ASRE: Adaptive Spatial Resolution Wearable EEG

Yongchao Yang[1], Ye Sun[1,2]
[1]Department of Mechanical Engineering-Engineering Mechanics, Michigan Technological University, Houghton, MI
[2]Department of Mechanical and Aerospace Engineering, University of Virginia, Charlottesville, VA
yyang14@mtu.edu, dzv7sg@virginia.edu

Abstract— **Electroencephalography (EEG) has been used as a gold standard in various clinical and research applications including disease diagnoses and cognitive understanding. It is also being used as brain-machine interfaces in robotics and assistive technologies. Wearable EEG systems provide a good solution for out-of-hospital recording; however, they are still not suitable for long-term monitoring due to the bulky placement of electrodes over the scalp. The goal of this study is to develop an adaptive spatial resolution framework for wearable EEG systems that can use a limited number of EEG electrodes to achieve high spatial resolution detection. It also shows the high feasibility for achieving high-density and ultra-high-density EEG from traditional 10-20 or 10-10 systems. The proposed method utilized the matrix completion technique to recover high-resolution EEG field from only a limited number of electrodes, which enables simplification of hardware design for wearable EEG that can achieve a compatible performance of P300 detection. The results show that 75% reduced electrodes can achieve a comparable performance as regular EEG with the RMSE under 5%.**

Keywords—High-density EEG, wearable EEG, super-resolution, adaptive spatial resolution

2021 IEEE Sensors | 978-1-7281-9501-8/21/$31.00 ©2021 IEEE | DOI: 10.1109/SENSORS47087.2021.9639244

I. Introduction

Electroencephalography (EEG) is a standard technique for measuring scalp electrical signals generated by brain activities, which is widely used for disease diagnoses and treatments as well as brain-machine interfaces. Clinical EEG systems normally adopt standard electrode placements such as the international 10-20 or 10-10 system with 10 to 64 electrodes over the scalp. Biomarkers are then extracted from the detected multi-channel signals for different diagnosis purposes. Compared to other imaging techniques for neurological measurement, EEG offers a less invasive, less expensive, and more convenient solution for brain activity measurement. In recent years, high-density EEG (HD-EEG) and ultra-high-density EEG (UHD-EEG) with 256 to 1000 electrodes are successfully developed and utilized in clinical and research applications [2]-[4], which enable EEG as a high temporal resolution imaging modality [1].

Clinical EEG systems normally use wet electrodes and usually require abrasion of human skin to reduce skin-electrode impedance and increase signal quality. Wearable EEG systems developed from ambulatory EEG are smaller and lighter devices for EEG recording in daily applications. Wearable EEG systems have higher comfort, biocompatibility, and operability, and thus provide an excellent solution for identifying potential biomarkers beyond clinical settings. However, low spatial resolution in wearable conditions may not meet clinical standards for diagnosis whereas high spatial resolution can cause wearable issues and high power consumption in long-term monitoring in out-of-hospital settings.

In such cases, it is valuable to reconstruct an EEG recording with high spatial resolution from a lower spatial resolution electrode placement. Mathematically, it is an ill-posed inverse problem without analytical solutions to infer the full-field (high spatial resolution) signals with only limited (low spatial resolution) measurements. A traditional super-resolution approach is to acquire a low-resolution grid of measurements at the uniform locations, and then use an averaging-based interpolation function (such as bi-cubic) to construct a high-resolution approximation. However, the averaging process can easily lose the local, fine-detailed information.

In this study, we propose a matrix completion based computational framework for adapting spatial resolution of EEG signals. We propose to use the state-of-the-art interpolation approach that exploits the implicit feature structure of the two-dimensional (2D) signals and formulates it as a matrix completion problem, which is solved by the emerging convex optimization techniques [5], [6]. The proposed method is capable of significantly enhancing the spatial resolution of international 10-10 EEG systems and lowering power consumption simultaneously. The results show that 75% reduced electrodes can achieve a comparable performance as regular EEG with the RMSE under 5%. This study provides the theoretical basis and computational method for using traditional EEG signals to achieve HD-EEG and UHD-EEG as well as reducing the usage of electrodes for wearable EEG system design towards an adaptive spatial resolution computational framework.

II. Theoretical Basis

A. EEG Systems

EEG systems measure the surface electrical potentials on the scalp caused by neuronal action within the brain. The clinical wet electrodes are based on Silver/Silver-Chloride and usually require skin preparation. In recent years, wearable EEG systems are commercially available, which often use dry electrodes held in place by a cap. For EEG recording, there are multiple electrode placement standards including the most commonly used international 10-10 or 10-20 systems. In this study, we adopted the EEG measurement using the international 10-10 system with the electrode placement shown in Fig. 1.

