subjects were instructed to extend both their wrists. After a baseline interval of 1s, an inward drifting grating was visually presented. Then, after an unpredictable delay, the stimulus changed speed, after which the subjects had to increase their wrist extension on the one cued side only. This experimental design is illustrated in Figure 1. Magneto-encephalography (MEG) data was collected using a 151-channel CTF system. Also, electromyography (EMG) data was collected from electrodes attached to the bilateral musculus extensor carpi radialis longus.

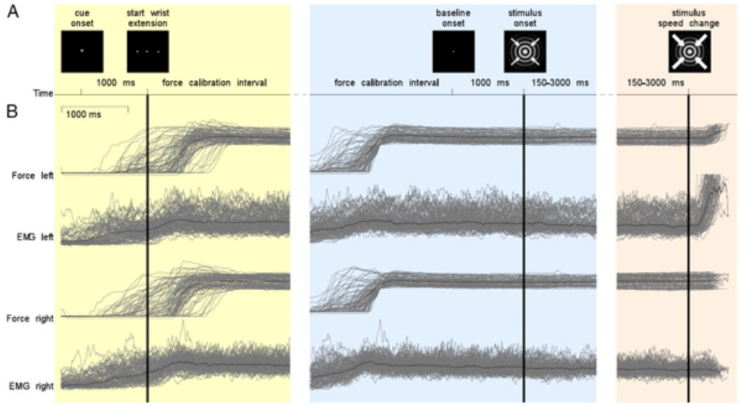
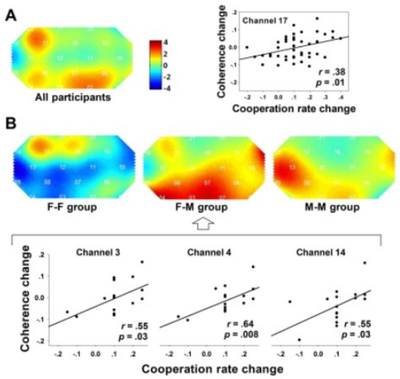


Figure 1: illustration of the experimental paradigm.

Hyperscanning system

“男女搭配”是否“干活不累”？研究者们将这一有趣的主题搬进了实验室。研究中，数名男性和女性被随机分配到异性组（F-M组）或同性组（M-M男组、F-F组）。互不认识的他们将搭档完成一项合作任务——在指示灯亮起时同时按反应键。每一试次后，屏幕将提示两名被试谁快谁慢，被试需要根据反馈来调整自己的反应速度，使得最终两人的按键尽可能同步。该实验采用超扫描的技术（hyperscanning），运用近红外光谱仪（NearInfraredSpectrumInstrument，NIRS）同时记录两名被试的大脑活动信号。



超扫描技术下，近红外光谱仪的大脑活动信号记录显示异性组的额区活动有明显相干性

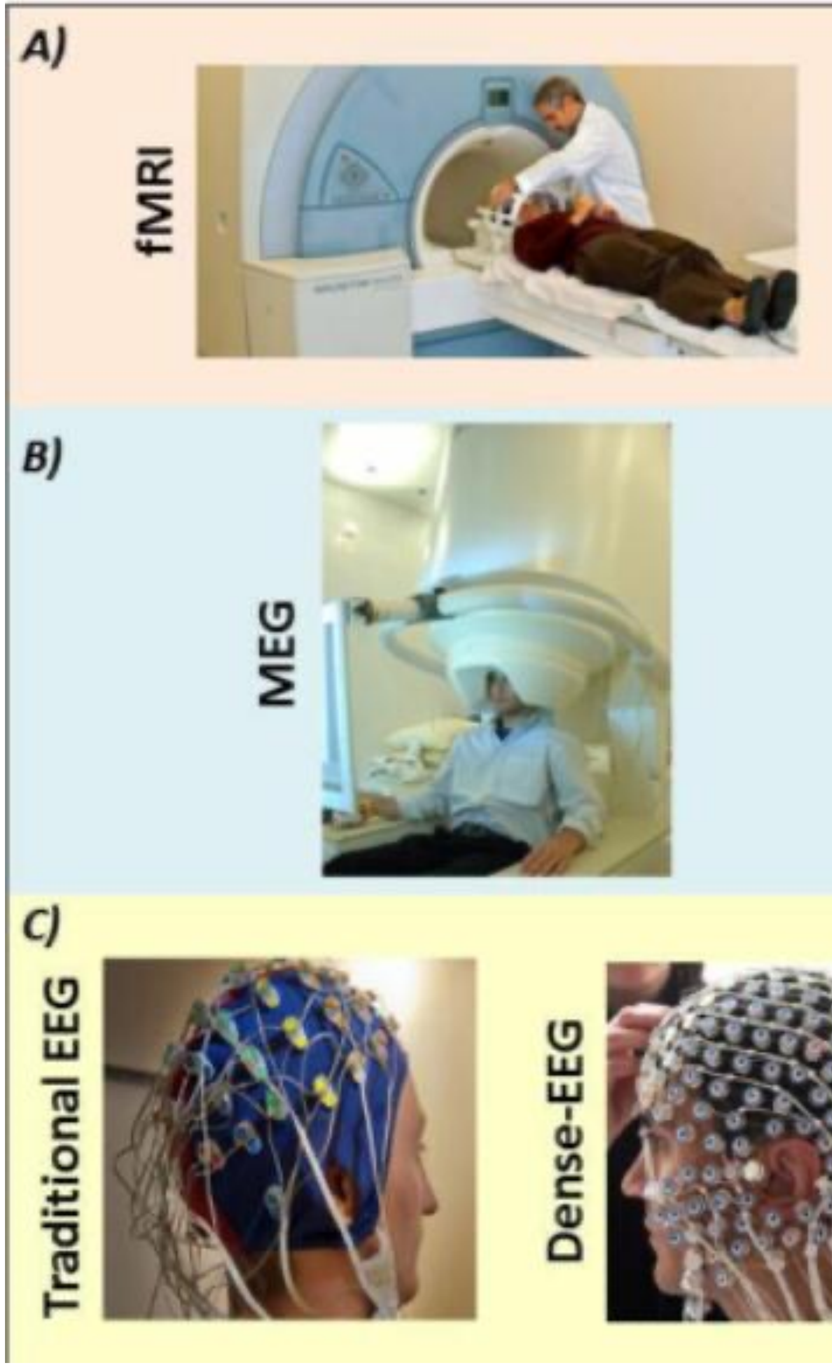
实验结果表明，异性组和同性组在行为成绩上并没有显著差异，即“男女搭配”并非不累。然而有趣的是，在进行合作时，异性组的两名被试的额区活动表现出了明显的相干性（即信号的同步性，coherence），且其相干性的变化与合作的绩效变化存在显著的相关。而对同性组的数据分析则并未发现这一现象。

fMRI

- Indirect signal
- Non-neural physiological influences (e.g Vascular properties, respiration)
- Low temporal resolution
- Spatial smoothing in fMRI preprocessing
- Possible inhomogeneity and instationarity of the hemodynamic response

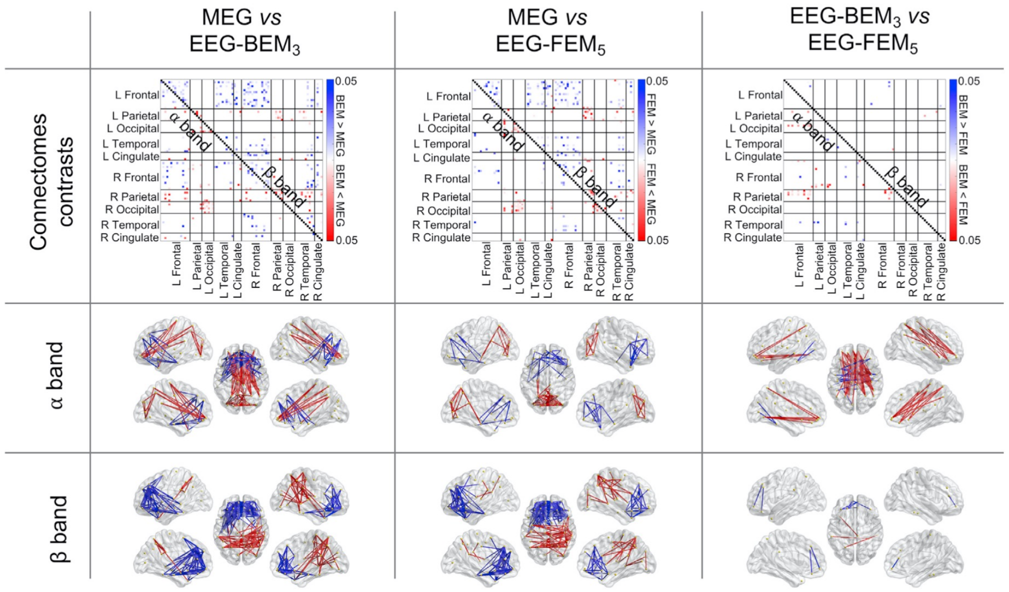
EEG/MEG

- Limited number of sensors, incomplete coverage
- Physiological artifacts and environmental noise
- Volume conduction
- Different sensitivity to deep/shallow or radial/tangential source
- Reference effect in the EEG



MEG VS hDEEG

Dense array EEG provide similar Network analysis result as MEG, but more suitable to clinical bedside



MEG

EEG

http://opencc.co.uk/blog/out-of-touch-manual-keypads-and-controllers-face-competition-from-new-hands-free-computer-interfaces/

Contents lists available at ScienceDirect

NeuroImage

journal homepage: www.elsevier.com/locate/neuroimage

Comparing MEG and high-density EEG for intrinsic functional connectivity mapping

N. Coquelet [a,*], X. De Tiège [a,b,c], F. Destoky [a], L. Roshchupkina [a,c], M. Bourguignon [a,d,e], S. Goldman [a,b], P. Peigneux [c], V. Wens [a,b]

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Types of Connectivity

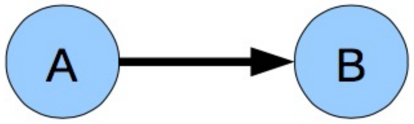
- Structure connectivity

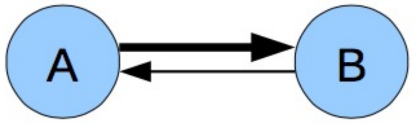
  anatomical connections

- Functional connectivity

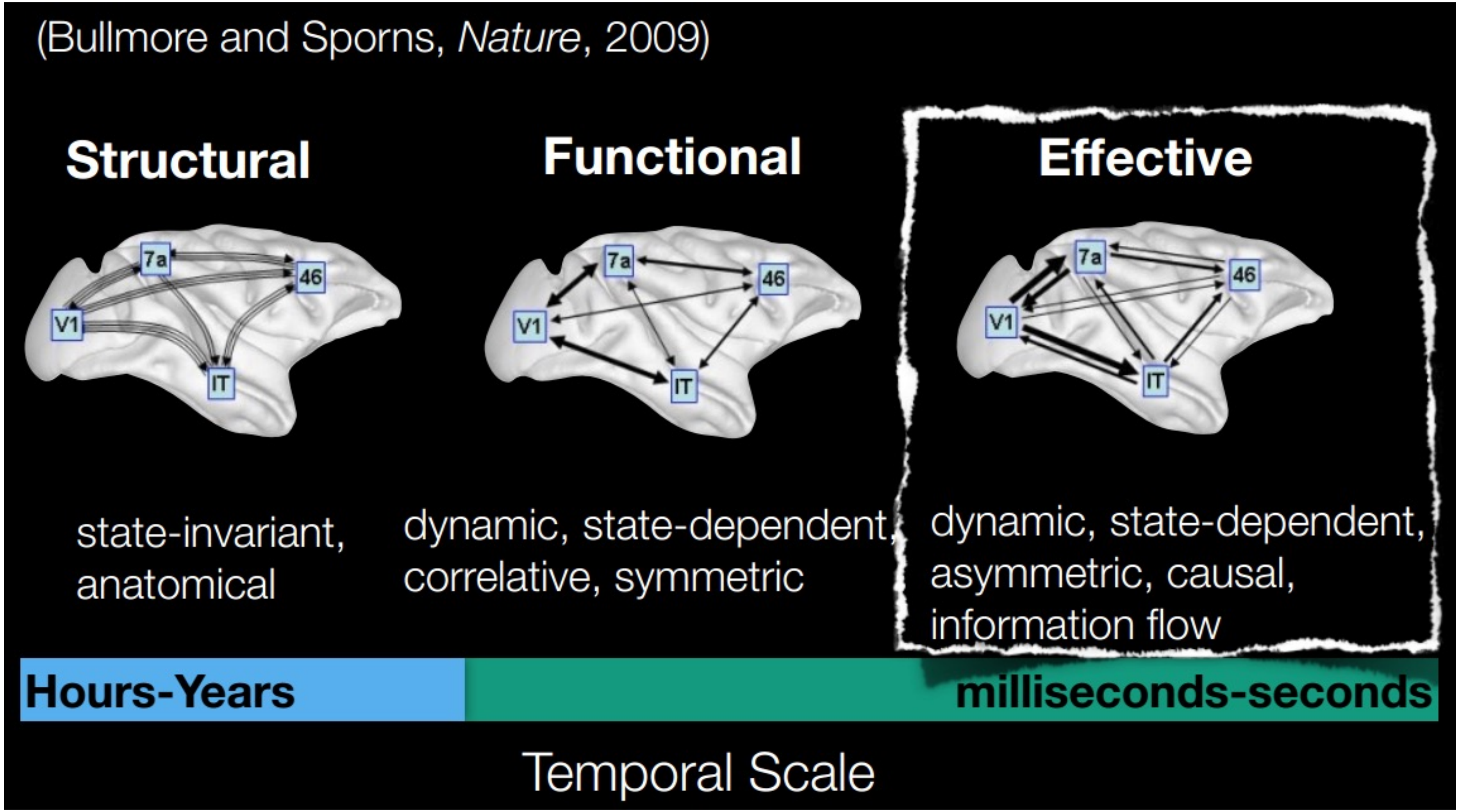
  Statistical correlations between activity in different brain regions

- Effective connectivity



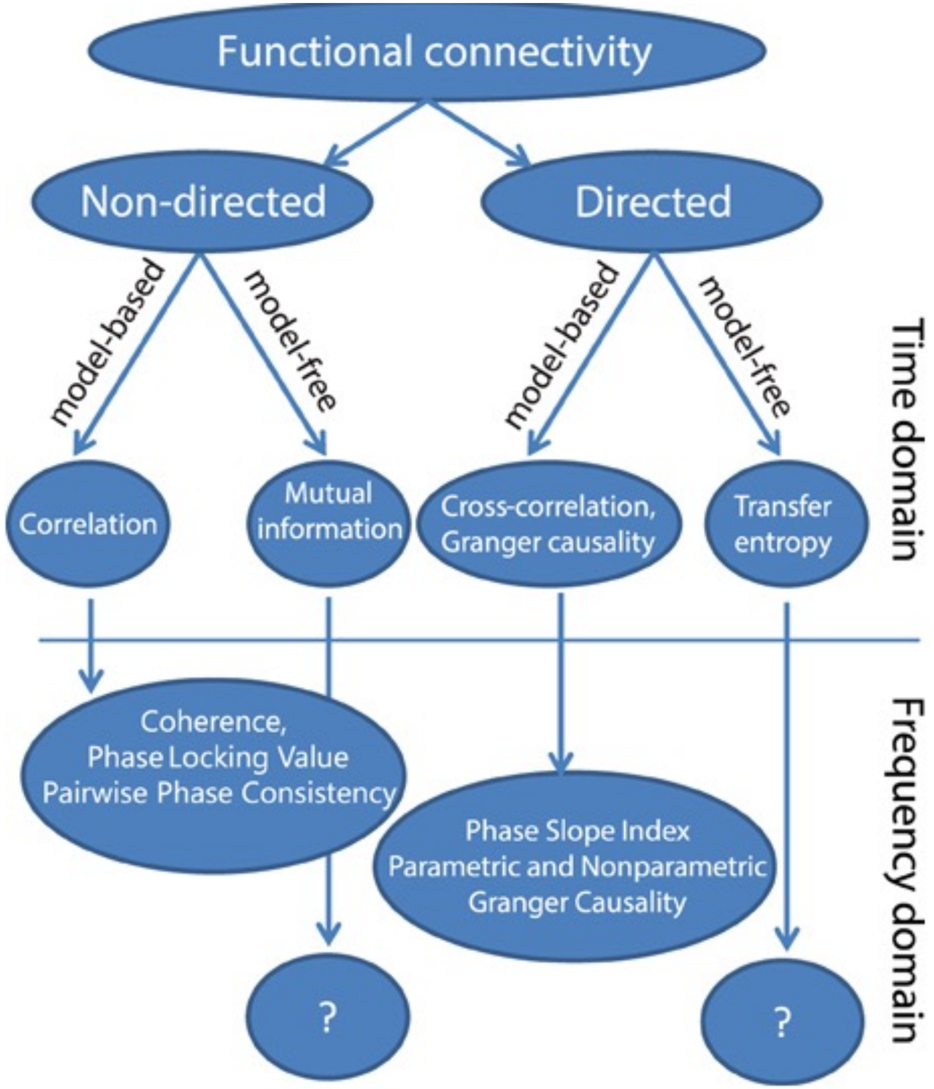


connectivity



Parameters

- Pearson,Spearman
- Covariance, correlation, coherence
- PLV PLS, PLI, IMC, WPLI, dWPLI
- Granger causality
- Mutual information



