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Graph learning from EEG data improves brain fingerprinting compared to correlation-based connectomes

Maliheh Miri [a,b,c,*], Vahid Abootalebi [a], Enrico Amico [c], Hamid Saeedi-Sourck [a], Dimitri Van De Ville [c,d], Hamid Behjat [c,b]

[a] Department of Electrical Engineering, Yazd University, Yazd, Iran
[b] Department of Biomedical Engineering, Lund University, Lund, Sweden
[c] Neuro-X Institute, Ecole Polytechnique Federale de Lausanne, Geneva, Switzerland
[d] Department of Radiology and Medical Informatics, University of Geneva, Geneva, Switzerland

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ABSTRACT

A growing body of research in the past decade has revealed that functional interaction between brain regions entail subject-specific idiosyncrasies that are highly replicable. As such, functional connectivity patterns can be seen as an individual's brain fingerprint, enabling their identification within a population, in health and disease. The conventional method involves constructing the functional connectome by treating brain regions as vertices and utilizing pairwise measures of statistical dependence, such as Pearson's correlation coefficient, between the regional time-courses as edge weights. However, by focusing on EEG data in our study, we propose an alternative approach to learn a sparse graph structure from an individual's EEG data using principles from graph signal processing. The inferred subject-specific graphs encode subtle instantaneous spatial relations between the ensemble set of EEG electrodes in such way that EEG maps are seen as smooth functions residing on the graph. We validated the inferred graphs on two publicly available EEG datasets, demonstrating that the learned graphs outperform correlation-based functional connectomes in fingerprinting performance. This talk provides an overview of our proposed method and related results, which was presented at the 2023 European Signal Processing Conference in Helsinki, Finland. The work was selected as the second-best student paper; aside from the talk, a poster was presented as part of the contest, segments of which can be found as figures in the present article.

Video to this article can be found online at https://doi.org/10.1016/j.sctalk.2024.100330.

* Corresponding author at: Department of Electrical Engineering, Yazd University, Yazd, Iran.
E-mail address: maliheh.miri@epfl.ch (M. Miri).

