2023 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC) | 979-8-3503-2447-1/23/$31.00 ©2023 IEEE | DOI: 10.1109/EMBC40787.2023.10340978

An Automated Algorithm for the Identification of Somatosensory Cortex Using Magnetoencephalography

Kevin Tyner*[1], Srijita Das[1], Matthew McCumber[1], Mustaffa Alfatlawi†[1], Stephen V. Gliske†[1]

***Abstract*— The localization of eloquent cortex is crucial for many neurosurgical applications, such as epilepsy and tumor resection. Non-invasive localization of these cortical areas using magnetoencephalography (MEG) is generally performed using equivalent current dipoles. While this method is clinically validated, source localization depends on several subjective parameters. This paper aimed to develop an automated algorithm for identifying the cortical area activated during a somatosensory task from MEG recordings. Our algorithm uses singular value decomposition to outline the cortical area involved in this task. For proof of concept, we evaluate our algorithm using data from 10 subjects with epilepsy. Our algorithm has a statistically significant overlap with the somatosensory cortex (the expected active area in healthy subjects) in 6 of 10 subjects. Having thus demonstrated proof of concept, we conclude that our algorithm is ready for further testing in a larger cohort of subjects.**

***Clinical relevance*— Our algorithm identifies the dominant cortical area and boundary of the cortical tissue involved in a task-related response.**

I. Introduction

Around 30% of patients with epilepsy suffer from drug-resistant epilepsy. Surgical intervention to remove the epileptogenic zone, the brain region responsible for seizure generation, is the most useful treatment option for these patients [1]. However, focal cortical resection risks damage or injury to eloquent cortices adjacent to the resected area. Therefore, it is necessary to define the extent of resection to balance maximizing the resected volume and minimizing damage or injury to eloquent or association cortices alongside the resection boundary. [2].

Functional mapping aims to localize the cortical region activated in the context of task-related activities. A common practice for localizing eloquent cortices is intraoperative cortical stimulation mapping [3]. While it is considered a gold standard for localization, it is invasive. It can further complicate patient care by prolonging the duration of surgery or eliciting seizures as a result of stimulation [4], [5]. Moreover, a number of studies have demonstrated a significant association between intraoperative mapping and long-term functional deficits [6]. Thus, non-invasive methods for mapping eloquent cortices could serve as a more efficient alternative, allowing for higher spatial and temporal resolution while covering the entire cortex over a more extended period.

Functional brain mapping involves an inverse modeling problem to estimate the location of recorded neurophysiological activity. The objective of the inverse problem is to describe the underlying neurophysiological activity as discrete or distributed sources. One method of discrete source modeling is equivalent current dipoles (ECDs), a simplistic representation of the location of one or a few cortical sources. It requires estimating those sources' neural activity and location in response to a task-related paradigm [7]. While ECDs are FDA-approved, they may not represent the entire brain volume, and channels used for examination must be selected before analysis by clinicians [7], which introduces subjectivity and variability in the analysis [8].

Contrary to discrete source modeling, distributed source modeling considers the entire brain a source for the recorded neurophysiological activity. However, these methods alone do not produce the spatial characteristics required to localize the recorded signal. This study discusses an automated procedure that includes post-processing a distributed source model to identify the boundaries of a region of tissue that is activated in response to task-related activities. Specifically, we expand the distributed sources as a linear combination of temporally independent sources using singular value decomposition (SVD). This expansion provides a linearly separable representation for the initial distributed source, such that the brain regions in each group have similar temporal evolution.

Our objective for this paper was to develop an automated algorithm for localizing the somatosensory cortex in a cohort of epilepsy subjects using MEG. Our algorithm uses distributed source methods and blind source separation techniques to identify the boundary and location of cortical tissue involved in a somatosensory task. The contribution of this work lies in its clinical utility, addressing two weaknesses with the current clinical practice: first, our method does not involve subjective analysis, and second, it provides a cortical region of activation as opposed to a single point.

II. Materials and Methods

A. Subjects

We analyzed a retrospective pool of subjects with epilepsy who received MEG imaging as part of their presurgical evaluation at the University of Nebraska Medical Center. We evaluated all subjects who received their MEG scan between May 2020 and December 2021, resulting in a cohort of 58 subjects. To be included in the analysis, subjects must have performed the somatosensory task during the MEG recording, were at least 19 years of age at the time of recording, and had data of sufficient quality for analysis. Of the 58 subjects examined, 10 met the inclusion criteria. For subject demographic information, see Table 1.