Coherence(Rosenberg 1989)

$S_{XX}(f)$: autospectrum of Xat frequency f

$S_{YY}(f)$: autospectrum of Yat frequency f

$S_{XY}(f)$: cross - spectrum of X and Yat frequency f

$$Coherence(f) = \frac{S_{XY}(f)}{\sqrt{S_{XX}(f) \cdot S_{YY}(f)}}.$$

Coherence-the frequency domain equivalent to
the time domain cross-correlation function

Prog. Biophys. molec. Biol., Vol. 53, pp. 1–31, 1989.
0079–6107/89 $0.00 + .50

THE FOURIER APPROACH TO THE IDENTIFICATION OF FUNCTIONAL COUPLING BETWEEN NEURONAL SPIKE TRAINS

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CONTENTS

Coherence or coherency

Cross Spectrum

$$S_{ij}(f) \equiv \langle x_i(f) x_j^*(f) \rangle$$

Coherency

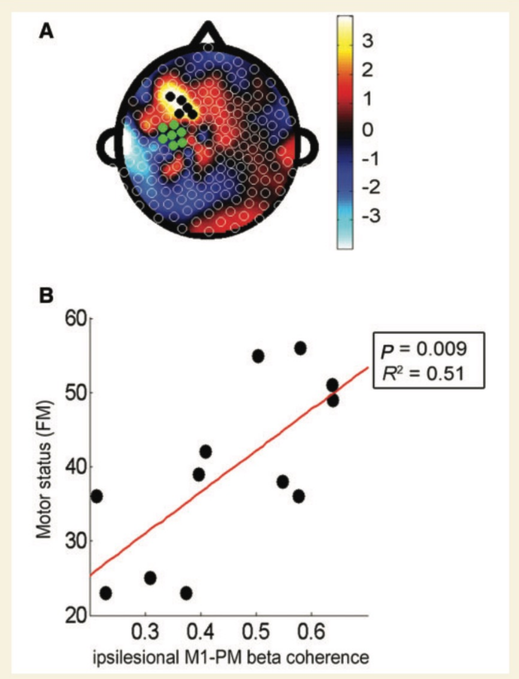
$$C_{ij}(f) \equiv \frac{S_{ij}(f)}{(S_{ii}(f) S_{jj}(f))^{1/2}}$$

Coherence

$$\mathrm{Coh}_{ij}(f) \equiv |C_{ij}(f)|$$

Network analysis to evaluate result after stroke （Jennifer Wu, 2015）

Connectivity measure are robust biomarker of cortical function and plasticity after stroke



BRAIN
A JOURNAL OF NEUROLOGY

Connectivity measures are robust biomarkers of cortical function and plasticity after stroke

Jennifer Wu,[1,2] Erin Burke Quinlan,[1,2] Lucy Dodakian,[2] Alison McKenzie,[2,3] Nikhita Kathuria,[2] Robert J. Zhou,[2] Renee Augsburger,[2] Jill See,[2] Vu H. Le,[2] Ramesh Srinivasan[4] and Steven C. Cramer[1,2]

Valid biomarkers of motor system function after stroke could improve clinical decision-making. Electroencephalography-based measures are safe, inexpensive, and accessible in complex medical settings and so are attractive candidates. This study examined specific electroencephalography cortical connectivity measures as biomarkers by assessing their relationship with motor deficits across 28 days of intensive therapy. Resting-state connectivity measures were acquired four times using dense array (256 leads) electroencephalography in 12 hemiparetic patients (7.3 ± 4.0 months post-stroke, age 26–75 years, six male/six female) across 28 days of intensive therapy targeting arm motor deficits. Structural magnetic resonance imaging measured corticospinal tract injury and infarct volume. At baseline, connectivity with leads overlying ipsilesional primary motor cortex (M1) was a robust and specific marker of motor status, accounting for 78% of variance in impairment; ipsilesional M1 connectivity with leads overlying ipsilesional frontal-premotor (PM) regions accounted for most of this ($R^2 = 0.51$) and remained significant after controlling for injury. Baseline impairment also correlated with corticospinal tract injury ($R^2 = 0.52$), though not infarct volume. A model that combined a functional measure of connectivity with a structural measure of injury (corticospinal tract injury) performed better than either measure alone ($R^2 = 0.93$). Across the 28 days of therapy, change in connectivity with ipsilesional M1 was a good biomarker of motor gains ($R^2 = 0.61$). Ipsilesional M1–PM connectivity increased in parallel with motor gains, with greater gains associated with larger increases in ipsilesional M1–PM connectivity ($R^2 = 0.34$); greater gains were also associated with larger decreases in M1–parietal connectivity ($R^2 = 0.36$). In sum, electroencephalography measures of motor cortical connectivity—particularly between ipsilesional M1 and ipsilesional premotor—are strongly related to motor deficits and their improvement with therapy after stroke and so may be useful biomarkers of cortical function and plasticity. Such measures might provide a biological approach to distinguishing patient subgroups after stroke.

PLV and PLS （Jean 1999）

Jean(Laboratoire de Neuroscience congnitives et Imagerie):

- Unlike the more traditional method of spectral coherence, PLS separates the phase and amplitude components and can be directly interpreted in the framework of neural integration.
- We also apply PLS to investigate intracortical recordings from an epileptic patient performing a visual discrimination task. We find large-scale synchronies in the gamma band (45 Hz), e.g., between hippocampus and frontal gyrus, and local synchronies,within a limbic region, a few cm apart.
- We argue that whereas long-scale effects do reflect cognitive processing,short-scale synchronies are likely to be due to volume conduction.

◆ Human Brain Mapping 8:194–208(1999) ◆

Measuring Phase Synchrony in Brain Signals

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Abstract: This article presents, for the first time, a practical method for the direct quantification of frequency-specific synchronization (i.e., transient phase-locking) between two neuroelectric signals. The motivation for its development is to be able to examine the role of neural synchronies as a putative mechanism for long-range neural integration during cognitive tasks. The method, called phase-locking statistics (PLS), measures the significance of the phase covariance between two signals with a reasonable time-resolution (<100 ms). Unlike the more traditional method of spectral coherence, PLS separates the phase and amplitude components and can be directly interpreted in the framework of neural integration. To validate synchrony values against background fluctuations, PLS uses surrogate data and thus makes no a priori assumptions on the nature of the experimental data. We also apply PLS to investigate intracortical recordings from an epileptic patient performing a visual discrimination task. We find large-scale synchronies in the gamma band (45 Hz), e.g., between hippocampus and frontal gyrus, and local synchronies, within a limbic region, a few cm apart. We argue that whereas long-scale effects do reflect cognitive processing, short-scale synchronies are likely to be due to volume conduction. We discuss ways to separate such conduction effects from true signal synchrony. *Hum Brain Mapping 8:194–208, 1999.*

Key words: neural synchrony; phase-locking; coherence; EEG; EcoG; epilepsy; gamma-band; deblurring

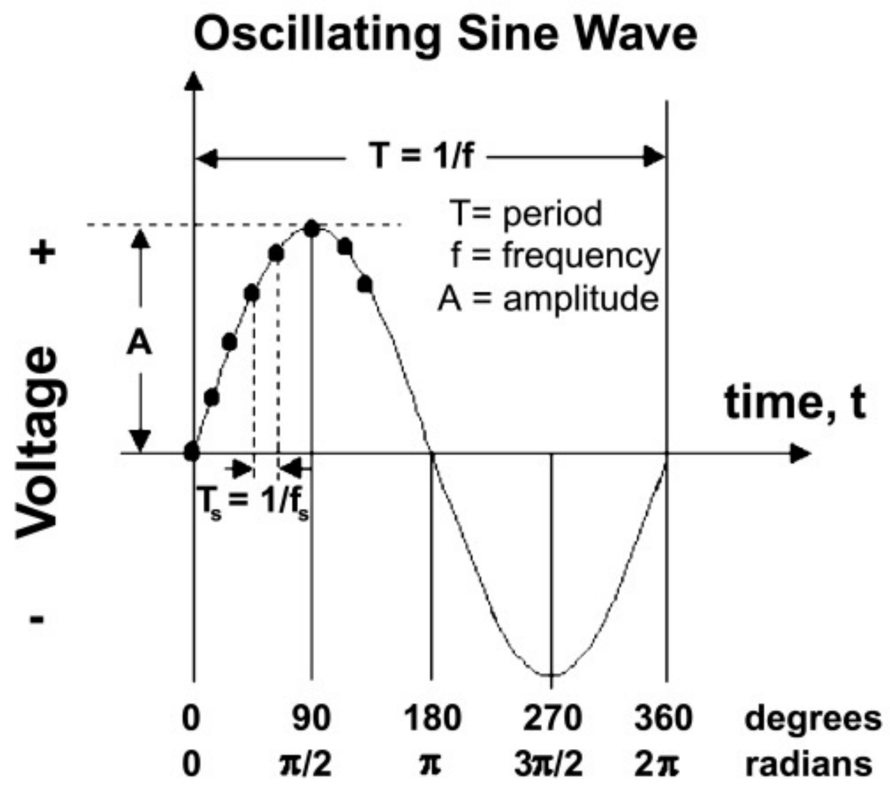
Why not Coherence

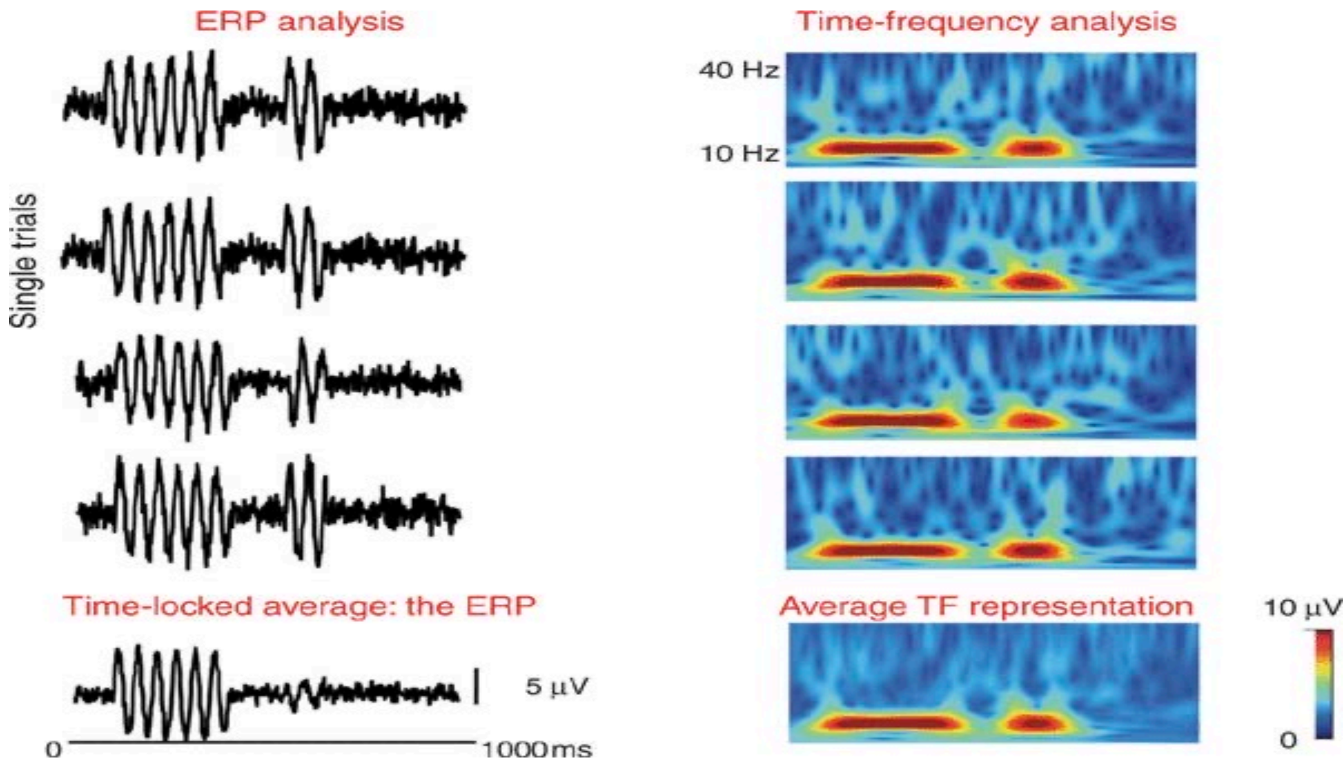
1. Coherence can only be applied to stationary signals

2. Coherence does not specifically quantify phase-relationships

Phase synchronization

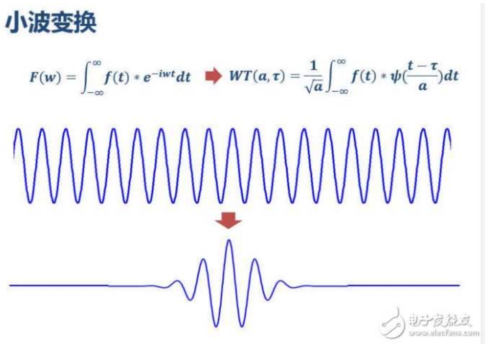
reasonable neural explanation





Induced VS evoked potential

PLV and PLS （Jean 1999）



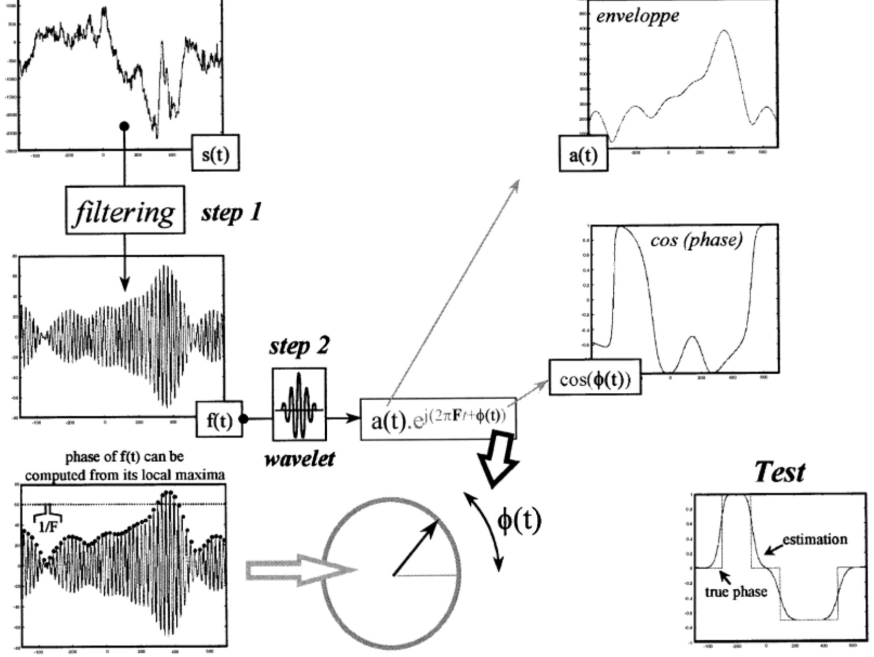
- Step 1. band-pass filter

- Step2 . Wavelet convolution

$$G(t,f)=\exp\left(-\frac{t^2}{2\sigma_t^2}\right)\exp\{j2\pi ft\}.$$

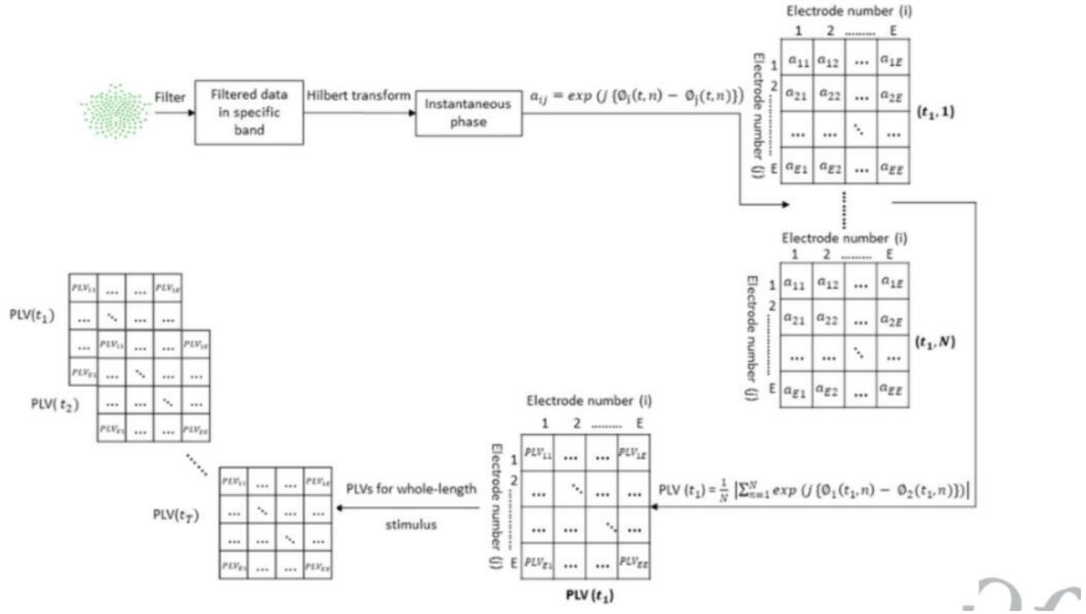
- Step3 PLV

$$PLV_t=\frac{1}{N}\left|\sum_{n=1}^{N}\exp\left(j\theta(t,n)\right)\right|$$



Autism classification from EEG-based network

Autism classification using network and machine learning



Classification of Autism Spectrum Disorder from EEG-based Functional Brain Connectivity Analysis