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Figures and tables

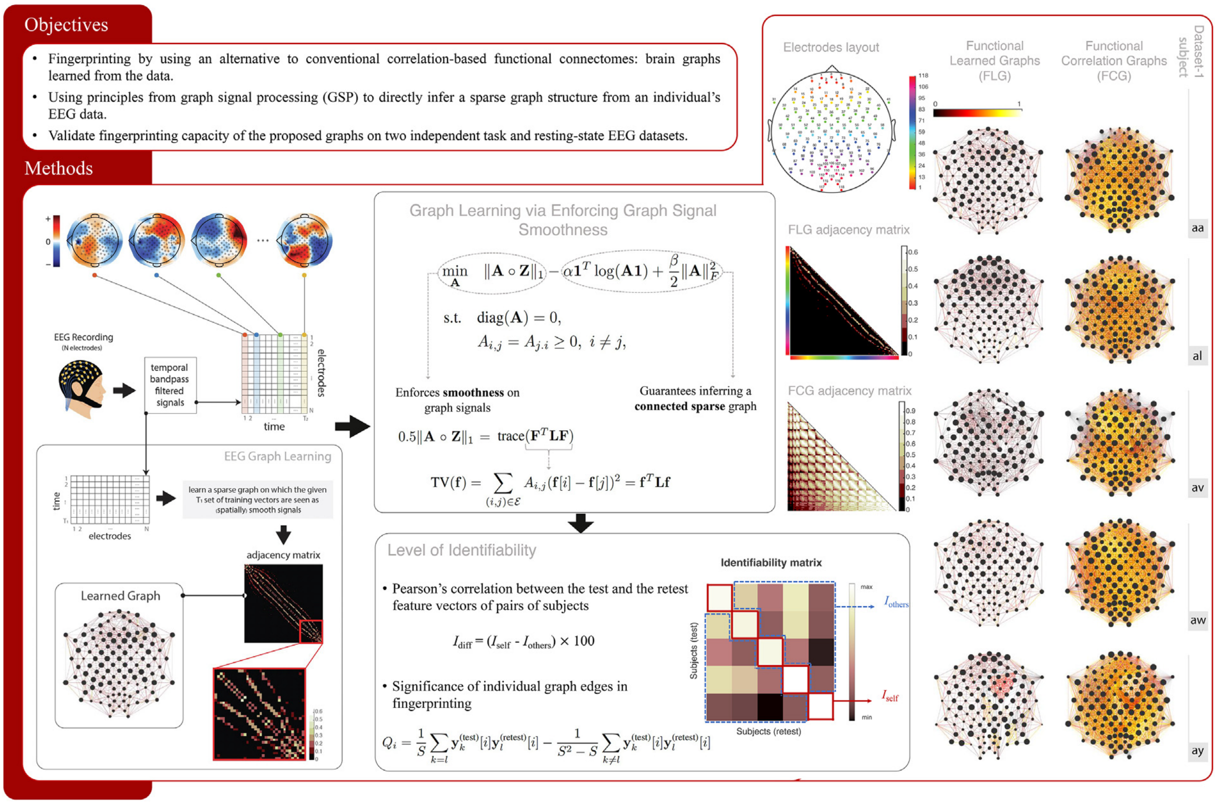

Fig. 1. Objectives and methods. Top: objectives of the study. Bottom: a schematic overview of the proposed methodology for finding graph representations from EEG maps [1]. A set of EEG recordings from N electrodes is used to learn a sparse graph on which EEG maps are seen as spatially smooth signals [2,3]. The optimization presented in the middle box is used to learn a graph adjacency matrix **A** by enforcing smoothness on graph signals, using a measure of total variation (TV) [4]. Penalties in the second and third terms guarantee finding a connected sparse graph. To evaluate the proposed method, the concept of "level of identifiability" is utilized which quantifies the identifiability capability [5]. For this mean, data of each subject is divided into two sets of test and retest and the identifiability matrix is obtained by computing the Pearson's correlation between each pair of test and retest feature sets. I_{self} is the average of the main diagonal elements, and I_{others} is the average of the off-diagonal elements. Higher values of I_{diff} indicate greater individual fingerprinting. Right: Functional Correlation Graphs (FCG) and Functional Learned Graphs (FLG) across five subjects of Dataset-1 [6]. Edge widths and colors reflect edge weights, and vertex sizes reflect nodal degrees. Electrodes layout and their corresponding graph vertex indices as well as a representative set of the FCG and FLG adjacency matrices are shown next to the graphs. For better interpretation of graph matrices, a colormap is added to enable linking the row/column order of the matrices to the electrodes layout.