* Corresponding author: kevin.tyner@unmc.edu
† Authors contributed equally to this work.
[1]Department of Neurosurgery University of Nebraska Medical Center, Omaha, NE

B. Measurements

We acquired T1-weighted MR images for each subject and performed cortical parcellation using FreeSurfer [9]. MEG data were recorded with a whole-head instrument equipped with 102 magnetometers and 204 planar gradiometers with a bandwidth of 0.1 - 330 Hz and a sampling rate of 1 kHz (MEGIN Neuromag, Helsinki, Finland). All recordings were performed in a magnetically shielded room. Neuromagnetic responses were elicited by electrical stimulation of the median nerve of the left (upper left, UL) or right (upper right, UR). We completed at least 160 trials per limb for each subject.

C. MEG Data Preprocessing

We sought to localize evoked responses from subjects who performed the somatosensory task. We performed data preprocessing, ECD, and source localization in Python using the MNE toolbox [10]. We applied a notch filter at 60 Hz and its harmonics to eliminate electrical interference. Cardiac and ocular artifacts were removed using signal space projections [12]. We removed additional artifacts by performing independent component analysis using the Picard algorithm [13]. We created epochs by filtering the data from 2 - 120 Hz and extracting the signal from 50 ms before to 250 ms after stimulation, with the first 50 ms used for baseline correction [14]. We generated evoked responses by averaging at least 160 artifact-free trials. We then estimated the underlying cortical activity by projecting the evoked data to the subject's source space (cortical surface) using sLORETA. We chose sLORETA as this method has been shown to have near zero localization error [15]. We then extracted the location and activation of each source ($\approx 20,000$) for further analysis.

D. Identification of Somatosensory Cortex

Our goal was to delineate the boundary of the somatosensory cortex using numerical methods. We first created models of the individual subject's pial surface using FieldTrip in MATLAB (2022a, MathWorks) [16]. We then performed SVD on the subjects' source space data to obtain the left (spatial) and right (temporal) singular vectors ranked based on their associated singular values. We visualized the cortical area activated during the somatosensory task using the second left singular vector to represent the activity of the underlying neuronal assemblies and spatially filtered with a search radius of 5 mm. Here, the second left singular vector was chosen as the first vector contained artifacts related to electrical stimulation. Points were averaged together, thresholded to 90% of their maximum value, and plotted on the subject's cortical surface. To identify the time at which this response occurred, t_{max}, we identified the location of the maximum value in the second right singular vector.

E. Statistics

We sought to determine the accuracy of the cortical area identified by the algorithm and assess its statistical significance. We classified points as anatomically accurate in their location if they reside in the central sulcus or post-central gyrus in either the left or right hemisphere, as these regions are known to be activated in response to median nerve stimulation [17], [18]. Probability values were calculated by randomly selecting an area the same size as the area identified by the algorithm. We performed this permutation 1,000 times per task, and p-values indicate the percentage of random trials containing more anatomically correct points than the algorithm, with values less than 0.05 indicating statistical significance.

Subject ID	Age [years]	Sex	Handedness
Sub-01	29	Female	Left
Sub-02	52	Female	Right
Sub-03	55	Female	Right
Sub-04	25	Female	Right
Sub-05	29	Male	Right
Sub-06	30	Female	Right
Sub-07	46	Female	Right
Sub-08	33	Male	Right
Sub-09	35	Male	Right
Sub-10	26	Male	Left

TABLE I
SUBJECT DEMOGRAPHIC INFORMATION.

III. RESULTS

A. Dipole Fitting

We first sought to localize the neuromagnetic recordings as discrete activation sources through ECD modeling. We preprocessed the subjects' data to generate an evoked response. For an example of an evoked response of Sub-03 performing the UR task, see Fig. 1. We used the neuromagnetic response to fit ECDs approximately 25 and 35 ms post-stimulus [16]. For dipole localization, see Fig. 2. While these dipoles were fit approximately 12 ms apart, they were separated by a Euclidean distance of roughly 6 mm.