Noura Alotaibi , Koushik Maharatna

> Author and Article Information

Neural Computation 1–27.

https://doi.org/10.1162/neco_a_01394 **Article history**

Abstract

Autism is a psychiatric condition that is typically diagnosed with behavioral assessment methods. Recent years have seen a rise in the number of children with autism. Since this could have serious health and socioeconomic consequences, it is imperative to investigate how to develop strategies for an early diagnosis that might pave the way to an adequate intervention. In this study, the phase-based functional brain connectivity derived from electroencephalogram (EEG) in a machine learning framework was used to classify the children with autism and typical children in an experimentally obtained data set of 12 autism spectrum disorder (ASD) and 12 typical children. Specifically, the functional brain connectivity networks have quantitatively been characterized by graph-theoretic parameters computed from three proposed approaches based on a standard phase-locking value, which were used as the features in a machine learning environment. Our study was successfully classified between two groups with approximately 95.8% accuracy, 100% sensitivity, and 92% specificity through the trial-averaged phase-locking value (PLV) approach and cubic support vector machine (SVM). This work has also shown that significant changes in functional brain connectivity in ASD children have been revealed at theta band using the aggregated graph-theoretic features. Therefore, the findings from this study offer insight into the potential use of functional brain connectivity as a tool for classifying ASD children.

Neural Connectivity pattern predict Autism

electroencephalography measures of neural connectivity at 3 months of age predict autism symptoms at 18 months

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Biological Psychiatry: Cognitive Neuroscience and Neuroimaging

Volume 6, Issue 1, January 2021, Pages 59-69

Archival Report

Multivariate Neural Connectivity Patterns in Early Infancy Predict Later Autism Symptoms

Abigail Dickinson [a], Manjari Daniel [a], Andrew Marin [d], Bilwaj Gaonkar [b], Mirella Dapretto [c], Nicole M. McDonald [a], Shafali Jeste [a]

Volume condution

- The problem of volume-conduction is especially large for scalp EEG and MEG data, because of their low
- spatial resolution.

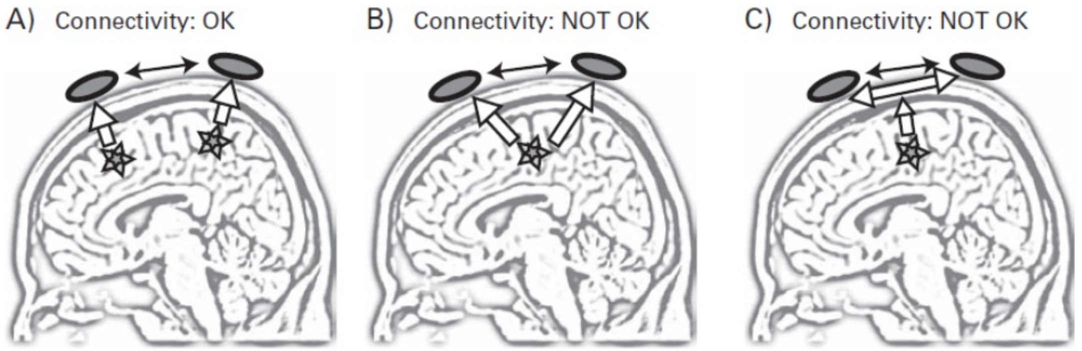


Figure 25.2

Illustration of the danger of volume conduction for interpreting interelectrode connectivity results. The black/gray rings represent electrodes, the black arrow between them illustrates measured connectivity, the stars represent neural sources in the brain, and the white arrows represent the path of electrical or magnetic activity from those sources. Ideally (panel A), each electrode measures only neural activity below the electrode, and thus, connectivity between two electrodes reflects connectivity between two physically distinct brain regions. Unfortunately, however, this situation cannot be assumed for EEG analyses: each electrode measures activity from overlapping brain regions (panel B), thus leading to the possibility that connectivity between two electrodes simply reflects those electrodes measuring activity from the same brain source. Furthermore, electrical fields can spread tangentially through the skull/scalp, causing further concern for EEG connectivity analyses (panel C).

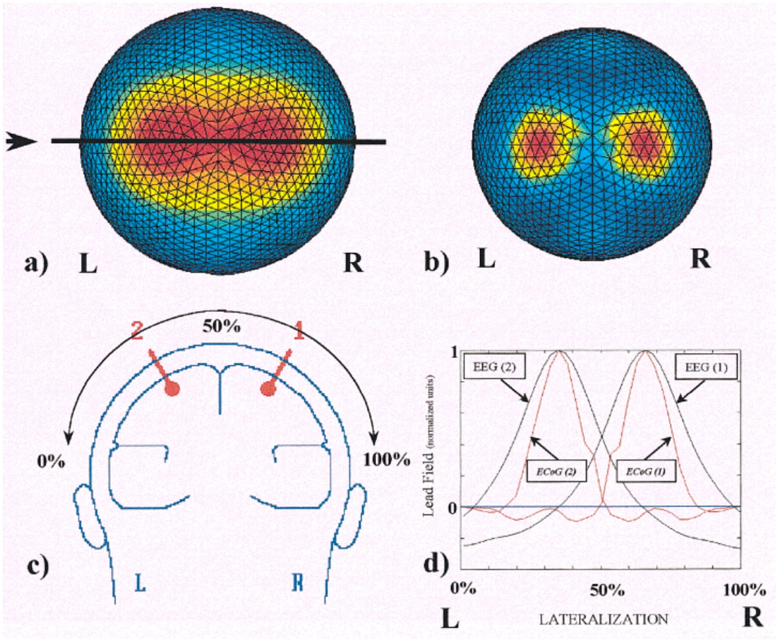


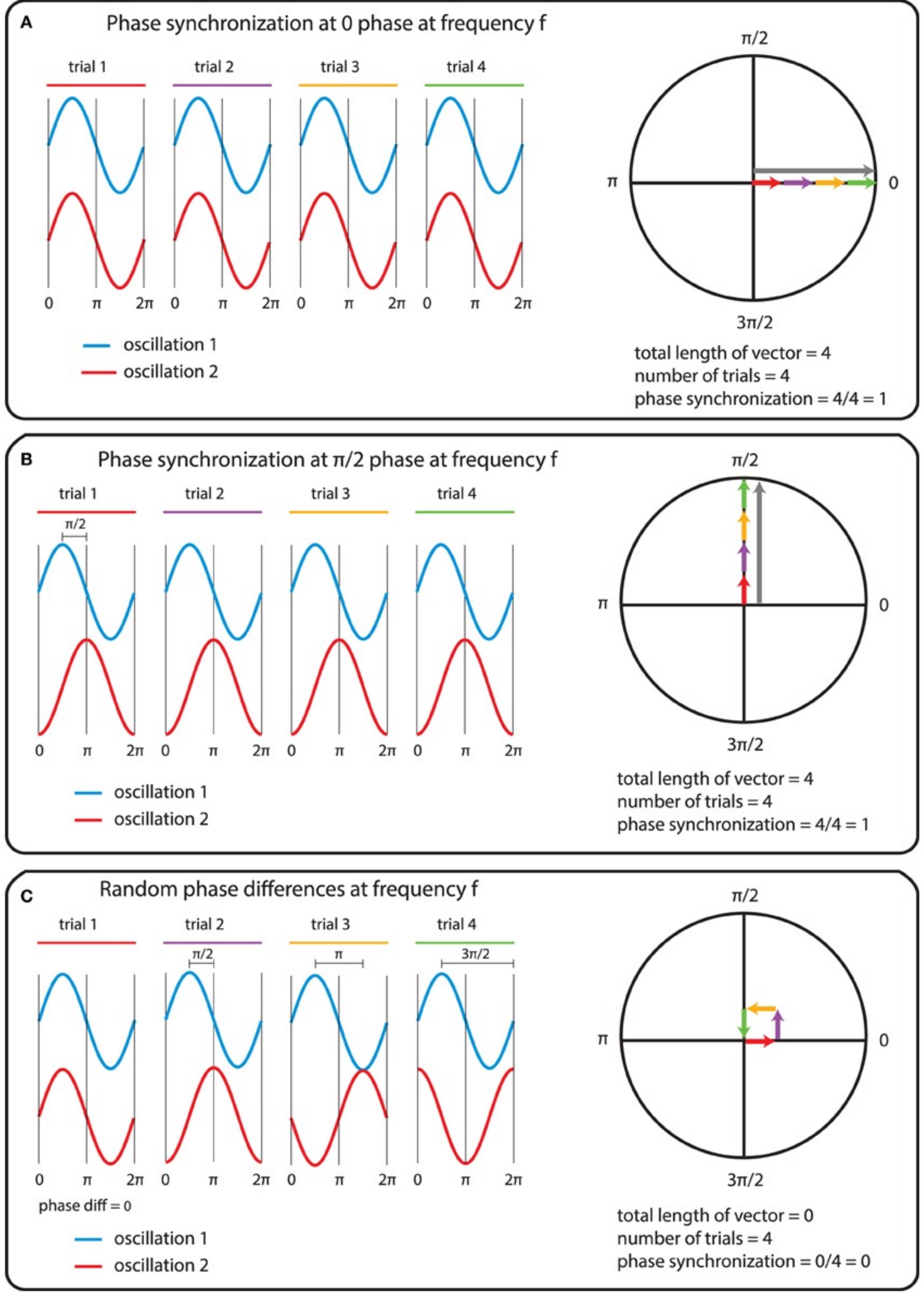
Figure 6.

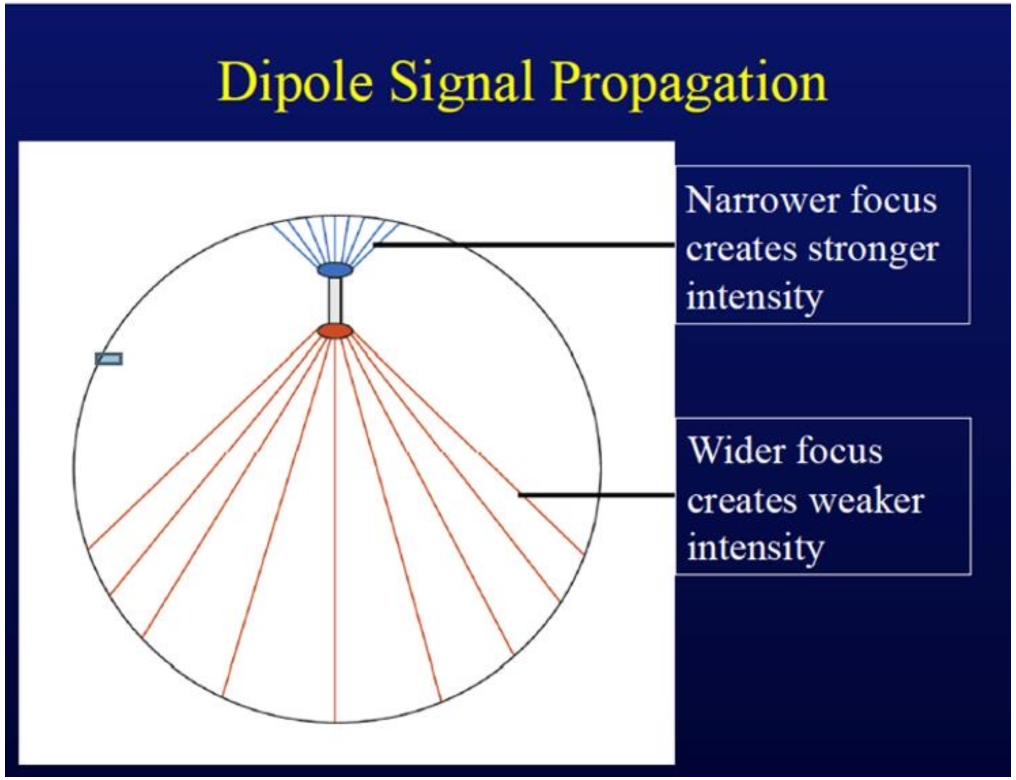
Simulation of an EEG and its corresponding ECoG. Two radial dipoles were placed in symmetric positions in the (T7-Cz-T8) plane, containing both ears and the head's vertex (**c**). EEG generated by these dipoles was computed, and ECoG reconstructed using a deblurring technique. (**a**) EEG cartography for two dipoles with same amplitude (**b**) corresponding ECoG. (**d**) EEG and ECoG contributions of each dipole as a function of laterality along a T7-Cz-T8 axis.

Perfect synchronization

Synchronization with time lag

No Synchronization





Common reference

- Mathematically similarly, for EEG one always needs a reference. If this reference is the same for the electrode pairs being studied, it can contribute significantly to the coherence, and thus, relative power changes may also affect coherencies without reflecting a change in coupling (Fein et al., 1988; Florian et al., 1998).

solution

- 1 inverse solution
- 2 Laplacian
- 3 parameters not sensitive to VC and Ref

Imaginary part of coherency

- Nolte(2004, Human Motor Control Section, NINDS, NIH,)

:The main obstacle in interpreting EEG/MEG data in terms of brain connectivity is the fact that because of volume conduction,the activity of a single brain source can be observed in many channels. Here, we present an approach which is insensitive to false connectivity arising from volume conduction.

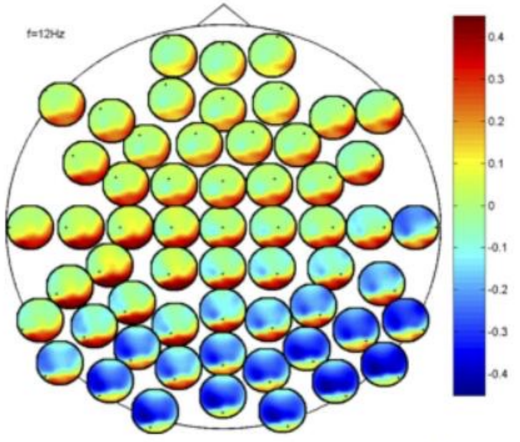


Fig. 3. Imaginary part of coherency in the alpha range for the same subject as in Fig. 1.