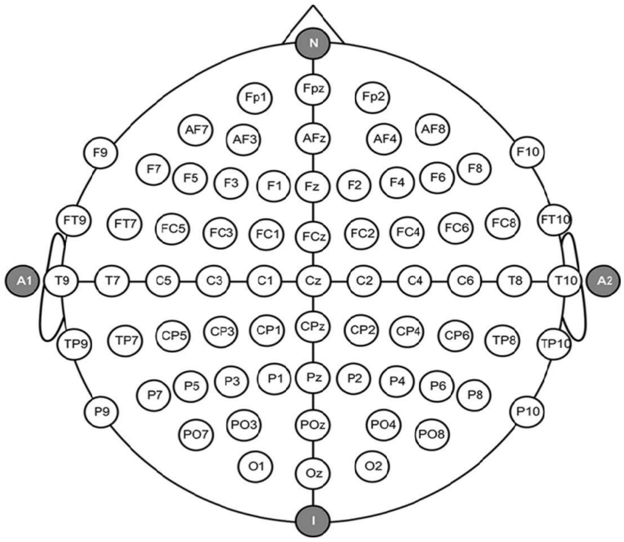

Fig. 1. EEG electrode placement using 10-10 system [7].

B. Computational Framework for Adaptive Spatial Resolution EEG

The proposed computational framework is based on matrix completion and convex optimization. Theoretically it can exploit the implicit feature of the spatiotemporal EEG signals. Assuming we perform measurements at a limited set of random positions of the unknown full-field $\boldsymbol{X} \in R^{m \times N}$ (m channels and N time samples for each channel), the available measurement data $\boldsymbol{B}$ is a random subset $\boldsymbol{\Omega}$ of the complete $\boldsymbol{X} \in R^{m \times N}$,

$$\boldsymbol{B} = P_{\Omega}(\boldsymbol{X}) \tag{1}$$

where is an operator that randomly (following a uniform random distribution) selects a subset of elements from $\boldsymbol{X}$ such that $B_{ij} = X_{ij},\ (i,j) \in \Omega$; $B_{ij} = 0$ elsewhere. Using only the available information of a limited set of randomly positioned measurements $\boldsymbol{B}$ with M' ($<< m \times M$)entries and $P_{\Omega}(\cdot)$ containing the random measurement positions, $\boldsymbol{X} \in R^{m \times N}$ can be accurately recovered with an overwhelming probability of success by solving the following convex optimization program:

$$(P*):\ \boldsymbol{X}^* = \arg min \left\| \hat{\boldsymbol{X}} \right\|_* \text{ subject to } \left\| P_{\Omega}(\hat{\boldsymbol{X}}) - \boldsymbol{B} \right\|_F < \delta \tag{2}$$

provided that the measurement number exceeds $M' \propto Nr \log N$, or roughly speaking if the true unknown $\boldsymbol{X} \in R^{m \times N}$ is sufficiently low-rank. $\|\boldsymbol{X}\|_* := \sum_i \sigma_i(\boldsymbol{X})$ is termed the nuclear norm of the matrix $\boldsymbol{X}$, which summates its singular values; $\|\boldsymbol{X}\|_F := \sqrt{\sum_i \sigma_i^2}$ is the Frobenius norm of $\boldsymbol{X}$, and δ is some bounding parameter related to the small dense noise level.

The nuclear norm is the tightest convex approximation to the rank of a matrix. ($P*$) can be interpreted as finding an $\boldsymbol{X}^* \in R^{m \times N}$ with minimal nuclear norm (lowest rank) that explains the available measurements $B_{ij} = X^*_{ij},\ (i,j) \in \Omega$ within a bounded noise level δ . The convex ($P*$) program can be implemented using a fixed-point continuation (FPC) method. From the virtue of the convex program, the solution to ($P*$) found by FPC is always globally optimal. Note that ($P*$) is implemented without knowledge of the distribution, magnitudes, and number of singular values of the original strain matrix $\boldsymbol{X}$. The only assumption is that its rank is low, so those missing (unmeasured) entries of $\boldsymbol{X}$ can be accurately recovered from the limited set of randomly positioned available measurements $\boldsymbol{B}$. Thus, with limited EEG channel recordings, it is theoretically highly possible to recover the overall EEG recordings over the field. Also, with commonly used 20-64 electrode systems, it is feasible to infer high-density EEG.