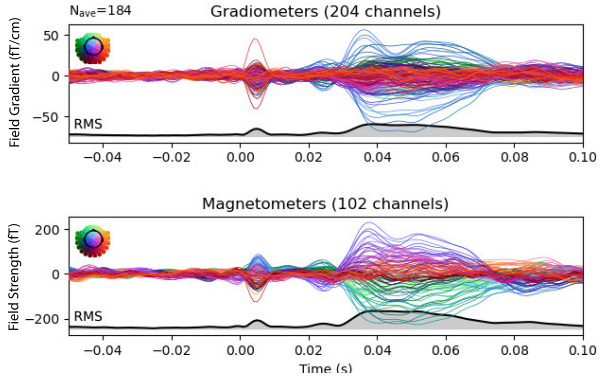


Fig. 1. A butterfly plot of MEG evoked response of Sub-03 performing the UR task. For this run, the subject received stimulation 184 times. The peak occurring at approximately 6 ms corresponds to electrical interference from stimulation. Peaks at 25, 35, and 55 ms post-stimulus correspond to typical somatosensory responses.

Subject ID	Task	t_{max} [ms]	% Overlap	p-val
Sub-01	UR	5	0	1
Sub-02	UR	102	0	1
Sub-03	UR	50	100	≤ 0.001
Sub-04	UR	198	33.3	0.04
Sub-05	UR	138	100	≤ 0.001
Sub-06	UR	36	100	≤ 0.001
Sub-07	UR	69	100	≤ 0.001
Sub-08	UR	203	27.3	0.006
Sub-09	UR	100	0	1
Sub-10	UR	159	0	1

TABLE II

A SUMMARY OF THE LOCALIZATION FOR ALL SUBJECTS THAT PERFORMED THE UR TASK. t_{max} INDICATES THE TIME OF MAX RESPONSE IDENTIFIED BY THE SECOND RIGHT SINGULAR VECTOR. WE CALCULATED p-VALUES BY COMPARING THE PERCENT OF CORRECT POINTS TO 1,000 ITERATIONS OF RANDOMLY SELECTED POINTS.

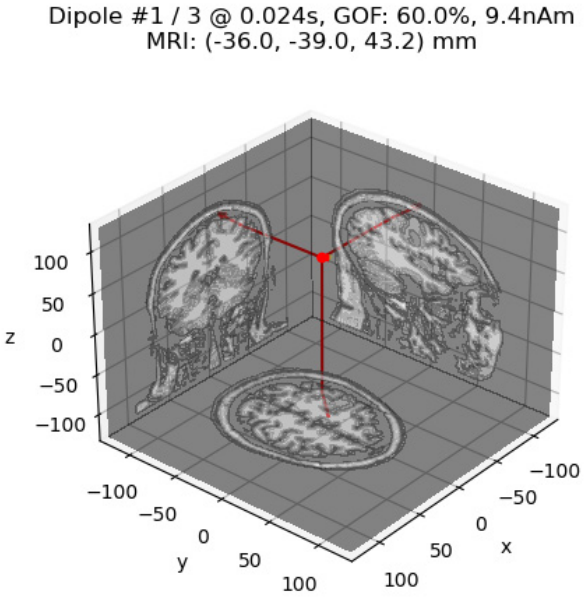
B. Localizing Somatosensory Related Neuronal Populations

We sought to model the underlying cortical activity of the recorded neuromagnetic response as a time sequence of activation events of spatially distributed neuronal assemblies. Evoked responses were projected to the subjects' cortical surface using sLORETA. We then performed SVD on the source localized data. The second left singular vector was plotted on the subject's cortical surface to represent neuronal populations activated in response to task-related activities. See Fig. 3 for the cortical localization of the UR task of Sub-03, along with the projection of the recorded data on the chosen mode. The sharp negative peak seen at approximately 6 ms is an artifact from electrical stimulation. We next calculated the percentage of anatomically correct points and the associated p-values; see Table 2. We observe a 100% overlap in 4 of 10 subjects and statistically significant p-values in 6 of 10 subjects. We obtained similar results for the UL task for these subjects (data not shown).