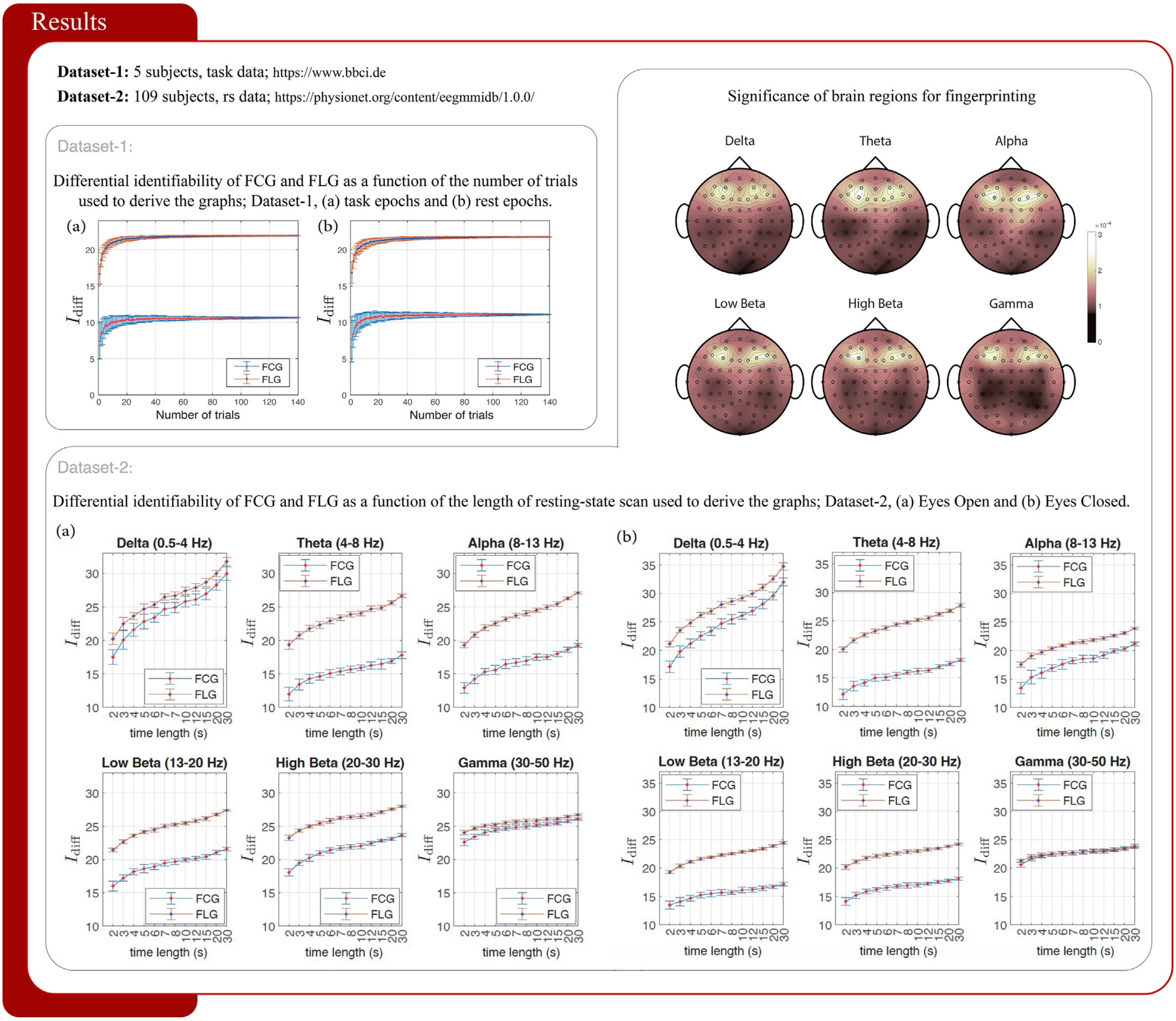

Fig. 2. Fingerprinting results on Dataset-1 [6] and Dataset-2 [7] in terms of I_{diff} and accuracy are shown in the tables. The results show superior performance of learned graphs compared to correlation-based graphs in both I_{diff} and accuracy measures. Differential identifiability power of FCG and FLG as a function of the number of trials/length of epochs used to build and learn the graphs are shown for Dataset-1 and Dataset-2 in the left and right plots, respectively. In this analysis, half of the data were treated as the test set and the other half as the retest set. Differential identifiability was obtained as the average of bootstraps for each instance of number of trials/length of epochs. Error bars show the standard deviation across bootstrap iterations. In both datasets, fingerprinting performance enhances as a function of the time length of EEG data used for graph learning. Bottom-left: significance of brain regions for fingerprinting [8], where significance was computed using the method described in Fig. 1. The results show spatially localized patterns, mainly in the frontal lobe, in all frequency bands.

Conclusions & Outlook

- Brain graphs learned from EEG data show superior performance in identifying individuals, as an alternative to conventional correlation-based functional connectomes.
- In both datasets, fingerprinting performance enhances as a function of length of epochs, and results show spatially localized patterns that are mainly in the frontal lobe.
- **Outlook:** Mapping on the harmonic basis of Laplacian matrices of the learned graphs can provide a novel spectral representations of EEG maps that can be utilized in applications such as motor imagery decoding and cognitive neuroscience; see the outlook illustration below.

