A comparison of automated and manual co-registration for magnetoencephalography

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Abstract

Magnetoencephalography (MEG) is a neuroimaging technique that accurately captures the rapid (sub-millisecond) activity of neuronal populations. Interpretation of functional data from MEG relies upon registration to the participant's anatomical MRI. The key remaining step is to transform the participant's MRI into the MEG head coordinate space. Although both automated and manual approaches to co-registration are available, the relative accuracy of two approaches has not been systematically evaluated. The goal of the present study was to compare the accuracy of manual and automated co-registration. Resting MEG and T1-weighted MRI data were collected from 90 participants. Automated and manual coregistration were performed on the same subjects, and the inter-rater reliability of the two methods compared using the intra-class correlation. Mean coregistration error for both methods was within acceptable limits. Reliability was in the fair range. These results suggest that the output of the automated coregistation procedure is comparable to that achieved using manual coregistration.

Introduction

Magnetoencephalography (MEG) is a neuroimaging technique that accurately captures the rapid (sub-millisecond) activity of neuronal populations. Indeed, MEG can only detect signal from the synchronous firing of neuronal populations in a cortical patch of approximately 10 mm^2 or larger (Lü & Williamson, 1991), making it essentially a network-detection technique. Due to a relative scarcity of reimbursable MEG-based clinical procedures, historically MEG was available at only a relatively limited number of cutting-edge research and clinical institutions (Bagić, 2011). However, interest in MEG has grown as the technique's potential has been revealed over the past four decades, with increased recognition of MEG as a means of directly evaluating neuronal networks and their relevance to a range of disorders as well as to typical cognitive and affective processes.

As is the case for other functional neuroimaging approaches such as fMRI, interpretation of functional data from MEG relies upon registration to an anatomical or template MRI (Hämäläinen, 1991). Because the data for the two modalities are collected on different scanners and in different coordinate spaces, the procedure for MRI-MEG co-registration is somewhat more involved than is the case for MRI-fMRI registration. Typically during preparation for an MEG scan, three to four head position coils are affixed to the participant's scalp, and then a 3D digitizing pen is used to digitize important points including the coil locations, anatomical landmarks that typically include the nasion and preauricular points, as well as a detailed headshape using approximately 150 points. The headshape points are collected from the brow, bridge of the nose, and skull, avoiding the lower jaw and cartilaginous or fatty tissue that would be expected to shift when the participant moves or might be compressed by the head coil during the participant's MRI scan. Because this preparation process can be somewhat labor-intensive and subject to variability in technician skill, alternatives such as use of a bite bar (Adjamian et al., 2004), 3-D camera (Vema Krishna Murthy, MacLellan, Beyea, & Bardouille, 2014), or 3-D

laser scanner (Bardouille, Krishnamurthy, Ghosh Hajra, & D'Arcy, 2012) have also been explored but are not widely used.

During the MEG scan session, the head position coils are energized at known frequencies, which permits the precise measurement of their locations relative to the MEG sensor array. Because at the conclusion of an MEG scan the relative locations of the sensors, coils, anatomical landmarks, and headshape points are known, transforming the MEG data to the participant's head coordinate space is relatively simple. The key remaining step is to transform the participant's MRI into the MEG head coordinate space. This transformation is the focus of the MEG-MRI co-registration process.

The co-registration process itself is straightforward. A high-resolution 3-D head surface based on the skin-air boundary can be extracted from a T1-weighted MRI using readily-available analysis toolkits such as Freesurfer. Incorporation of this surface into the co-registration process has been shown to improve the quality of the co-registration (Whalen, Maclin, Fabiani, & Gratton, 2008) and is the standard in MNE-python and its predecessor, MNE (Hämäläinen, 2001). Similar procedures are used in other MEG analysis packages. In the absence of significant MRI artifacts, the participant's distinguishing features, including the face and the anatomical landmarks collected during MEG preparation, are clearly visible on this surface. The anatomical landmarks and MEG headshape can be used to co-register the MRI head surface (and therefore the MRI data) to the participant's head coordinate space. Typically this involves manually identifying the anatomical landmarks on the MRI head surface, using these values to perform an initial transformation, and then using a least-squares approach (Besl & McKay, 1992) to assist in refining the transformation until the distance between the MEG headshape and the MRI head surface has been minimized. This can be accomplished using template MRIs, but MEG data can be localized with higher confidence when the individual participant's own structural MRI is used for their co-registration. Numerous toolkits are available to assist the analysist in co-registration, including but not limited to MNE-python, SPM, Fieldtrip,

BrainStorm, and Nutmeg. Importantly, although both automated and manual approaches to co-registration are available, the relative accuracy of two approaches has not been systematically evaluated. The goal of the present study was to evaluate the comparability of manual and automated co-registration using MNE-python.