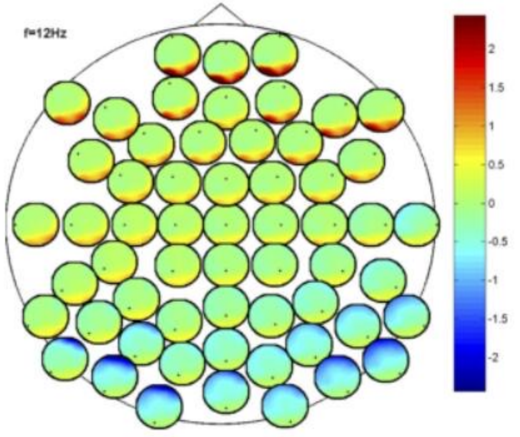


Fig. 4. Phase of coherency in the alpha range for the same subject as in Fig. 1.

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Clinical Neurophysiology 115 (2004) 2292–2307

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Identifying true brain interaction from EEG data using the imaginary part of coherency

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Accepted 17 April 2004

Available online 10 July 2004

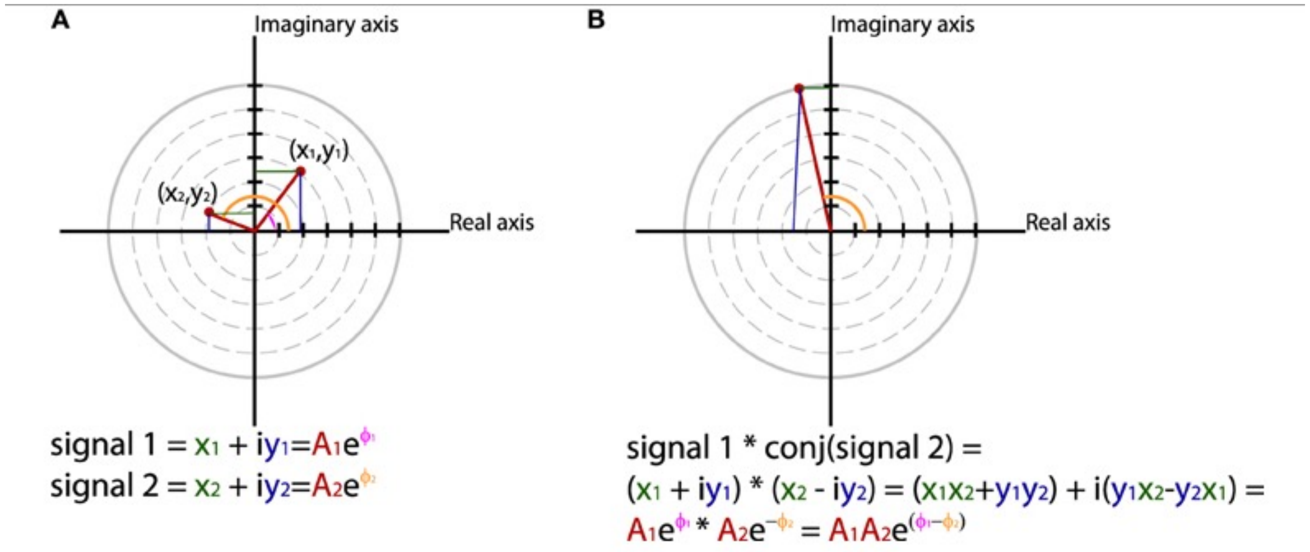
IMC(Imaginary part of coherency)

Coherency

$$c = \frac{\langle A_1 A_2 e^{i\Delta\phi} \rangle}{\sqrt{\langle A_1^2 \rangle \langle A_2^2 \rangle}}$$

Imaginationay part

$$\mathrm{Im}\{c\} = \frac{\langle A_1 A_2 \ \sin \Delta\phi \rangle}{\sqrt{\langle A_1^2 \rangle \langle A_2^2 \rangle}}$$



PLI(stam 2007)

- The major aim of introducing the PLI is to obtain reliable estimates of phase synchronization that are invariant against the presence of common sources (volume conduction and/or active reference electrodes in the case of EEG). the central idea is to discard phase differences that center around 0.

$$PLI_{xy} = \left| n^{-1} \sum_{t=1}^{n} \operatorname{sgn}\left(imag\left(S_{xyt}\right)\right) \right|$$

PLI(stam 2007)

- To address the problem of volume conduction and active reference electrodes in the assessment of functional connectivity, we propose a novel measur to quantify phase synchronization, the phase lag index (PLI), and compare its performance to the we known phase coherence (PLV), and to the imaginary component of coherency (ImC).

- PLI and Plv were more sensitive than ImC to increasing levels of true synchronization in the model

- The PLI performed at least as well as the PLV in detecting true changes in synchronization in model and real data but, at the same token and like-wise the ImC, it was much less affected by the influence of common sources and active reference electrodes

$$PLI = |\langle \mathrm{sign}[\Delta\phi(t_k)] \rangle|$$

◆ Human Brain Mapping 28:1178–1193 (2007) ◆

Phase Lag Index: Assessment of Functional Connectivity From Multi Channel EEG and MEG With Diminished Bias From Common Sources

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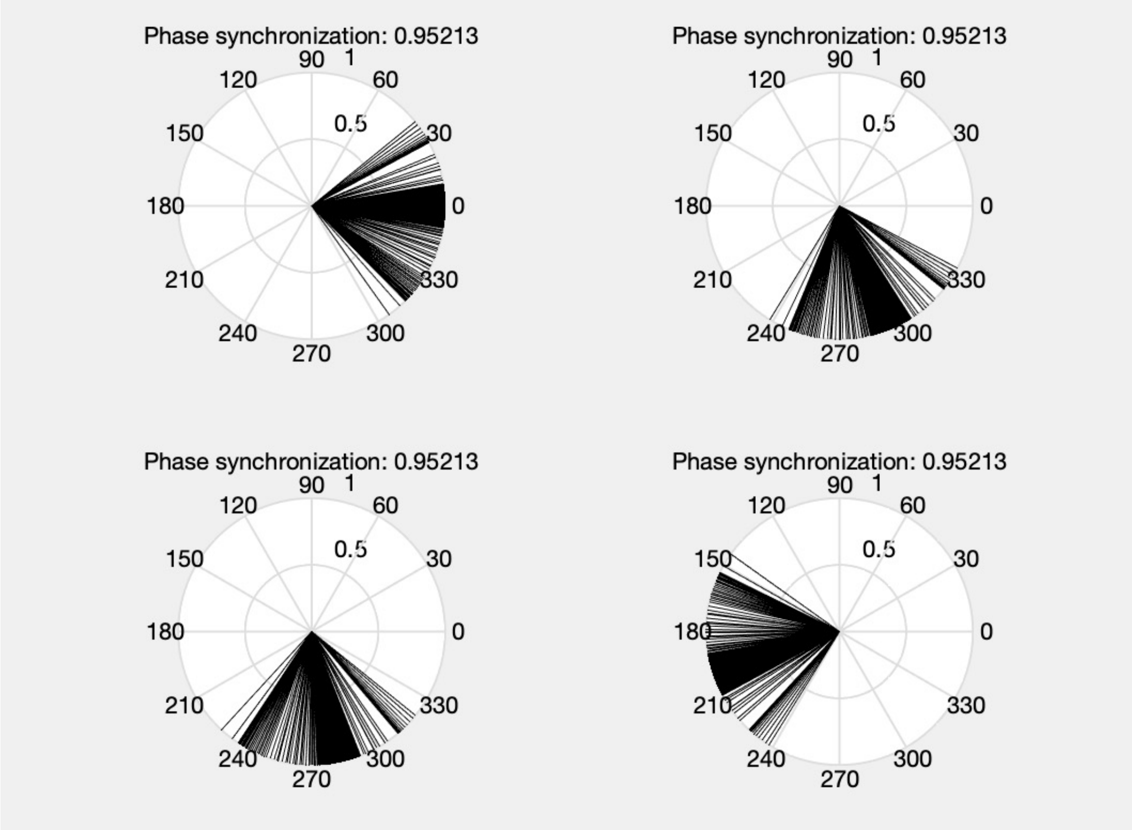
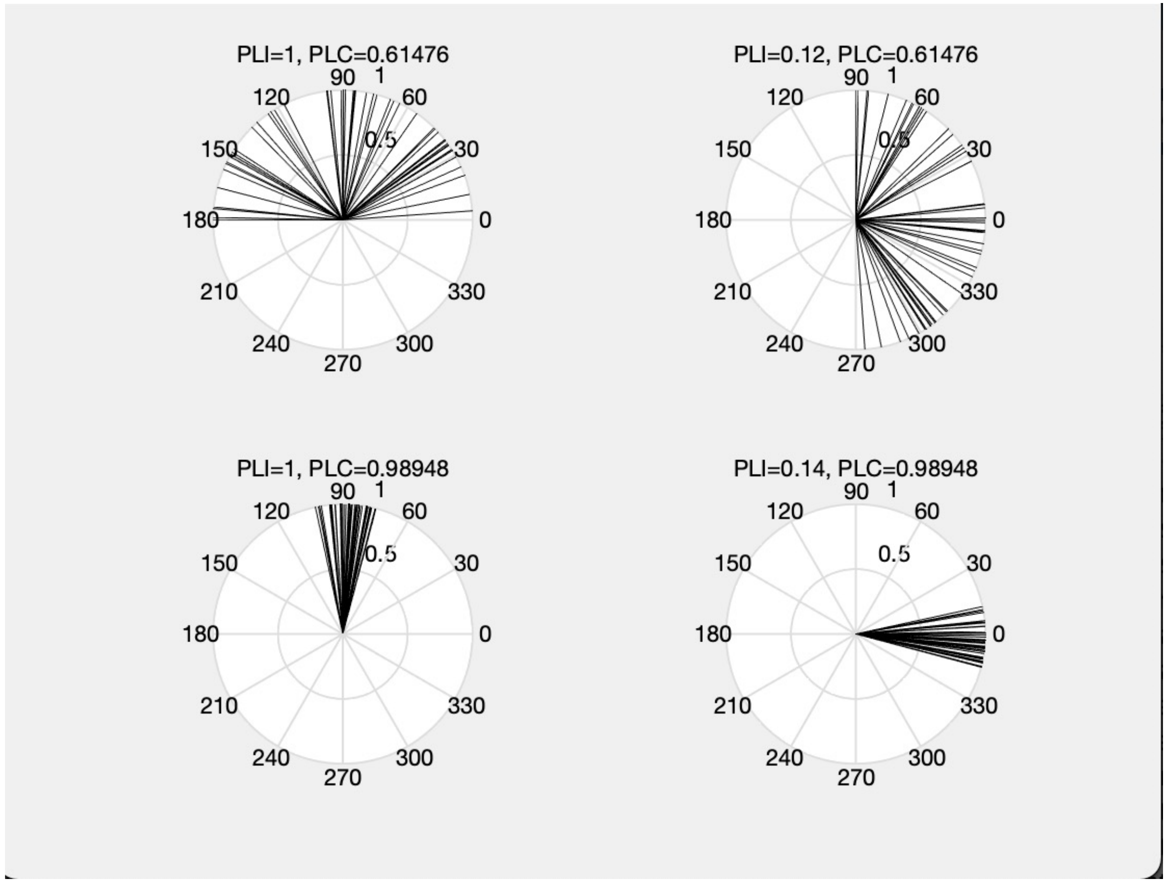
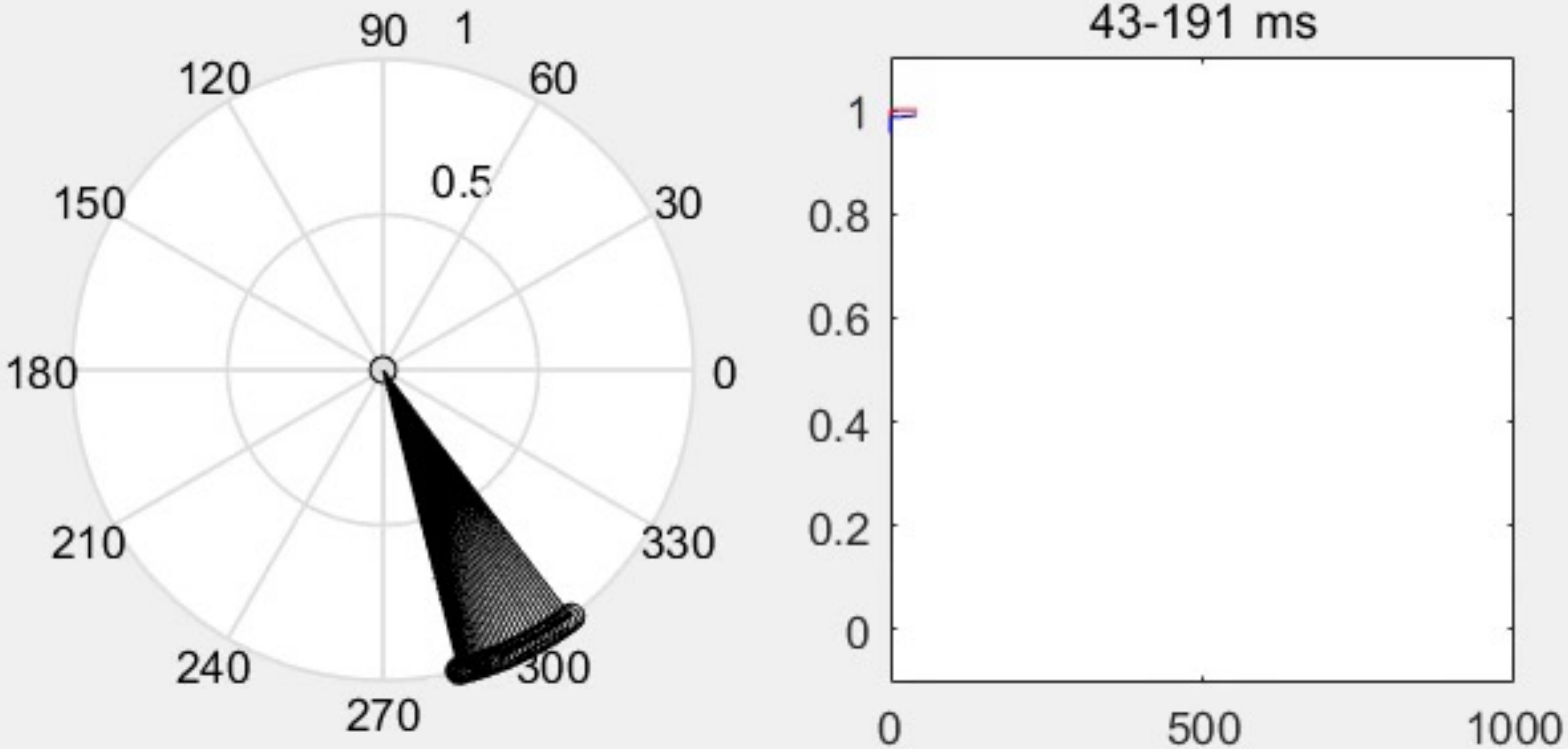
[4]*Institute for Fundamental and Clinical Movement Sciences, VU, Amsterdam, The Netherlands*


Phase synchronization: 0.95213
Phase synchronization: 0.95213
Phase synchronization: 0.95213
Phase synchronization: 0.95213


PLI=1, PLC=0.61476
PLI=0.12, PLC=0.61476
PLI=1, PLC=0.98948
PLI=0.14, PLC=0.98948



90
1
120
60
0.5
150
30
180
0
210
330
240
300
270
43-191 ms
1
0.8
0.6
0.4
0.2
0
0
500
1000

Wpli and dwpli(Vinck 2011)

- (i) the presence of a common reference,
- (ii) volume-conduction of source activity,
- (iii) the presence of noise sources, and
- (iv) sample-size bias.

$$wPLI_{xy} = \frac{n^{-1}\sum_{t=1}^{n} \left|imag\left(S_{xyt}\right)\right| \operatorname{sgn}\left(imag\left(S_{xyt}\right)\right)}{n^{-1}\sum_{t=1}^{n} \left|imag\left(S_{xyt}\right)\right|}$$

Bias related to difference in sample size

	Coherence and PLV	ImC (Nolte et al., 2004)	PLI (Stam et al., 2007)	WPLI
Construction index (Existing indices of phase-synchronization and The weighted phase-lag index sections).	Uses imaginary and real part equally.	Expected value of imaginary component cross-spectrum, normalized by expected value of signals' power.	Consistency of sign of imaginary component cross-spectrum.	Expected value of imaginary component cross-spectrum, normalization by expected value of magnitude imaginary component cross-spectrum.
Effect of volume-conduction correlated sources of interest (Volume conducting correlated sources of interest section).	Strong increase or decrease, depending on phase of coherency and sign volume-conduction coefficients.	Increase or decrease, depending on phase coherency and volume-conduction coefficients.	Unaffected.	Unaffected.
Effect of adding volume-conducted, uncorrelated noise sources (Addition of uncorrelated, volume-conducted noise sources section).	Strong increase or decrease, depending on phase of coherency and volume-conduction coefficients.	Always decreases, because signal amplitudes always increase.	Depending on distribution relative phase, increase (e.g., for some bimodal or asymmetric distributions) or decrease (e.g. for symmetric, unimodal distributions).	Decrease, insofar sign of imaginary component cross-spectrum changes. Less noise-sensitive than PLI.
Effect of change in phase of coherency between sources of interest (Influence of phase of coherency on WLPI, PLI and ImC section).	Decrease or increase, depending on volume-conduction coefficients.	Strong increase or decrease possible, range of statistic depends on phase coherency (see also Stam et al. (2007)).	Range statistic is always [0,1], PLI only changes if distribution of sign imaginary component of cross-spectrum is affected.	Range statistic is always [0,1], WPLI only changes if distribution of sign imaginary component of cross-spectrumis affected.
Detecting phase-synchronization.	Strong tendency to generate false positives, false positives rate cannot be controlled.	Reduced sensitivity in detection vs. PLI. (Stam et al., 2007). False positives rate controlled.	Even without added noise, PLI may fail to detect phase-synchronization for bimodal/asymmetric relative phase distributions. However, false positives rate controlled.	Even without added noise: Steeper relationship with true phase-consistency (e.g., as measured by PLV) than PLI, always detects non-zero coherence, WPLI estimator has higher z-score than PLI estimator.