C. Evaluation Metrics

To evaluate the performance of using low spatial resolution EEG to recover higher resolution, we used the measured dataset [8] to compare the original signal with the recovered signal using our proposed method. We use the root-mean-square error (RMSE) as the evaluation metrics, which is widely used for performance evaluation and can be calculated using (3) and (4) for 1D and 2D, respectively.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(R_i - R_i^F\right)}{N}} \times 100\% \tag{3}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\sum_{j=1}^{M}\left(R(i,j) - R_{NM}^F(i,j)\right)^2}{N \times M}} \times 100\% \tag{4}$$

where R is the original EEG signal for one or more channels; R^F is the recovered EEG signal using our method. The RMSE computes the reconstruction error and evaluates how accurate the reconstructed data is in representing the original data.

III. Experiment and Results

A. Data

In this study, we used the EEG data available in the MIT-BIH database [8] in which subjects performed different motor/imagery tasks while 64-channel EEG signals were recorded using the BCI2000 system [9], [10]. The data contains 64 EEG signals per the international 10-10 system with the sampling frequency of 160 Hz excluding electrodes Nz, F9, F10, FT9, FT10, A1, A2, TP9, TP10, P9, and P10.

B. Validation Experiment

To validate our result, we use the above dataset of measured EEG. During the experiment, we reduced the EEG channels and used partial EEG recordings to recover the original 64-channel EEG. First of all, we reduced the total EEG recordings to 50% (32 channels), 25% (16 channels), and 10% (6 channels) to simulate the limited electrode placement for EEG measurement. Then we recovered 64-channel EEG signals from these reduced cases using our proposed method described in Section II-B. To better evaluate the performance, we calculated the RSME with channel reduction for recovering. The results are shown in the following Section III-C.

C. *EEG Recovery Results*

Figure 2 shows the spatiotemporal recovery results with 50%, 25%, and 10% electrode placement compared to the original 64-channel EEG. Each image is a spatiotemporal visualization of the 64-channel data recovered from different percentages. With a 50% or 75% channel reduction, the recovered 64-channel results are still close to the original 64-channel EEG; whereas with a 90% reduction which means recovering 64 channels from only 6 electrodes, the major patterns can still be seen but some features are lost.

To quantitively evaluate the recovery performance with reduced EEG electrodes, we also calculated the RMSE between the original 64-channel EEG signals and the recovered 64 channel signals in different electrode placement percentages (percentage of partial measurement) as shown in Fig. 3. The y-axis is 1-RMSE to show the closeness to the original EEG. The x-axis shows the percentage of electrode placement percentage. With the increase of electrode placement percentage, the recovered EEG is closer to the original 64 channel recordings.

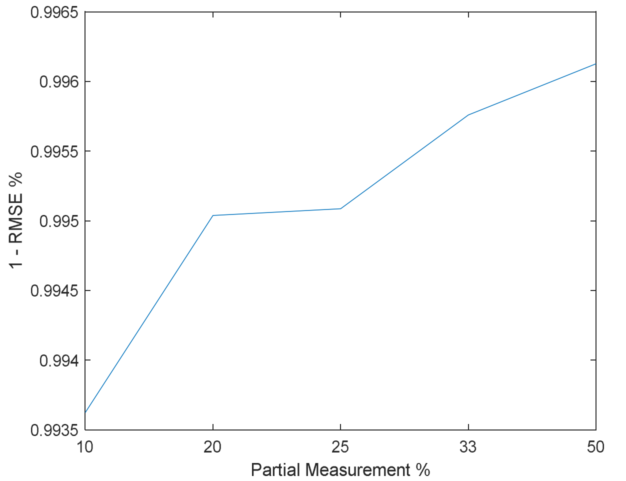

Fig. 3 RMSE increasing with the decrease of the percentage of electrode placement. The y-axis is 1-RMSE to show the closeness to the original EEG. The x-axis shows the percentage of electrode placement percentage. With the increase of electrode placement percentage, the recovered EEG is closer to the original 64 channel recordings.

IV. Conclusion

In this study, we developed a computational framework for adaptive spatial resolution EEG systems, which is capable of using a limited number of EEG electrodes to achieve high spatial resolution measurement. The method can be directly applied for guiding wearable EEG system design as well as achieving HD-EEG from traditional clinical systems. The proposed method is based on the matrix completion technique that can exploit the implicit feature structure of the spatiotemporal EEG signals. The results validate the high recovery accuracy with the RMSE under 5% with 75% electrode placement reduction.

Acknowledgment

This work is partially supported by National Science Foundation Grant No. 1710852 and No. 1751454. We appreciate the support to enable this research.