Method

As part of an ongoing study, resting MEG and T1-weighted MRI data were collected from 90 participants (mean age = 35.20 years (SD=10.04), 42.2% female, 50% Hispanic). MRI data were collected on a Siemens 3T Trio Tim system (Siemens Healthcare, Erlangen, Germany) using a 32-channel head coil. Paper tape was placed across each participant's forehead to reduce motion. Structural images were collected with magnetization-prepared 180° radiofrequency pulses and rapid gradient-echo sequence (MPRAGE; TE = 1.64, 3.5, 5.36, 7.22, and 9.08 ms; TR = 2.53 s; FA = 7°; number of excitations = 1; slice thickness = 1 mm; FOV = 256 mm; resolution = 256×256). Standard preprocessing was conducted using the Freesurfer image analysis suite (Fischl, 2012), which is documented and freely available for download online (http://surfer.nmr.mgh.harvard.edu/).

MEG data were collected in a magnetically and electrically shielded room (VAC Series Ak3B, Vacuumschmelze GmbH) using an Elekta Neuromag whole-cortex 306-channel MEG array (Elekta Oy, Helsinki, Finland). Before positioning the participant in the MEG, four coils were affixed to the participant's head—two on the forehead and one behind each ear. Additional positioning data was collected using a head position device (Polhemus Fastrak). Participants were instructed to keep their eyes open and focused on a fixation cross back-projected onto a screen during the scan. MEG data were sampled at a rate of 1000 Hz, with a bandpass filter of 0.10 to 330 Hz. Head position was monitored continuously throughout the MEG session. Five minutes of raw single-trial data were collected and stored.

Each MEG scan had previously been manually co-registered to its corresponding MRI using MNE (Hämäläinen, 2001). Automated co-registration in MNE-python was performed by

transforming standard landmark coordinates (nasion, preauricular points) from the MNI-305 brain to each participant's native space, performing an initial fit to the MRI head surface using only the landmarks, then applying several iterations of a least-squares algorithm, eliminating outlier head points (i.e., those > 5 mm away from the head surface), and applying the least-squares algorithm again. The final affine transformation was then saved and the errors (i.e., the distance between each MEG headshape point and the nearest point on the MRI head surface) preserved. Errors for manual coregistrations were obtained by applying the affine transformations from the manual coregistration to the MEG headshape and computing the distance between each MEG headshape point and the nearest point on the MRI head surface. The inter-rater reliability of coregistration error for manual and automated co-registration was compared using the intraclass correlation (ICC model 3,1: Shrout & Fleiss, 1979).

Results

Median coregistration error for manual coregistration was 1.37 mm (IQR 1.17-1.63), and for automatic coregistration 1.58 mm (IQR 1.23-2.05). The difference in localization error between manual and automated co-registration was approximately 0.313 mm (SD 0.555 mm). The inter-rater reliability for the two methods was ICC = 0.472, which is in the "fair" range (Cicchetti & Sparrow, 1981).

Discussion

In our data, both manual and automated co-registration yielded acceptable results. The coregistration error obtained for both processes in the present study is consistent with that of other studies. For instance, a study using bite bars to reduce motion found a mean coregistration error of 1.16 mm (Adjamian et al., 2004), while a study using a 3D scanner found mean error of 2.2 mm (Bardouille et al., 2012), and one using a 3D camera (Kinect) observed a mean error of 1.62 mm (Vema Krishna Murthy et al., 2014).

The moderate inter-rater reliability suggests that the outputs of manual and automated co-registration processes are similar. That is, despite the extensive training and time requirements

of manual co-registration, it conferred no substantial advantage in accuracy over automated co-registration, at least for the coregistration error metric we evaluated, which described the distance between the MRI-derived participant's head points and head shape points collected at the time of the MEG scan.

It is worth noting that the MRI scans included in the present study appear to have been relatively artifact-free. Data from participants with common sources of susceptibility artifact such as braces, permanent retainers, other dental work, and certain hair products (Chenji et al., 2017) would likely result in distortions of the MRI head surface, requiring greater attention and the potential for substantial manual intervention during co-registration.

Conclusion

Until devices capable of collecting both MRI and MEG data become commercially available (Vesanen et al., 2013), co-registration will remain a limiting factor in the localization accuracy of MEG data. Reporting of co-registration error is considered a best practice for MEG (Gross et al., 2013) but adoption has been slow. The recent implementation of procedures to estimate co-registration error in analysis packages such as MNE-python (Gramfort et al., 2014) may help to accelerate this. Our results suggest that in many cases a simple automated processes performed using freely-available and open-source software can co-register MEG and MRI data with no loss of quality, avoiding the time and training requirements of manual co-registration.