Bedside detect conscious level

alpha network metrics were good at distinguishing UWS versus MCS patients, relative delta band power averaged over all channels was very good at discriminating MCS from MCS + patients

delta network centrality predicts outcomes

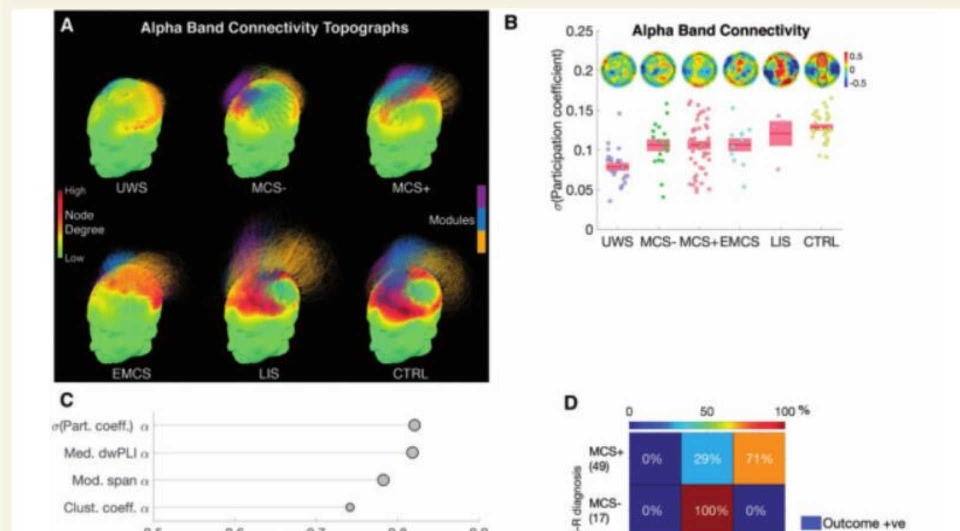
Mohawk software(only support EGI format)
Does not support lower than 128ch

doi:10.1093/brain/awx163 BRAIN 2017: 140; 2120–2132 |

BRAIN
A JOURNAL OF NEUROLOGY

Brain networks predict metabolism, diagnosis and prognosis at the bedside in disorders of consciousness

Srivas Chennu,[1,2] Jitka Anne
Helena Cassol,[3] Géraldine M
David Menon[9] and Steven La



However, this analysis of dwPLI-based networks was based on sensor-level EEG data, and hence references to regions allude to areas over the scalp rather than specific regions of underlying brain anatomy.

- Phase Slope Index （Nolte 2008, directed）
- Partial coherence （Rosenberg 1998）
- Pearson,Spearman
- Partial correlation
- …..

Real part of coherence-COH

Connectivity analysis to TMS-EEG study

2.7. EEG Connectivity Analysis. Within Matlab [24], EEG channels were averaged according to 10 predefined regions over both hemispheres (see Supplementary Figure S1 for brain regions and electrodes). Autoregressive models were calculated for each segment using the mvfreqz.m and mvar.m function implemented within the BioSig toolbox [23]. The multivariate autoregressive models were calculated for all region × region combinations and for the three frequency bands of interest (alpha: 7-13 Hz, low gamma: 40-50 Hz, and high gamma: 51-79 Hz) with a model order 15, chosen in order to adhere to the proposed ratio of 3 : 1 between given samples and the number of estimates [25]. From the multivariate autoregressive model, we derived two measures of interaction: ordinary coherence (COH), which is an undirected measure considering the real part of the complex-valued coherence [23], and the full frequency directed transfer function (ffDTF), a directed measure of interaction normalized with respect to all the frequencies in the predefined frequency interval [26].

Connectivity Analysis during Rubber Hand Illusion—A Pilot TMS-EEG Study in a Patient with SCI

Vanessa N. Frey[1,2] **Aljoscha Thomschewski**[1,2,3] **Patrick B. Langthaler,**[1,2,3] **Alexander B. Kunz**[1,4] **Yvonne Höller**[1,5] **Eugen Trinka**[1,2,3] **and Raffaele Nardone**[1,2,4,6]

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Academic Editor: Yasuo Terao

Background. Bodily self-perception is an important concept for several neurological disorders, including spinal cord injury (SCI). Changing one's bodily self-perception, e.g., via rubber hand illusion (RHI), induces alterations of bottom-up and top-down pathways and with this the connectivity between involved brain areas. We aim to examine whether (1) this process can be manipulated by changing cortical excitability, (2) connectivity between relevant brain areas differ when the RHI cannot be evoked, and (3) how this projection differs in a patient with SCI. *Method.* We applied RHI and facilitatory theta burst stimulation (TBS) on the right primary somatosensory cortex (S1) of 18 healthy participants and one patient with incomplete, cervical SCI. During RHI, we recorded high-density electroencephalography (HD-EEG) and extracted directed and nondirected connectivity measures. *Results.* There is no difference in connectivity between sham and real TBS or in the effectivity of RHI. We observed a higher laterality in the patient, i.e., higher connectivity of the right and lower of the left hemisphere. Besides this, connectivity patterns do not differ between healthy participants and the patient. *Conclusion.* This connectivity pattern might represent a neuroplastic response in the attempt to overcome the functional impairment of the patient resulting in a similar overall connectivity pattern to the healthy participants, yet with a higher sensitivity towards RHI and a higher laterality. The cortico-cortical communication was not altered depending on whether the illusion was provoked or not; hence, the perceptory illusion could not be observed in the EEG analysis.

NETWORK MODEL BASED ON 'PDI' for AD and MCI patients

Alzheimer's disease (AD) is a neurodegener ative disorder that causes a loss of connections between neurons. The goal of this paper is to construct a complex network model of the brain-electrical activity, using high-density EEG (HD-EEG) recordings, and to compare the network organization in AD, mild cognitive impaired (MCI), and healthy control (CNT) subjects

IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, VOL. 15, NO. 1, JANUARY 2019

Brain Network Analysis of Compressive Sensed High-Density EEG Signals in AD and MCI Subjects

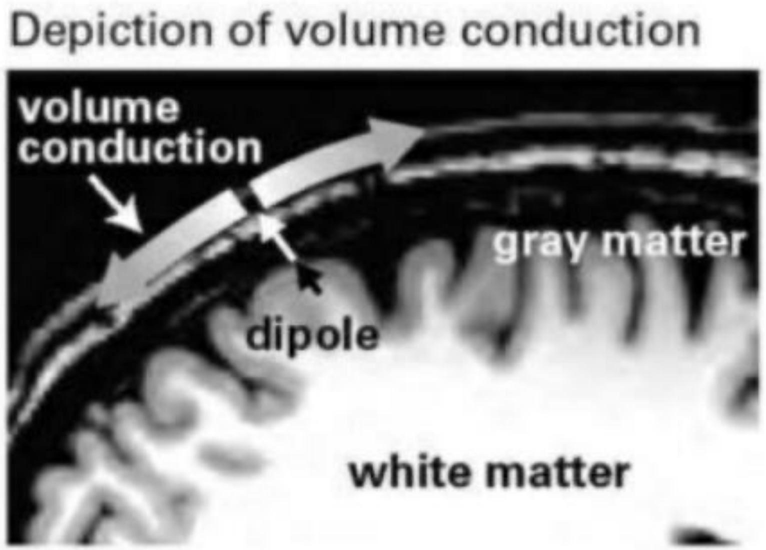
Nadia Mammone, *Member, IEEE*, Simona De Salvo, Lilla Bonanno, Cosimo Ieracitano, Silvia Marino, Angela Marra, Alessia Bramanti, and Francesco C. Morabito, *Senior Member,*

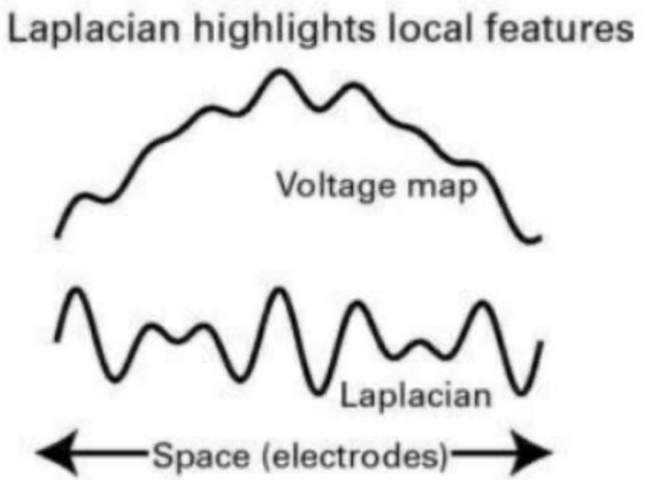
THE incidence of dementia is gradually increasing due to aging world population [1]. Alzheimer's disease (AD) is the most common form of dementia as it is estimated to account for 60% of all the dementia cases [1]. Experts postulated that AD arises with a subtle preclinical stage, develops through an intermediate amnestic mild cognitive impairment (MCI) stage, and ends up with a final dementia stage, when cognitive impairment affects the ability to live independently [2]. The early diagnosis of AD, which would dramatically improve patient's treatment, would be possible only if the current diagnostic tools were improved. High-density EEG (HD-EEG) could make a significant contribution, thanks to its significantly higher spatial resolution than standard EEG. Two main features commonly

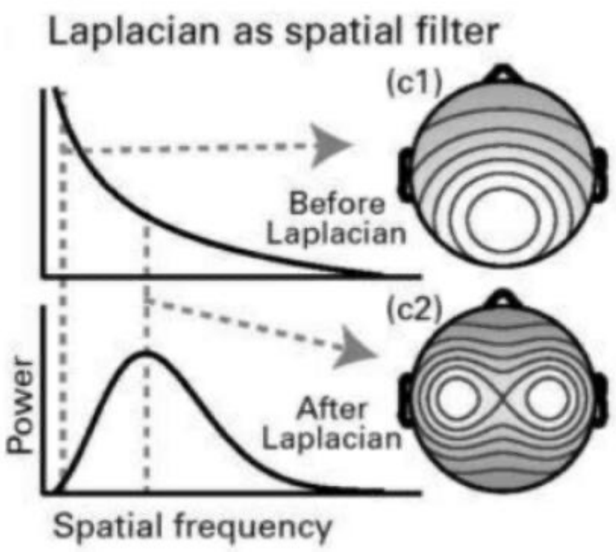
N. Mammone *et al.*, "Permutation disalignment index as an indirect, EEG-based, measure of brain connectivity in MCI and AD patients," *Int. J. Neural Syst.*, vol. 27, 2017, Art. no. 1750020, doi: 10.1142/S0129065717500204.

Laplacian transform

- For EEG data with a spatially dense, controlled arrangement of electrode positions, the problem of a common reference can be addressed by computing local Laplacians (i.e., second derivatives of raw potentials), also known as current–source–density analysis. This approach in essence removes the effect of a common reference (Nunez and Srinivasan (2006)).







Accuracy of surface Laplacian

- In general, having more electrodes is better. Sixty-four electrodes is a reasonable minimum, and > 100 electrodes will provide more accurate results

- use individual skull shape and precise electrode positions to improve the accuracy of surface Laplacian

Electrical Geodesics, Inc. Technical Note

Theory and Calculation of the Scalp Surface Laplacian

Thomas C Ferree and Ramesh Srinivasan
August 24, 2000

This note describes in physical terms the motivation for using the scalp surface Laplacian in EEG research. It also describes two algorithms for its computation. We do not consider the so-called Hjorth surface Laplacian (Hjorth, 1975) because, despite its frequent mention in EEG research, the Hjorth algorithm for calculating the two-dimensional second derivative is valid only for evenly spaced data points falling on an orthogonal Cartesian grid (Press et al., 1992). This is not the case for conventional EEG electrode arrays, which seek even spacing but do not generally follow a Cartesian grid (Tucker, 1991). Instead, we describe the calculation of the surface Laplacian based upon two common methods of spline interpolation: the spherical splines (Perrin et al., 1989; 1990) and the three-dimensional thin-plate splines (Perrin et al., 1987; Law et al., 1993). Each method is described in detail in the EGI Technical Note SplineInterpolation.pdf, and this note assumes knowledge of that material.

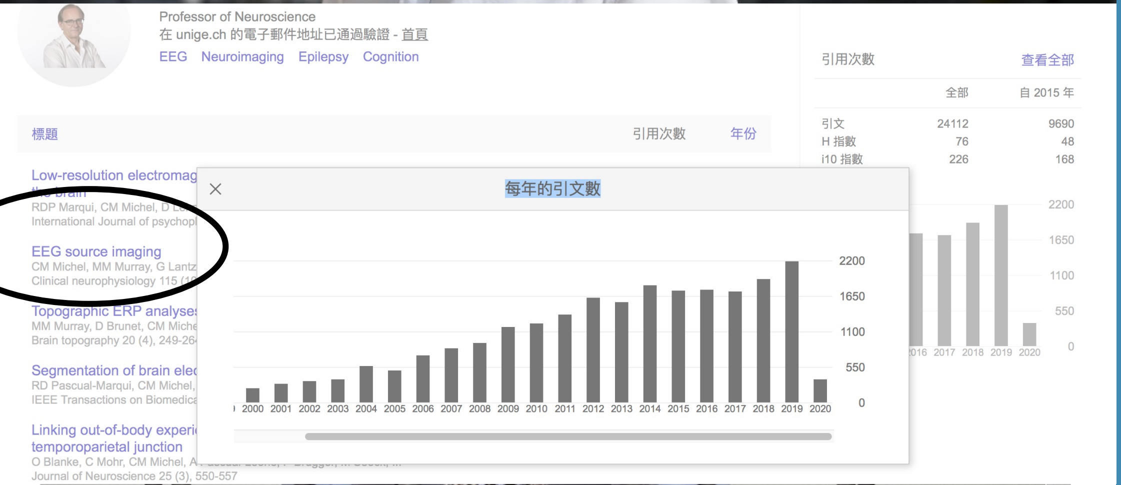
Source VS Sensor

- sensor level (No) → Source Level (Yes)

The future

- sensor level (No) → Source Level (Yes)

- Low spatial resolution(No) → dense array EEG (Yes)