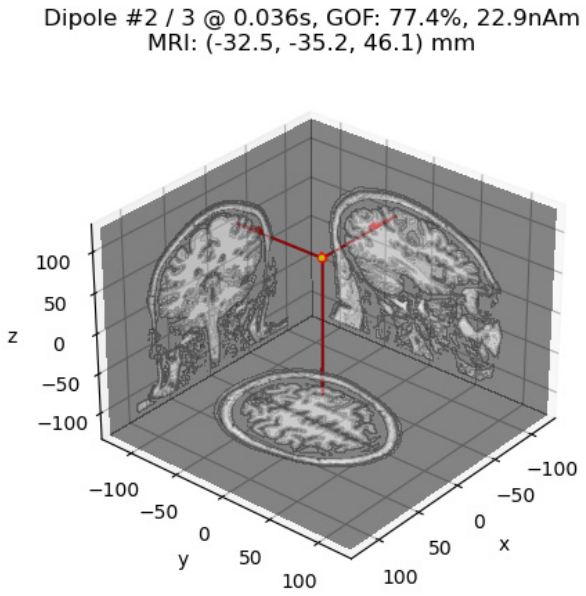
IV. DISCUSSIONS AND CONCLUSIONS

Our automated algorithm can successfully identify the somatosensory cortex from MEG data and provide a predicted boundary of cortical activation instead of a single point provided by ECD. Our results indicate that the cortical area identified by the algorithm has a statistically significant overlap with anatomically appropriate areas in 6 of 10 subjects performing the UR task.

We observed considerable variability in the overlap between our algorithm and the expected anatomical regions. Currently, the algorithm contains no parameters to reject data that may be of lower quality, such as with Sub-02, 09, and 10, which have no readily identifiable peaks in their evoked response. As the algorithm only analyzes the second component, it is possible that other components better localize the somatosensory response. Finally, as all subjects have been diagnosed with epilepsy, they may have atypical somatosensory representation, which could result in the reduced overlap observed. This cortical reorganization may have reduced the overlap observed in Sub-01, where most of their identified points fell in the post-central sulcus.



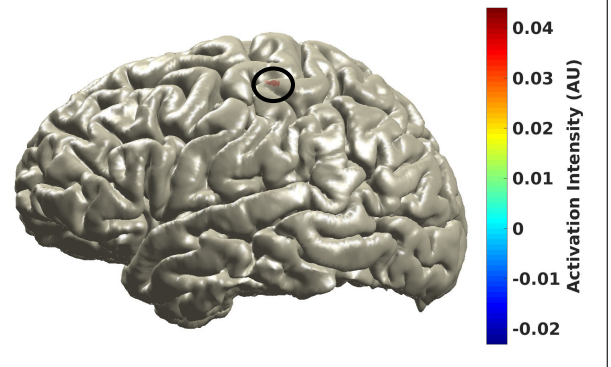
(a)



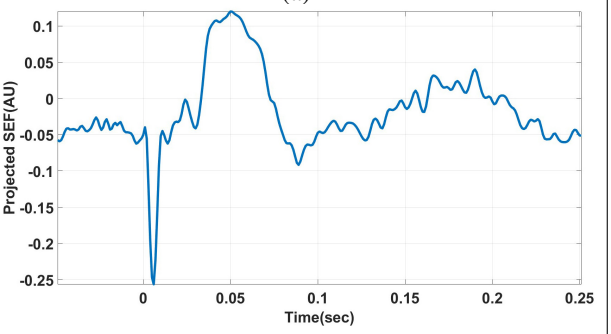
(b)

Fig. 2. (a) The dipole location fit 24 ms post-stimulus. This dipole had a goodness of fit (GOF) of 60%. It resided -36 mm lateral, -39 mm posterior, and 43.2 mm superior to the center of the recording volume and localized to the cerebral white matter in the left hemisphere. (b) The dipole location fit 36 ms post-stimulus. This dipole had a GOF of 77.4%. It resided -32.5 mm lateral, -35.2 mm posterior, and 46.1 mm superior to the center of the recording volume and localized to the precentral gyrus in the left hemisphere.

While dipole fitting is currently the clinically accepted practice for localizing task-related cortical areas, it is essential to note that the source localization identified by the dipole depends on the time the dipole was fit. For example, during a somatosensory task, dipoles fit during the first 60



(a)



(b)

Fig. 3. (a) Cortical location (solid black circle), which activates dominantly in response to a sensory task, as determined by our method, and (b) the time response that approximates the neuronal activity.

ms tend to localize to the primary somatosensory cortex contralateral to stimulation. However, dipoles fit 90 ms after stimulation localize to the secondary somatosensory cortex [16]. Thus, fitting a single dipole may localize the task-related response to a region outside the area of interest. Our algorithm addresses this problem by utilizing the entire evoked recording to identify the dominant cortical areas involved in the task-related response, reducing the time required for analysis and eliminating the subjectivity of localization observed with dipole fitting.