Ethical approval and informed consent statement

All study protocols were approved by the University of New Mexico Institutional Review Board (http://irb.unm.edu). All procedures were carried out in accordance with the relevant guidelines and regulations. Documented informed consent was obtained from all participants.

Acknowledgements

Research reported in this publication was supported by the National Institute on Alcohol Abuse and Alcoholism under award numbers K01AA021431 and R01AA023665. The content is solely

the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.

References

Adjamian, P., Barnes, G. R., Hillebrand, A., Holliday, I. E., Singh, K. D., Furlong, P. L., … Route, P. J. G. (2004). Co-registration of magnetoencephalography with magnetic resonance imaging using bite-bar-based fiducials and surface-matching. *Clinical Neurophysiology*, *115*(3), 691–698. https://doi.org/10.1016/j.clinph.2003.10.023

Bagić, A. I. (2011). Disparities in clinical magnetoencephalography practice in the United States: a survey-based appraisal. *Journal of Clinical Neurophysiology: Official Publication of the American Electroencephalographic Society*, *28*(4), 341–347.

Bardouille, T., Krishnamurthy, S. V., Ghosh Hajra, S., & D'Arcy, R. C. N. (2012). Improved Localization Accuracy in Magnetic Source Imaging Using a 3-D Laser Scanner. *IEEE Transactions on Biomedical Engineering*, *59*(12), 3491–3497. https://doi.org/10.1109/TBME.2012.2220356

Besl, P. J., & McKay, H. D. (1992). A method for registration of 3-D shapes. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *14*(2), 239–256. https://doi.org/10.1109/34.121791

Chenji, S., Wilman, A. H., Mah, D., Seres, P., Genge, A., & Kalra, S. (2017). Hair product artifact in magnetic resonance imaging. *Magnetic Resonance Imaging*, *35*, 1–3. https://doi.org/10.1016/j.mri.2016.08.023

Cicchetti, D. V., & Sparrow, S. A. (1981). Developing criteria for establishing interrater reliability of specific items: Applications to assessment of adaptive behavior. *American Journal of Mental Deficiency*, *86*, 127–137.

Fischl, B. (2012). FreeSurfer. *NeuroImage*, *62*(2), 774–781. https://doi.org/10.1016/j.neuroimage.2012.01.021

Gramfort, A., Luessi, M., Larson, E., Engemann, D., Strohmeier, D., Brodbeck, C., … Hämäläinen, M. (2014). MNE software for processing MEG and EEG data. *NeuroImage*, *86*, 446–460. https://doi.org/10.1016/j.neuroimage.2013.10.027

Gross, J., Baillet, S., Barnes, G. R., Henson, R. N., Hillebrand, A., Jensen, O., … Schoffelen, J.-M. (2013). Good practice for conducting and reporting MEG research. *NeuroImage*, *65*, 349–363. https://doi.org/10.1016/j.neuroimage.2012.10.001

Hämäläinen, M. (1991). Anatomical correlates for magnetoencephalography: integration with magnetic resonance images. *Clinical Physics and Physiological Measurement*, *12*(A), 29–32. https://doi.org/10.1088/0143-0815/12/A/006

Hämäläinen, M. (2001). MNE (Version 2.7.3). Retrieved from http://www.nmr.mgh.harvard.edu/martinos/userInfo/data/MNE_register/index.php

Lü, Z.-L., & Williamson, S. J. (1991). Spatial extent of coherent sensory-evoked cortical activity. *Experimental Brain Research*, *84*(2), 411–416. https://doi.org/10.1007/BF00231463

Shrout, P., & Fleiss, J. L. (1979). Intraclass correlations: Uses in assessing rater reliability. *Psychological Bulletin*, *86*, 420–428.

Vema Krishna Murthy, S., MacLellan, M., Beyea, S., & Bardouille, T. (2014). Faster and improved 3-D head digitization in MEG using Kinect. *Frontiers in Neuroscience*, *8*. https://doi.org/10.3389/fnins.2014.00326

Vesanen, P. T., Nieminen, J. O., Zevenhoven, K. C. J., Dabek, J., Parkkonen, L. T., Zhdanov, A. V., … Ilmoniemi, R. J. (2013). Hybrid ultra-low-field MRI and magnetoencephalography system based on a commercial whole-head neuromagnetometer. *Magnetic Resonance in Medicine*, *69*(6), 1795–1804. https://doi.org/10.1002/mrm.24413

Whalen, C., Maclin, E. L., Fabiani, M., & Gratton, G. (2008). Validation of a method for coregistering scalp recording locations with 3D structural MR images. *Human Brain Mapping*, *29*(11), 1288–1301. https://doi.org/10.1002/hbm.20465