RESEARCH **PUBLICATIONS** **PEOPLE** **CONTACT**

Our principal research interest is the organization and the dynamics of the large-scale neuronal networks of the human brain that characterize mental functions, and the understanding of disturbances of these networks in patients with brain dysfunctions. Electromagnetic imaging based on high-resolution EEG is our principal instrument to study these questions. Our group is working on the development of spatio-temporal signal analysis techniques that allow to characterize neuronal electric activity in time and space. By integrating these data into realistic head models based on the anatomical MRI, information flow within the individual brain can be visualized. In order to enhance spatial resolution, other functional imaging techniques, in particular functional MRI are included. Besides the combination of electromagnetic and haemodynamic brain imaging techniques, our research projects also integrate direct intracranial recordings in epileptic patients, neuropsychology and lesion studies as well as transcranial magnetic stimulation. We consider this multidisciplinary approach as essential for understanding the brain mechanisms underlying human mind and the disturbances and repair possibilities of these mechanisms. Our main cognitive neuroscience research areas are: visual and auditory perception, visuo-motor integration, multisensory interaction, language, memory and emotion. The major clinical

group leader

Prof. Christoph MICHEL

CHRISTOPH M. MICHEL

日内瓦大学教授，脑成像团队负责人

大脑研究领域殿堂级研究者，脑功能研究如脑成像诸多理论奠基人，在大脑研究领域如语言，记忆，神经基础理论均有涉及。最早提出大脑脑成像概念的学者之一，主张利用高密度脑电，并结合核磁，MEG等对大脑进行脑成像研究。在临床上是癫痫溯源理论的奠基人和开拓者。

作为脑成像理论的推动者，其对溯源理论的推动影响巨大。其于03年编著的《脑成像技术》综述被视为溯源圣经。其于93年提出的 LORETA等算法是脑电溯源技术的基础之一，是各类开源软件和商业软件的算法基础，影响了之后三十年的脑电系统和软件的开发。直到目前很多团队仍将掌握LORETA算法使用作为高精尖技术自居。其开发的cartool软件被认为是研究目前热门方法microstate的最好工具。

作为nature, brain等高水平杂志的常客，Michel及其领导的团队实力雄厚，团队里教授，副教授人员众多，拥有核磁，MEG，高密度脑电等脑认知领域所有研究工具。目前致力于将基于高密度脑电的脑网络技术应用于癫痫研究。

2019年
著作与论文

- frequency changes and functional MRI. *PLoS One 9 (11): e112103*.
- Cantonas L-M, Tomescu IM, Biria M, Jan R, Schneider M, Eliez S, Rihs T, Michel C.
- Abnormal development of early auditory processing in 22q11.2 deletion syndrome. Translational Psychiatry 2019;9(1):138. Damborska A, Piguet C, Aubry J-M, Daye C.
- Altered Electroencephalographic Resting-State Large-Scale Brain Network Dynamics in Euthymic Bipolar Disorder Patients. Frontiers in Psychiatry 2019;10(826). Sło Michel C, Richardson MP, Quairiaux C, Terry JR, Goodfellow M.
- Background EEG connectivity captures the time-course of epileptogenesis in a mouse model of epilepsy. eNeuro 2019;6(4):1-13. Brechet L, Brunet D, Birot G, Grue J.
- Capturing the spatiotemporal dynamics of self-generated, task-initiated thoughts with EEG and fMRI. NeuroImage 2019;194:82-92. Michel C, Vuilleumier P, Van De V
- Current opinions in brain imaging methods and applications. Brain Topography 2019;32(6):923-925. Luis Coito AL, Michel C, Vulliemoz S, Plomp G.
- Directed functional connections underlying spontaneous brain activity. Human Brain Mapping 2019;40(3):879-888. D'Croz-Baron DF, Baker M, Michel C, Karp T.
- EEG microstates analysis in young adults with autism spectrum disorder during resting-state. Frontiers in Human Neuroscience 2019;13:173.
- Perizzolo V, Berchio C, Moser DA, Puro Gomez C, Vital M, Arnautovic E, Torrisi R, Sandra RS, et al.
- EEG recording during an emotional face-matching task in children of mothers with interpersonal violence-related posttraumatic stress disorder. Psychiatry Research: 2019;283:34-44. Damborska A, Tomescu IM, Honzírková E, Barteček R, Hořínková J, Fedorová S, Ondruš Š, Michel C.
- EEG resting-state large-scale brain network dynamics are related to depressive symptoms. Frontiers in Psychiatry 2019;10:548. Michel C, He B. EEG source localizat Clinical Neurology 2019;160:85-101. He B, Astolfi L, Valdes-Sosa PA, Marinazzo D, Palva S, Benar CG, Michel C, Koenig T.
- Electrophysiological brain connectivity: theory and implementation. IEEE Transactions on Biomedical Engineering 2019;66(7):2115-2137. Rubega M, Carboni M, Seeb Tourbier S, Toscano G, Van Mierlo P, Hagmann P, et al.
- Estimating EEG source dipole orientation based on singular-value decomposition for connectivity analysis. Brain Topography 2019;32(4):704-719. Berchio C, Küng A- Dayer A, Aubry J-M, Michel C, Piguet C.
- Eye-gaze processing in the broader bipolar phenotype revealed by electrical neuroimaging. Psychiatry Research: Neuroimaging 2019;291:42-51. Michel C.
- High-resolution EEG. Handbook of Clinical Neurology 2019;160:185-201. Jorge J, Bouloc C, Brechet L, Michel C, Gruetter R.
- Investigating the variability of cardiac pulse artifacts across heartbeats in simultaneous EEG-fMRI recordings: A 7T study. NeuroImage 2019;191:21-35. Sheybani L, V Michel C, Quairiaux C.
- Large-scale 3-5 hz oscillation constrains the expression of neocortical fast ripples in a mouse model of mesial temporal lobe epilepsy. eNeuro 2019;6(1):1-13. Jan R, Sperdin HF, Franchini M, Custo A, Tomescu IM, Michel C, et al.
- Neural processing of dynamic animated social interactions in young children with autism spectrum disorder: a high-density electroe study. Frontiers in Psychiatry 2019;10:582. Seeber M, Cantonas L-M, Hoevels M, Sesia T, Visser-Vandewalle V, Michel C.
- Subcortical electrophysiological activity is detectable with high-density EEG source imaging. Nature Communications 2019;10(1):753 Rubega M, Iannotti GR, De Stefano P, Toscano G, Tourbier S, Pittau F, Hagmann PS, et al.
- The network integration of epileptic activity in relation to surgical outcome. Clinical Neurophysiology 2019;130(12):2193-2202. Rub Queralt JR, Van Mierlo P, Hagmann P, Plomp G, Michel C.
- Time-varying effective EEG source connectivity: the optimization of model parameters. IEEE Engineering in Medicine and Biology So Proceedings 2019:6438-6441. Berchio C, Rodrigues J, Strasser A, Michel C, Sandi C.

ARTICLE

https://doi.org/10.1038/s41467-019-08725-w OPEN

Subcortical electrophysiological activity is detectable with high-density EEG source imaging

Martin Seeber [1], Lucia-Manuela Cantonas[1], Mauritius Hoevels[2], Thibaut Sesia[2], Veerle Visser-Vandewalle[2] & Christoph M. Michel[1,3]

Subcortical neuronal activity is highly relevant for mediating communication in large-scale brain networks. While electroencephalographic (EEG) recordings provide appropriate temporal resolution and coverage to study whole brain dynamics, the feasibility to detect subcortical signals is a matter of debate. Here, we investigate if scalp EEG can detect and correctly localize signals recorded with intracranial electrodes placed in the centromedial thalamus, and in the nucleus accumbens. Externalization of deep brain stimulation (DBS) electrodes, placed in these regions, provides the unique opportunity to record subcortical activity simultaneously with high-density (256 channel) scalp EEG. In three patients during rest with eyes closed, we found significant correlation between alpha envelopes derived from intracranial and EEG source reconstructed signals. Highest correlation was found for source signals in close proximity to the actual recording sites, given by the DBS electrode locations. Therefore, we present direct evidence that scalp EEG indeed can sense subcortical signals.

ELSEVIER

Clinical Neurophysiology 115 (2004) 2195–2222

www.elsevier.com/l

Invited review

EEG source imaging

Christoph M. Michel[a,*], Micah M. Murray[a,1], Göran Lantz[a], Sara Gonzalez[a], Laurent Spinelli[b], Rolando Grave de Peralta[a]

[a]Functional Brain Mapping Laboratory, Neurology Clinic, University Hospital of Geneva, 24 rue Micheli-du-Crest, 1211 Geneva, Switz

[b]Presurgical Epilepsy Evaluation Unit, Neurology Clinic, University Hospital of Geneva, 24 rue Micheli-du-Crest, 1211 Geneva, Switz

Available online 28 July 2004

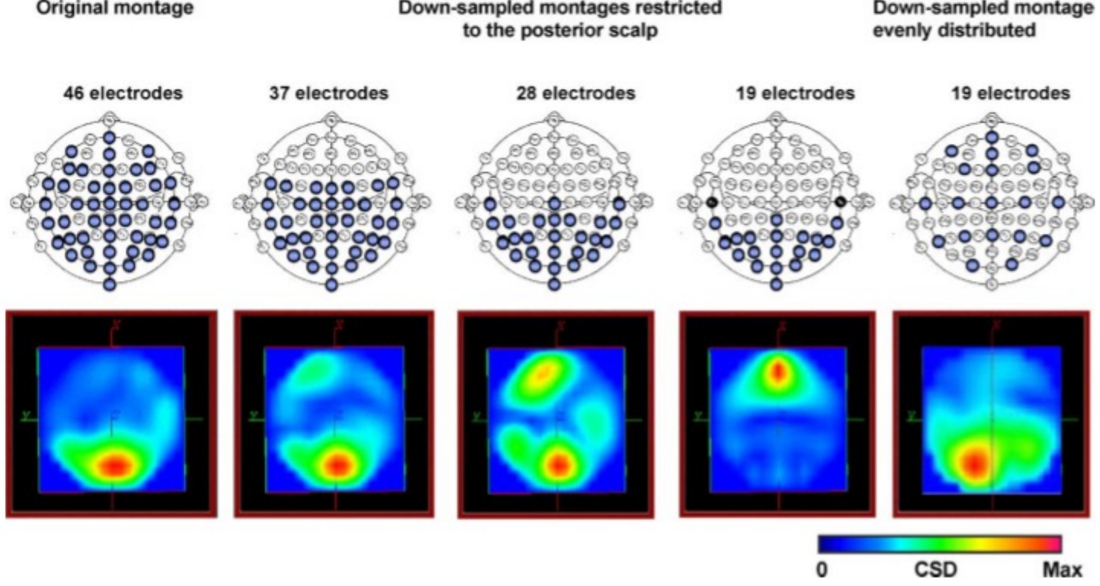
Abstract

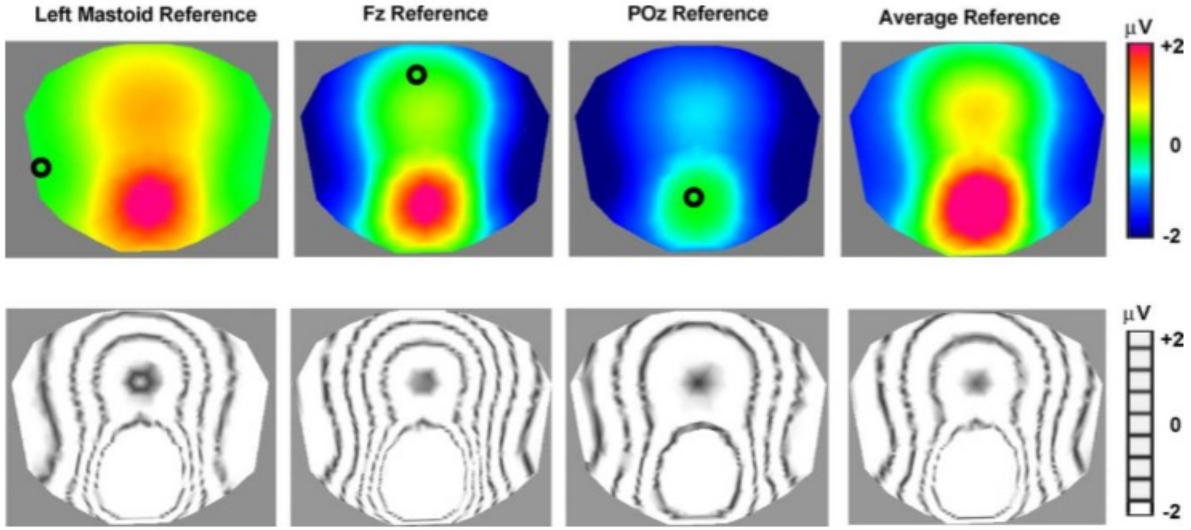
Objective: Electroencephalography (EEG) is an important tool for studying the temporal dynamics of the human brain's large-scale neuronal circuits. However, most EEG applications fail to capitalize on all of the data's available information, particularly that concerning the location of active sources in the brain. Localizing the sources of a given scalp measurement is only achieved by solving the so-called inverse problem. By introducing reasonable a priori constraints, the inverse problem can be solved and the most probable sources in the brain at every moment in time can be accurately localized.

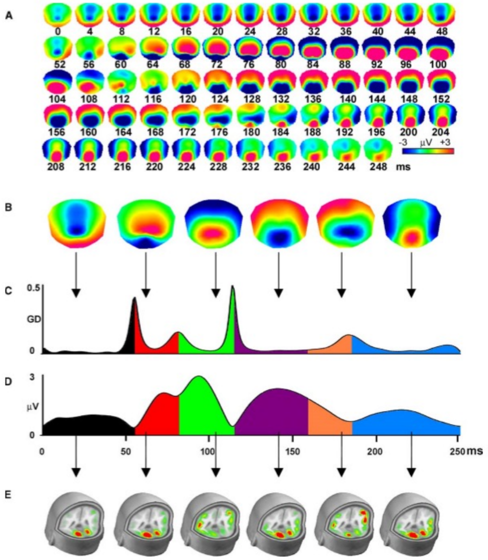
Methods and Results: Here, we review the different EEG source localization procedures applied during the last two decades. Additionally, we detail the importance of those procedures preceding and following source estimation that are intimately linked to a successful, reliabl algorithms, (3) the the statistical anal

Conclusions ar brain activity, ma neurosciences.

Keywords: EEG; So







magstim egi

Accuracy of Source Localization(Michel 2003)

- Enough number of Electrodes
- Even distribution of elecctrodes
- Accurage electrode position
- Algorithem(Loreta, Sloreta, MN…)
- Individual head model