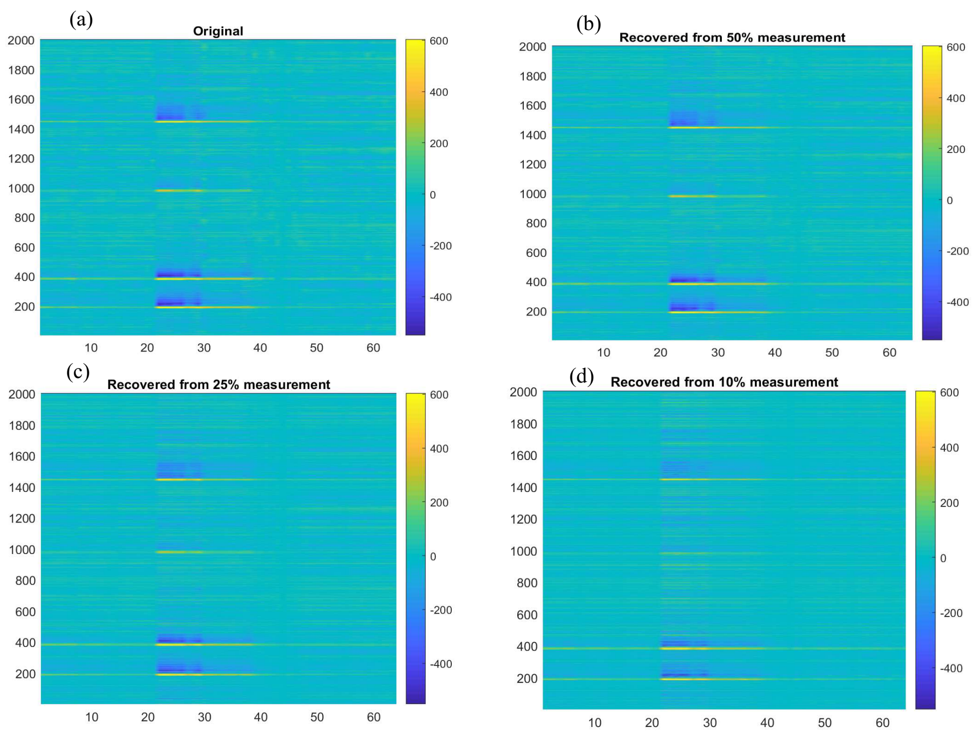

Fig.2 Recovered spatiotemporal EEG with different percentage of EEG placement. (a) Original EEG; (b) recovered EEG with 50% placement (32 channels); (c) recovered EEG with 25% placement (16 channels); (d) recovered EEG with 10% placement (6 channels).

REFERENCES

[1] A. Krishnan, R. Kumar, A. Etienne, A. Robinson, S. K. Kelly, M. Behrmann, M. J. Tarr, and P. Grover, "Challenges and opportunities in instrumentation and use of high-density EEG for underserved regions," In *International Conference on Innovations and Interdisciplinary Solutions for Underserved Areas* (pp. 72-82). Springer, Cham. 2018.

[2] A.K. Robinson, P. Venkatesh, M. J. Boring, M.J. Tarr, P. Grover, and M. Behrmann, "Very high density EEG elucidates spatiotemporal aspects of early visual processing," *Scientific Reports*, Vol. 7, pp.1-11, 2017.

[3] F. Siclari, G. Bernardi, J. Cataldi, and G. Tononi, "Dreaming in NREM sleep: a high-density EEG study of slow waves and spindles," *Journal of Neuroscience*, Vol. *38*(43), pp. 9175-9185, 2018.

[4] F. La Foresta, F. C. Morabito, S. Marino, and S. Dattola, "High-density EEG signal processing based on active-source reconstruction for brain network analysis in alzheimer's disease," *Electronics*, Vol. *8*(9), p.1031, 2019.

[5] E. Candès and B. Recht, "Exact matrix completion via convex optimization," *Foundations of Computational Mathematics,* Vol. 9 pp. 717-772, 2009.

[6] S. Ma, D. Goldfarb, and L. Chen, "Fixed point and Bregman iterative methods for matrix rank minimization," *Mathematical Programming*, Vol. 128, pp. 321-353, 2011.

[7] M. Balconi and D. Crivelli. Fundamentals of Electroencephalography and Optical Imaging for Sport and Exercise Science from: Handbook of Sport Neuroscience and Psychophysiology Routledge, 2018.

[8] Database. https://physionet.org/content/eegmmidb/1.0.0/

[9] BCI2000 http://www.bci2000.org

[10] G. Schalk, D.J. McFarland, T. Hinterberger, N. Birbaumer, J.R. Wolpaw, "BCI2000: A general-purpose brain-computer interface (BCI) system," *IEEE Transactions on Biomedical Engineering,* Vol. 51(6), pp. 1034-1043, 2004.