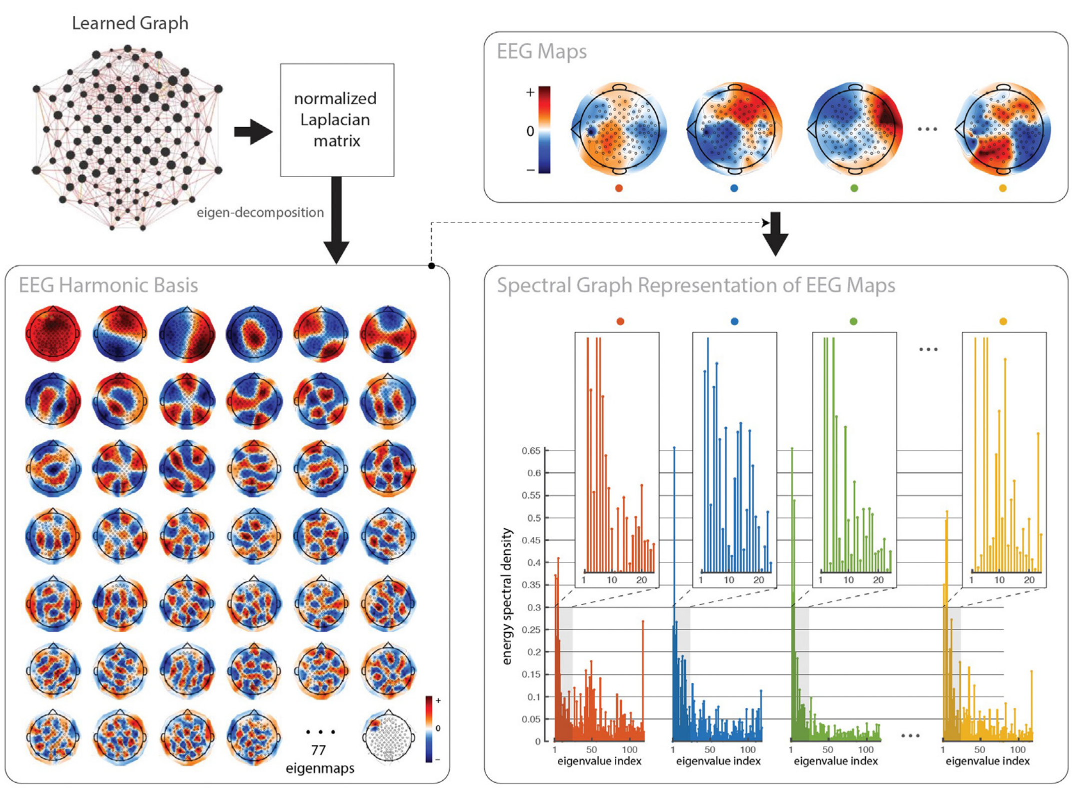

Fig. 3. Conclusions and outlook. By transforming the adjacency matrix to the Laplacian matrix, eigendecomposing the Laplacian matrix yields a set of eigenmodes that can be used as a basis for transforming EEG maps to a spectral representation for use in various applications such as motor imagery decoding [3]. Moreover, the spectrum and eigenbasis of learned EEG graphs may provide a more compact feature space [9] for the task of fingerprinting and beyond, in particular, via quantifying their distance in the form of normative modelling [10] to a population-level template [11,12] derived from a large sample of healthy subjects.

Table 1
Fingerprinting I_{diff} (%)/accuracy(%) on Dataset-1.

	Both Tasks	Task 1	Task 2	Rest
FLG	**21.9/100**	**21.7/100**	**22.1/100**	**21.8/100**
FCG	10.6/**100**	11.4/**100**	10.3/**100**	11.1/**100**

Table 2
Fingerprinting I_{diff} (%)/accuracy(%) on Dataset-2.

	Eyes Open		*Eyes Closed*	
	FLG	FCG	FLG	FCG
Delta	29.3/95.4	26.90/82.6	**32.0/99.1**	29.2/90.8
Theta	25.4/95.4	16.28/87.2	**26.6/99.1**	17.0/90.8
Alpha	**26.1/100**	17.9/83.5	23.0/**100**	20.0/82.6
Low Beta	**26.7/100**	20.7/96.3	23.8/**100**	16.35/92.7
High Beta	**27.4/100**	22.9/98.2	23.6/99.1	17.3/96.3
Gamma	**26.2/100**	25.6/98.2	23.1/97.2	23.2/96.3

CRediT authorship contribution statement

Maliheh Miri: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Vahid Abootalebi:** Conceptualization, Writing – review & editing. **Enrico Amico:** Writing – review & editing. **Hamid Saeedi-Sourck:** Writing – review & editing. **Dimitri Van De Ville:** Methodology, Writing – review & editing. **Hamid Behjat:** Conceptualization, Investigation, Methodology, Software, Supervision, Visualization, Writing – review & editing.