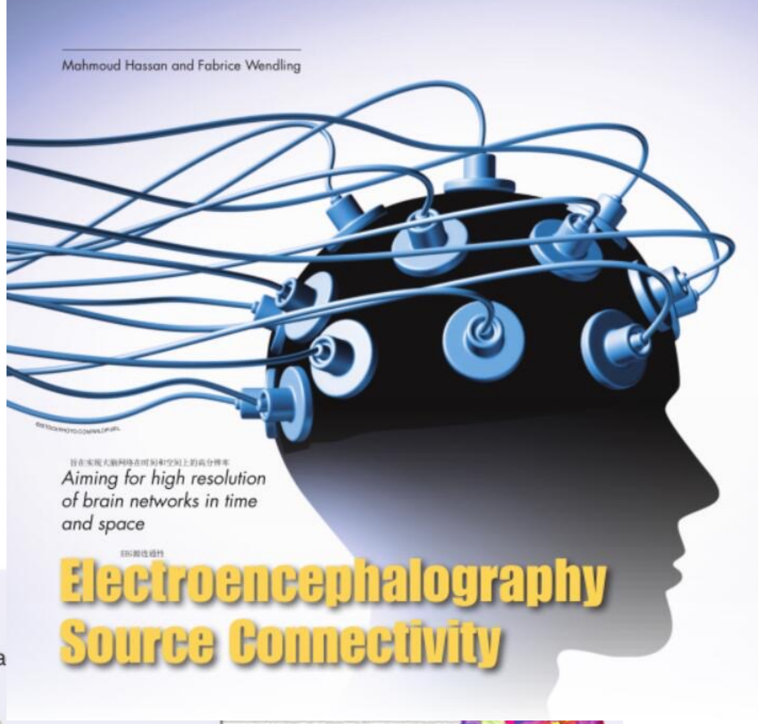
老贺和他的脑电

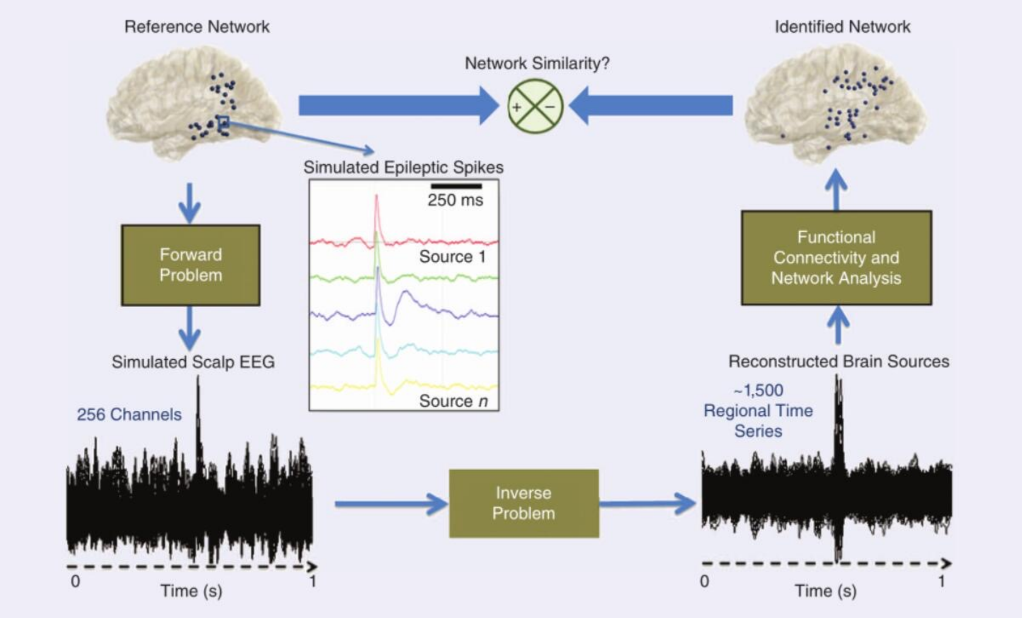
微信扫描二维码，关注我的公众号

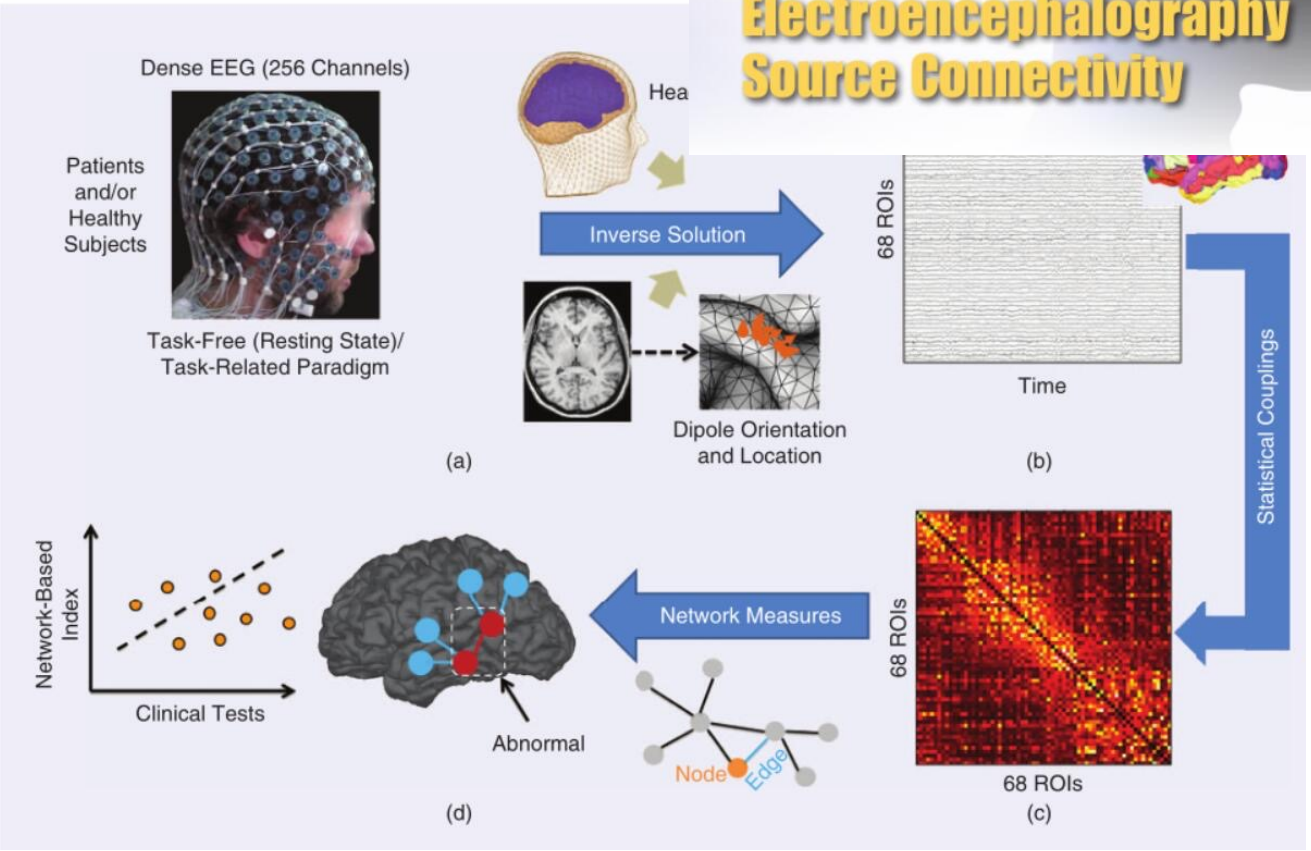
EGI 高密度脑电的核心理念（内含webina...

EEG source connectiviry （Hassan） 《IEEE Signal Processing Magazine》

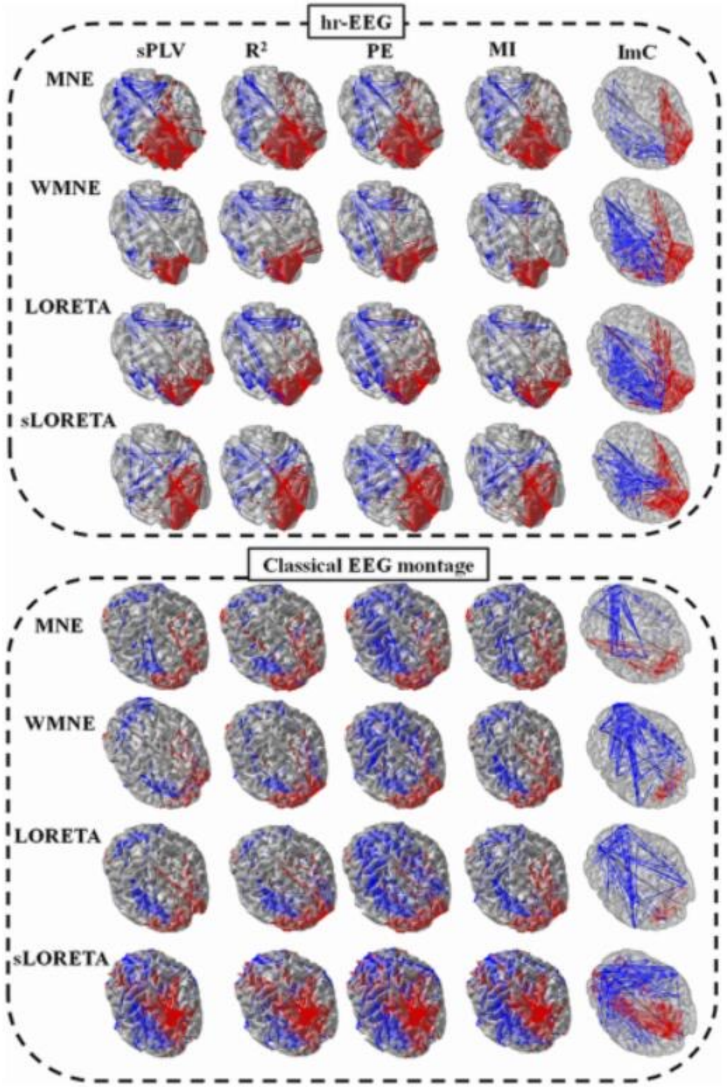
Talk in detail in what needed in EEG source connectiviry analysis and its application in clinical area.

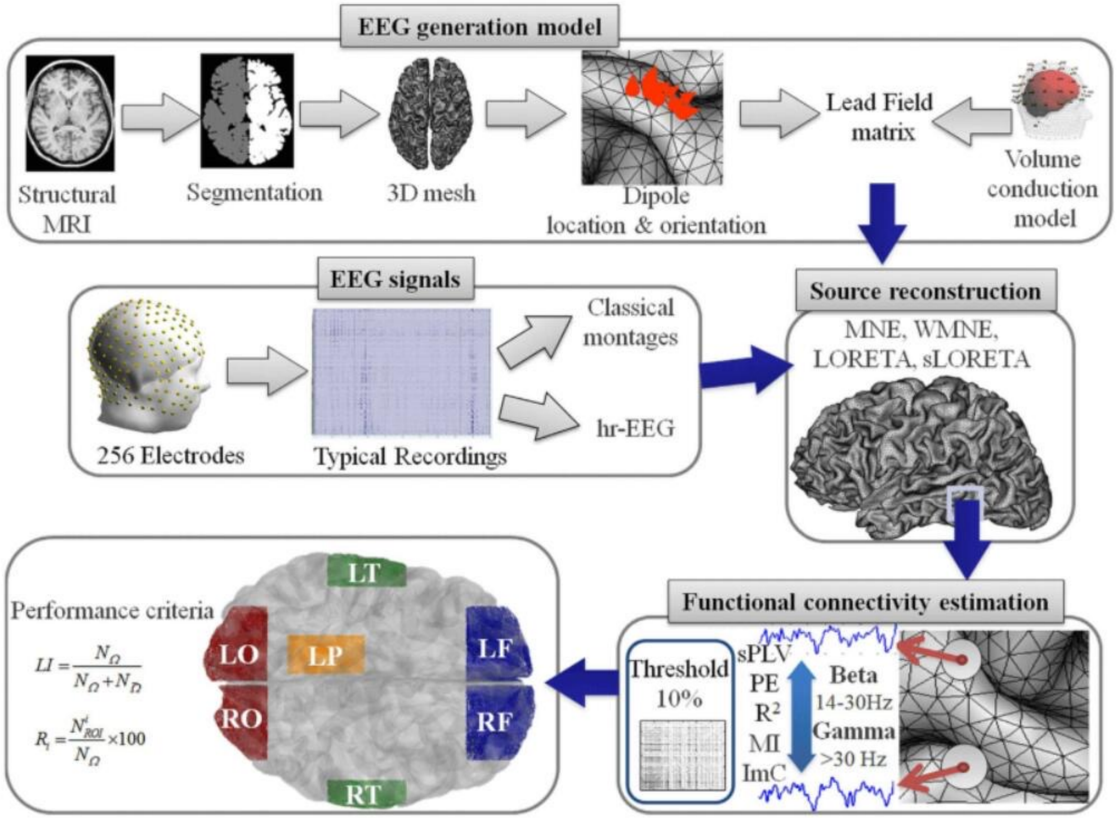






高密度脑电到脑网络





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PLOS ONE

EEG Source Connectivity Analysis: From Dense Array Recordings to Brain Networks

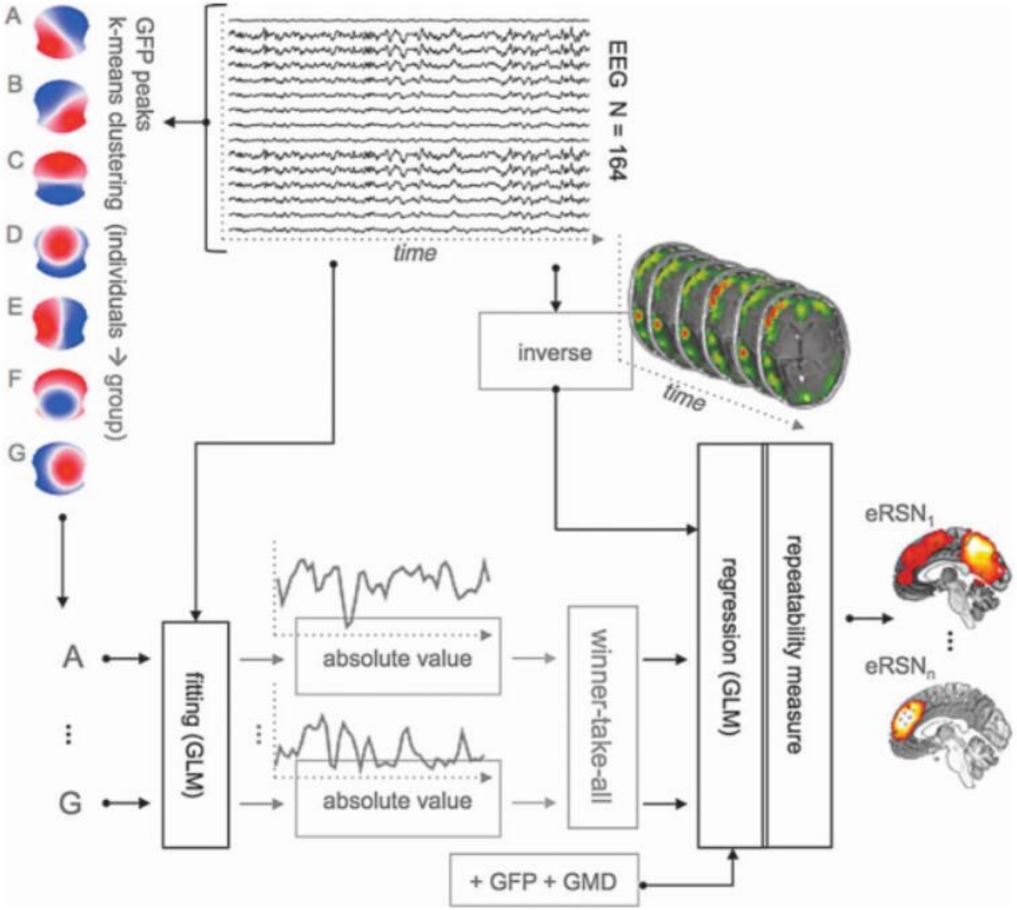
Mahmoud Hassan[1,2]*, Olivier Dufor[3], Isabelle Merlet[1,2], Claude Berrou[3], Fabrice Wendling[1,2]

1 INSERM, U642, Rennes, France, 2 Université de Rennes 1, LTSI, Rennes, France, 3 Télécom Bretagne, Institut Mines-Télécom, UMR CNRS Lab-STICC, Brest, France

Abstract

The recent past years have seen a noticeable increase of interest for electroencephalography (EEG) to analyze functional connectivity through brain sources reconstructed from scalp signals. Although considerable advances have been done both

Network， microstate， source



BRAIN CONNECTIVITY
Volume 7, Number 10, 2017
© Mary Ann Liebert, Inc.
DOI: 10.1089/brain.2016.0476

Electroencephalographic Resting-State Networks: Source Localization of Microstates

Anna Custo,[1,2] Dimitri Van De Ville,[2–4] William M. Wells,[5,6] Miralena I. Tomescu,[1]
Denis Brunet,[1,2] and Christoph M. Michel[1,2]

Depression

Network is a biomarker of Depression。

the Montreal Neurological Institute 152 template (36). The LORETA algorithm (upon which eLORETA is based) has been validated in several studies combining LORETA with fMRI (37–39), positron emission tomography (40,41), simultaneous EEG–fMRI (42,43), and intracranial recordings (44).

LPS, a measure that quantifies the nonlinear relationship between two regions after removal of the instantaneous contribution, was then computed across DMN and FPN ROIs. Instantaneous measures of EEG-based connectivity are known to be susceptible to the effects of volume conduction, which can lead to the detection of spurious functional coupling among separate regions. However, lagged connectivity corrects for this because it represents the connectivity between two regions after this zero-lag contribution has been excluded. In this respect, lagged connectivity is considered to represent a true measure of physiological connectivity. LPS between ROIs was computed for each artifact-free EEG segment in the frequency domain using normalized Fourier transforms. Based on previous factor analyses of distinct frequency bands (45), the frequency ranges were: delta (1.5–6 Hz), theta (6.5–8 Hz), alpha 1 (8.5–10 Hz), alpha 2 (10.5–12 Hz), beta 1 (12.5–18 Hz), beta 2 (18.5–21 Hz), and beta 3 (21.5–30 Hz). Additional details can be found in the Supplement.