Our algorithm successfully localizes the somatosensory cortex and provides a defined cortical area, in contrast to the single point identified by current clinical practice. Having demonstrated proof of concept with a small cohort of subjects, our algorithm is ready for further testing in a larger cohort. Our results then open the door for future research comparing our algorithm results with cortical stimulation mapping, a clinical gold standard. One strength of our algorithm is that it can be easily modified to localize other regions of eloquent cortex, such as visual, auditory, or language. Our results thus open the possibility for research into automated, non-invasive methods for identifying a broad range of eloquent cortex, adding essential information for presurgical planning.

V. Compliance with Ethical Standards

This study was performed in line with the principles of the Declaration of Helsinki. Approval was granted by the Institutional Review Board (IRB) of the University of Nebraska Medical Center in November 2021 (protocol #0714-21-EP)

VI. Acknowledgements

No funding was received for conducting this study. The authors have no relevant financial or non-financial interests to disclose. We want to thank Dr. Valentina Gumenyuk, Dr. Daniel Zhou, and Dr. Olga Taraschenko for their preparation of the IRB.

References

[1] Gunnarsdottir, Kristin M., et al. "Source-sink connectivity: A novel interictal EEG marker for seizure localization." Brain 145.11 (2022): 3901-3915.

[2] Zakaria, Jehad, and Vikram C. Prabhu. "Cortical mapping in the resection of malignant cerebral gliomas." Exon Publications (2017): 263-280.

[3] Solomon, Jack, Shaun Boe, and Timothy Bardouille. "Reliability for non-invasive somatosensory cortex localization: Implications for pre-surgical mapping." Clinical neurology and neurosurgery 139 (2015): 224-229.

[4] Kirsch, Heidi E., et al. "Predicting the location of mouth motor cortex in patients with brain tumors by using somatosensory evoked field measurements." Journal of neurosurgery 107.3 (2007): 481-487.

[5] Bittar, Richard G., et al. "Localization of somatosensory function by using positron emission tomography scanning: a comparison with intraoperative cortical stimulation." Journal of neurosurgery 90.3 (1999): 478-483.

[6] Giampiccolo, Davide, et al. "Long-term motor deficit in brain tumour surgery with preserved intra-operative motor-evoked potentials." Brain Communications 3.1 (2021): fcaa226.

[7] Tenney, Jeffrey R., Hisako Fujiwara, and Douglas F. Rose. "The value of source localization for clinical magnetoencephalography: beyond the equivalent current dipole." Journal of Clinical Neurophysiology 37.6 (2020): 537-544.

[8] Nakasato, Nobukazu, et al. "Cortical mapping using an MRI-linked whole head MEG system and presurgical decision making." Electroencephalogr Clin Neurophysiol Suppl 47 (1996): 333-341.

[9] Fischl, Bruce, et al. "High-resolution intersubject averaging and a coordinate system for the cortical surface." Human brain mapping 8.4 (1999): 272-284.

[10] Gramfort, Alexandre, et al. "MNE software for processing MEG and EEG data." Neuroimage 86 (2014): 446-460.

[11] Taulu, Samu, and Riitta Hari. "Removal of magnetoencephalographic artifacts with temporal signal-space separation: Demonstration with single-trial auditory-evoked responses." Human brain mapping 30.5 (2009): 1524-1534.

[12] Uusitalo, Mikko A., and Risto J. Ilmoniemi. "Signal-space projection method for separating MEG or EEG into components." Medical and biological engineering and computing 35 (1997): 135-140.

[13] Ablin, Pierre, Jean-François Cardoso, and Alexandre Gramfort. "Faster independent component analysis by preconditioning with Hessian approximations." IEEE Transactions on Signal Processing 66.15 (2018): 4040-4049.

[14] Bowyer, Susan M., et al. "Presurgical functional mapping with magnetoencephalography." Neuroimaging Clinics 30.2 (2020): 159-174.

[15] Pascual-Marqui, Roberto Domingo. "Standardized low-resolution brain electromagnetic tomography (sLORETA): technical details." Methods Find Exp Clin Pharmacol 24.Suppl D (2002): 5-12.

[16] Oostenveld, Robert, et al. "FieldTrip: open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data." Computational intelligence and neuroscience 2011 (2011): 1-9.

[17] Kakigi, Ryusuke, et al. "The somatosensory evoked magnetic fields." Progress in neurobiology 61.5 (2000): 495-523.

[18] Kanno, Akitake, et al. "Ipsilateral area 3b responses to median nerve somatosensory stimulation." Neuroimage 18.1 (2003): 169-177.