Data availability

No data was used for the research described in the article.

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Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Maliheh Miri is a PhD student in Electrical Engineering at Yazd University, Yazd, Iran. She spent a sabbatical year as a visiting student at Lund University and the Ecole Polytechnique Fédérale de Lausanne (EPFL) from November 2022 to November 2023. Her research interests are graph signal processing and pattern recognition, mainly focused on medical signal processing.

Vahid Abootalebi received the B.S. and M.S. degrees in electrical Engineering from Sharif University of Technology, Tehran, Iran, in 1997 and 2000, respectively. He received his Ph.D. degree in biomedical engineering from Amirkabir University of Technology, Tehran, Iran in 2006. Since 2007, he has been working as a faculty member of the Electrical Engineering Department of Yazd University, where he is currently an Associate Professor. His main research interests include biomedical signal processing and pattern recognition.

Dr. Enrico Amico is a physicist who graduated from the University Federico II of Naples, Italy. After earning his Master's degree in 2012, he decided to follow his passion for the scientific study of consciousness. He enrolled in a joint PhD program between the Coma Science Group of Prof. Steven Laureys at University of Liège, and the Marinazzo Lab at the University of Ghent, Belgium. During his four years there as a PhD student he mainly focused on implementing new methods for brain connectivity assessment across levels of consciousness. In 2016 he joined the CONNplexity Lab (headed by Prof. Joaquín Goñi) as a Postdoctoral researcher, where he made contributions on proposing new network science models for functional and structural brain connectomics. From 2020 to 2024 he was SNSF Ambizione Fellow at EPFL and University of Geneva. He is currently Lecturer and Principal Investigator at Aston University, where he leads his lab on different research lines in network neuroscience, brain fingerprinting and brain connectomics.

Hamid Saeedi-Sourck received his B.Sc., M.Sc., and Ph.D. degrees in Electrical Engineering from the Isfahan University of Technology (IUT), Iran, in 2000, 2003, and 2011, respectively. He served as a researcher at the Information & Communication Technology Institute of IUT from 2003 to 2007. He also spent a sabbatical year at Eindhoven University of Technology from 2009 to 2010. His research interests encompass Signal Processing for Wireless Communications, Multi-Carrier Modulation, Graph Signal Processing, and Wavelet Transform.

Dr. Dimitri Van De Ville received his Ph.D. degree in computer science engineering from Ghent University, Belgium, in 2002. He was a post-doctoral fellow (2002–2005) at the lab of Prof. Michael Unser at the Ecole Polytechnique Fédérale de Lausanne (EPFL), Switzerland, before becoming responsible for the Signal Processing Unit at the University Hospital of Geneva, Switzerland, as part of the CIBM Center for Biomedical Imaging. In 2009, he received a Swiss National Science Foundation professorship. In 2015 he became Associate Professor of Bioengineering at EPFL, jointly affiliated with the University of Geneva, Switzerland, and in 2024 was promoted to Full Professor. His main research interest is in computational neuroimaging to advance cognitive and clinical neurosciences. He was a recipient of the Pfizer Research Award 2012, the NARSAD Independent Investigator Award 2014, the Leenaards Foundation Award 2016, and was elected Fellow of the IEEE in 2020, IEEE SPS Distinguished Lecturer 2021–2022, and Fellow of the EURASIP in 2023.

Hamid Behjat received the B.S. degree in biomedical engineering from Amirkabir University of Technology, Tehran, Iran, in 2007, the M.Sc. degree in biomedical engineering from Linköping University, Linköping, Sweden, in 2012, and the Ph.D. degree in biomedical engineering from Lund University, Lund, Sweden, in 2018. He was a Swedish Research Council postdoctoral fellow (2019-2021) and is currently a Marie Curie research fellow. Dr. Behjat conducted his first postdoctoral studies at Harvard Medical School, Boston, USA. Since 2022 he is a postdoctoral researcher at the Ecole Polytechnique Fédérale de Lausanne (EPFL), Switzerland, and since 2023 he is also a researcher at the Clinical Memory Research Unit, Lund University. His main research interests are at the intersection of graph signal processing and human brain neuroimaging, with particular focus on developing methodologies for integrative spatial analysis of multimodal neuroimaging data.