Biological Psychiatry: CNNI

Archival Report

Electroencephalography Source Functional Connectivity Reveals Abnormal High-Frequency Communication Among Large-Scale Functional Networks in Depression

Alexis E. Whitton, Stephanie Deccy, Manon L. Ironside, Poornima Kumar, Miranda Beltzer, and Diego A. Pizzagalli

ABSTRACT

BACKGROUND: Functional magnetic resonance imaging studies of resting-state functional connectivity have shown that major depressive disorder (MDD) is characterized by increased connectivity within the default mode network (DMN) and between the DMN and the frontoparietal network (FPN). However, much remains unknown about abnormalities in higher frequency (>1 Hz) synchronization. Findings of abnormal synchronization in specific frequencies would contribute to a better understanding of the potential neurophysiological origins of disrupted functional connectivity in MDD.

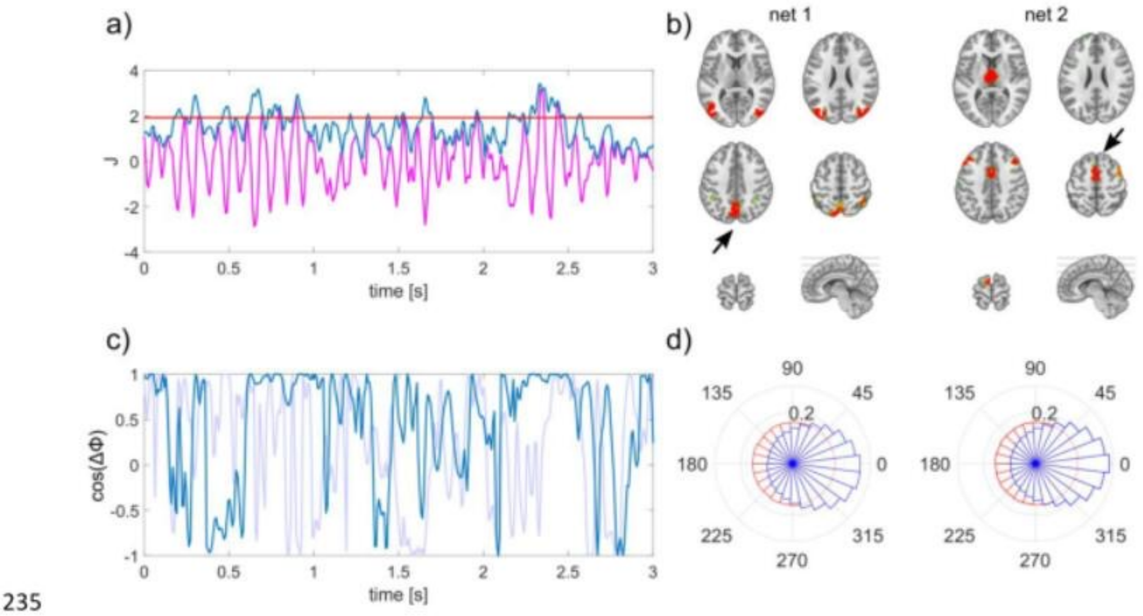
METHODS: We used the high temporal resolution of electroencephalography to compare the spectral properties of resting-state functional connectivity in individuals with MDD (n = 65) with healthy control subjects (n = 79) and examined the extent to which connectivity disturbances were evident in a third sample of individuals in remission from depression (n = 30). Exact low resolution electromagnetic tomography was used to compute intracortical activity from regions within the DMN and FPN, and functional connectivity was computed using lagged phase synchronization.

Zero phase connectivity_C M.Michel

the relevance of simultaneous zero-lag synchronization between brain areas in humans remains largely unexplored.

This negligence is due to the confound of volume conductionquasi

zero-phase related EEG source fluctuations are physiologically meaningful if spatial leakage is considered appropriately



Synchronous brain dynamics establish brief states of communality in distant neuronal populations

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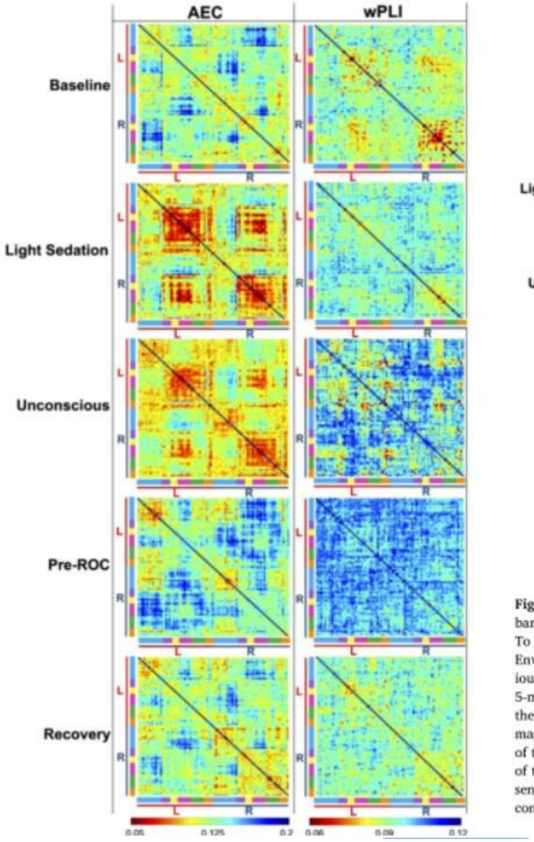
Conscious_AEC VS wPLI

AEC has better sensitivity than WPLI

Source level analysis



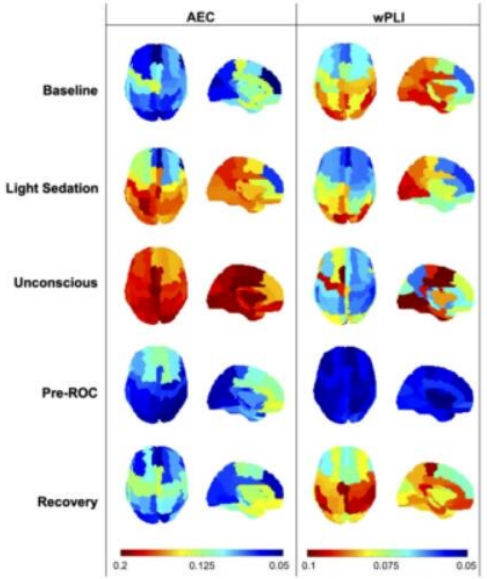
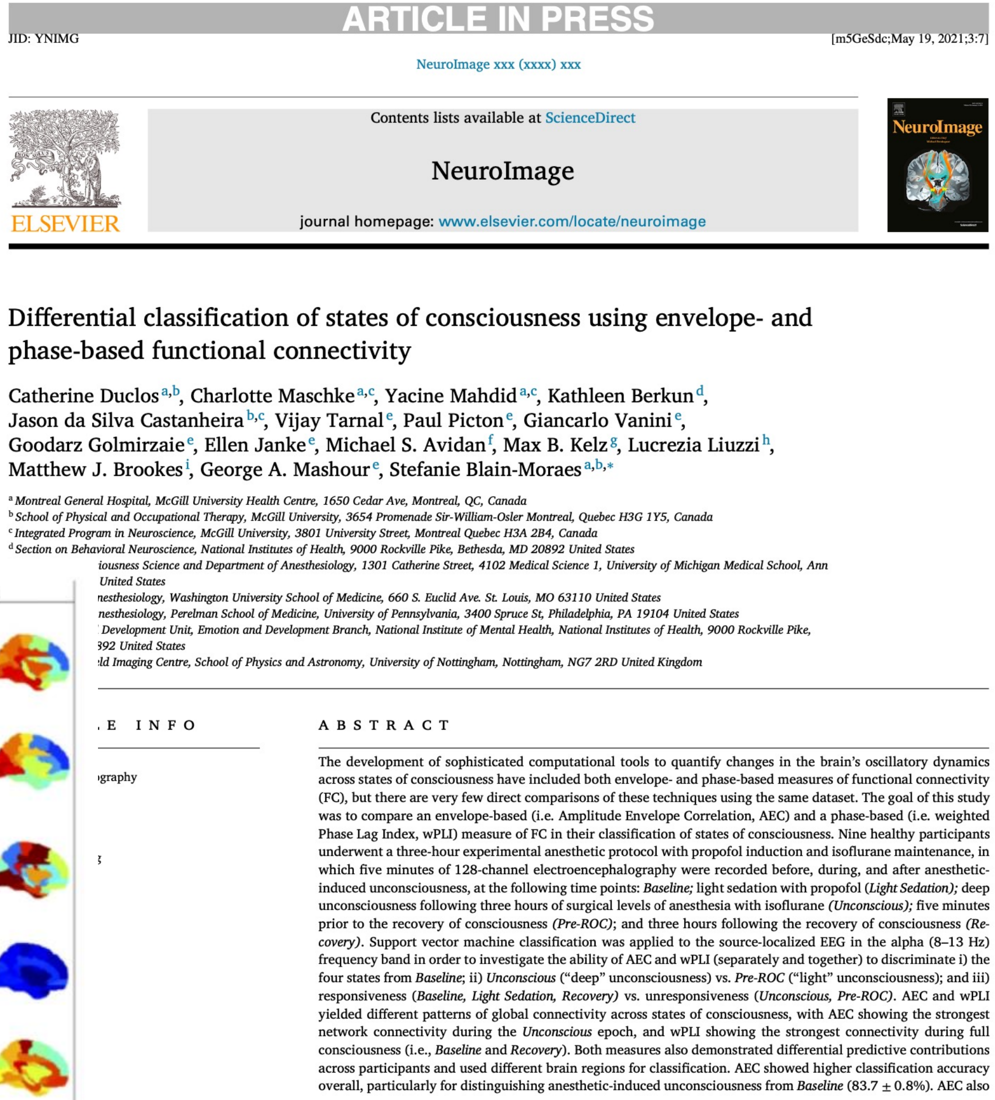


Fig. 3. Topographic maps of source-localized global connectivity in the alpha band between the 82 cortical regions of interest across states of consciousness. To compare and contrast the patterns of connectivity captured by Amplitude Envelope Correlation (AEC) and weighted Phase Lag Index (wPLI) across various states of consciousness, the group-level means of AEC and wPLI for each 5-minute epoch were displayed on 82 regions of a brain parcellated according to the AAL atlas. For each time point and for each measure, the same topographic map is depicted in 2 different views: axial top view (left), and mid-sagittal view of the left hemisphere (right). The average connectivity of each ROI to the rest of the brain regions defined in the AAL atlas is depicted by a color: red represents higher strength in connectivity, while blue represents lower strength in connectivity.



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Differential classification of states of consciousness using envelope- and phase-based functional connectivity

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E INFO

graphy

A B S T R A C T

The development of sophisticated computational tools to quantify changes in the brain's oscillatory dynamics across states of consciousness have included both envelope- and phase-based measures of functional connectivity (FC), but there are very few direct comparisons of these techniques using the same dataset. The goal of this study was to compare an envelope-based (i.e. Amplitude Envelope Correlation, AEC) and a phase-based (i.e. weighted Phase Lag Index, wPLI) measure of FC in their classification of states of consciousness. Nine healthy participants underwent a three-hour experimental anesthetic protocol with propofol induction and isoflurane maintenance, in which five minutes of 128-channel electroencephalography were recorded before, during, and after anesthetic-induced unconsciousness, at the following time points: *Baseline;* light sedation with propofol (*Light Sedation);* deep unconsciousness following three hours of surgical levels of anesthesia with isoflurane (*Unconscious);* five minutes prior to the recovery of consciousness *(Pre-ROC)*; and three hours following the recovery of consciousness *(Recovery)*. Support vector machine classification was applied to the source-localized EEG in the alpha (8–13 Hz) frequency band in order to investigate the ability of AEC and wPLI (separately and together) to discriminate i) the four states from *Baseline*; ii) *Unconscious* ("deep" unconsciousness) vs. *Pre-ROC* ("light" unconsciousness); and iii) responsiveness (*Baseline, Light Sedation, Recovery)* vs. unresponsiveness (*Unconscious, Pre-ROC)*. AEC and wPLI yielded different patterns of global connectivity across states of consciousness, with AEC showing the strongest network connectivity during the *Unconscious* epoch, and wPLI showing the strongest connectivity during full consciousness (i.e., *Baseline* and *Recovery*). Both measures also demonstrated differential predictive contributions across participants and used different brain regions for classification. AEC showed higher classification accuracy overall, particularly for distinguishing anesthetic-induced unconsciousness from *Baseline* (83.7 ± 0.8%). AEC also

Source level emotion

——IEEE Transactions on Affective Computing，来自官网截图

Identifying cortical brain directed connectivity networks from high-density EEG for emotion recognition

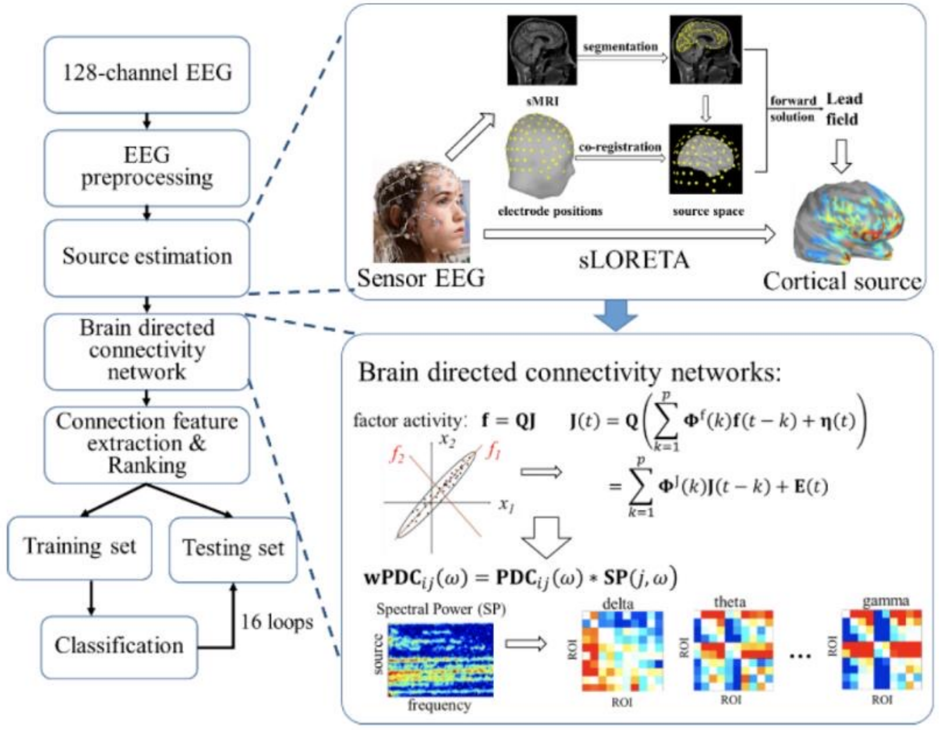
Publisher: IEEE　Cite This　PDF

Hailing Wang; Xia Wu; Li Yao　All Authors

2020年7月13日，国际知名IEEE杂志《IEEE Transactions on Affective Computing》发表了一篇题为《Identifying cortical brain directed connectivity networks from high-density EEG for emotion recognition》的研究文章，由北京师范大学邬霞团队等人利用高密度脑电EGI设备进行源定位信号研究，并以此用于情绪识别的大脑定向连接(BDC) 网络分析研究。

皮层源重建与BDC网络估计

在不同的脑组织不同情绪状态之间建立BDC网络，图3显示了获取BDC网络的通道重构的脑电信号源过程。



播或大脑区域之间的相互作用以及相关情绪的位置。此外，目前大多数研究使用低密度电极（小于128导）EEG 信号。迄今为止，尚未有根据高密度脑电设备进行EEG 信号采集并估计源信号用于情绪识别。我们设计了一个基于 BDC 网络的框架，使用 EEG 源信号来研究情绪识别，采用基于全脑皮层因子的多变量自回归(GCF-MVAR)方法提取情绪相关的 BDC 特征。我们的研究表明，结合 BDC 和 DE 特征的识别准确率高达 89.58%，高于单独从 BDC 特征和 DE 特征获得的识别准确率。与低密度 EEG 信号相比，高密度 EEG 信号的电极信号特征具有更高的识别精度。这些结果表明，从脑电源信号中提取的 BDC 特征能够更好地描述人类的情绪状态，对情绪识别具有重要意义。

Function connectivity in language study

- Findings suggest that resting state EEG network modularity is likely to serve as a reasonable, reliable, and cost-effective neural marker of the development of first language but not second language literacy skills.

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Brain and Language

Volume 220, September 2021, 104984

Resting state EEG network modularity predicts literacy skills in L1 Chinese but not in L2 English

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