Non-magnetic compliant finger sensor for continuous fine motor movement detection

Anterpal Sandhu¹ · Yasong Li¹ · Nicholas Peatfield¹ · Xin Yi Yong¹ · Ryan D’Arcy^{1,2} · Carlo Menon¹ · Teresa P. L. Cheung^{1,2}

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Abstract A non-magnetic MEG compatible device has been developed that provides continuous force and velocity information. Combined with MEG, this device may find utility in characterizing brain regions associated with force and velocity relative to individual digits or movement pattern. 15 healthy right-handed participants were given visual cues to perform random finger movements on the prototype finger sensor for 21 s and then rest for 21 s (7 times). Respective finger flexion data were obtained, during 151-channel MEG brain scanning, by feeding the signal from finger sensor into four input Analog to Digital Converter (ADC) channels in the MEG hardware. The source activity was reconstructed in beta band using a Linearly Constrained Minimum Variance (LCMV) beamformer in the beta band. The ADC channels were used as regressors for a continuous time General Linear Model (GLM) and a Region of Interest (ROI) was identified to examine activity. MEG analysis showed bilateral activation in the primary motor cortex region. Because individual digits could be isolated in the ADC data, somatotopy of the fingers were observed consistent with the homunculus except pinky finger. The total span was calculated to be 5.5662 mm. The study confirms that the finger sensor is magnetically compatible with MEG measurements and may potentially provide a means to study complex sensorimotor functions. Improved isolation of individual digit information along

with the use of machine learning algorithms can help retrieve more accurate results.

Keywords MEG compatible · Somatotopy · Sensorimotor · Force regressed contrast · Real-time motion data

1 Introduction

Magnetoencephalography (MEG) experimental paradigms finding correlations between the sensorimotor functions of hand and the brain activations can only deduce limited information from currently available motion sensors. Some of the commonly used sensors, such as motion capture sensors, measure angles at various joints accurately to calculate velocity and acceleration. In contrast, the simple finger sensor device we designed and fabricated is advantageous in comparison to the currently available motion capture devices due to a higher Signal to Noise Ratio (SNR) and providing real-time force and velocity information for individual fingers [1]. Earlier results have shown that the device does not interfere with MEG data collection [1]. This method enables the use of real-time motion data for individual fingers as a parameter in MEG data analysis, evidencing the potential of expanding the knowledge in motor functionality beyond the finger(s) position [2–4]. The real-time force and velocity data for individual fingers can be used to draw various contrasts of the brain activations for the individual finger movement. This new information can help provide more information about brain activations in sensorimotor studies and characterize continuous fine motor movements of hand and fingers. During the motor movements, there is a significant decrease in the amplitude of beta band activity (13–30 Hz) due to voluntary task execution and action preparedness [5].

✉ Teresa P. L. Cheung
tpc5@sfu.ca

¹ Faculty of Applied Sciences, Simon Fraser University, Burnaby, Canada

² Health Sciences and Innovation, Surrey Memorial Hospital, Fraser Health Authority, Surrey, Canada

Therefore, a maximum difference can be observed between resting and tapping states if source reconstruction can be performed in beta band (13–30 Hz). This beta activity also affords a strong signal for source reconstruction, which has shown both robust and precise source localization [6]. Moreover, it is known to follow the somatotopy, with single digits being differentiated by this neural response [7]. As such we will correlate this neural beta activity with the motor movements measured by the response device, and the particular individual digit movements.

2 Methods and tools

2.1 Design

The device is made of non-ferrous and non-conductive silicone elastomer (TC-5005, BJB Enterprise), which does not cause any interference with the MEG data collection [1]. It consists of four airtight chambers arranged in a cylindrical tube shape, where every chamber is connected to pressure sensors using a rubber tube as shown in Fig. 1a, b. The size of all chambers is equal such that a finger always presses on an individual chamber, except the thumb and index finger, which shared the same chamber. Finger presses on respective chambers result in a change in pressure within, which is detected by pressure sensors. The materials used in the construction of this device are non-magnetic while all the electronics were located outside the magnetically shielded room.

2.2 Participants

The data were acquired using a 151 channel MEG scanner (CTF, Port Coquitlam, Canada) on a group of 13 healthy

individuals between the ages 18–30 years. All the participants were confirmed to be right-hand dominant using the Edinburgh Handedness Inventory. The local Ethics Committee approved the experimental procedure, and all participants submitted their written informed consent before taking part in the study. The participants were compensated for their time and participation in the study.

2.3 Data acquisition

The participants were given clear instructions and trained briefly before starting every acquisition session. For data collection on every participant, the trials (Fig. 1c) began with a rest period and consisted of 13 alternating rest and tap periods of 21 s each. The participants held the finger sensor device in their right hand throughout the trial and were notified of the respective period at the beginning of every period using visual cues. The participants were instructed to remain relaxed and stationary during the rest phase and pressed any of the five fingers randomly or a combination of fingers onto the sensor during the tapping period. The pressing of a finger onto the device resulted in a change in pressure within respective chambers. This change in pressure within each chamber was converted into voltage change using pressure sensors (± 25 kPa, MPXV, freescale semiconductor) and all four channels fed into individual MEG ADC channels. These ADC channels contained the real time pressure information, which could be used to deduce force, and velocity information for all the individual fingers. Each participant's head shape was digitized (Polhemus, VT, USA), with at least 300 scalp positions, and three head coils were used. The resulting digitization was used to register the scalp shape to a database of MRIs. The matched MRI was used to construct the forward solution in the source reconstruction.

Fig. 1 a Finger sensor, b CAD model and c A trial for data collection

2.4 Data processing

During data processing, bad channels, identified during data collection, were removed from the data and the data were down-sampled by a factor of 4 from original sample rate of 1200 Hz after applying a low-pass filter with a cutoff frequency of 100 Hz. A single shell forward model along with an LCMV beamformer was used to reconstruct the source activity in the beta band (13–30 Hz). The beta band was selected based on previous findings, which reported beta band suppression during motor movements [6]. The resulting signals represented a 3 mm voxel grid over the entire brain volume. Because a single finger pressing could be mapped to a distinct chamber in the finger sensor, the area of a finger pressing onto the chamber was assumed constant. Since pressure is directly proportional to force, normalizing the real-time pressure information, stored in the ADC channels, also represented the normalized force information of every finger. This real-time force data, obtained from pressure data, were used as regressor weights for a GLM to get contrasts between rest and tap states. The regressor was designed consistent with the ‘Rest’ and ‘Tap’ instructions with ‘Rest’ represented as the OFF state and ‘Tap’ as the ON state. Because some fingers do not move independently but cause adjacent fingers to twitch as well, Independent Component Analysis (ICA) and Principal Component Analysis (PCA) were performed on the force data in an attempt to separate the individual finger components, which in turn were again used as regressors to generate t-contrast maps.

We previously reported significant beta band frequency suppression during the motor movements [1]. Therefore, the activity was reconstructed in 13–30 Hz range to observe the maximum contrast between rest and tapping states when using the GLM.

2.5 Voxel analysis

T-contrast maps were analyzed using voxel by voxel analysis by viewing contrasts in fslviewer and running statistics using fslmaths [8–10]. Applying a primary motor cortex mask to the t-contrasts helped in identifying a Region of Interest (ROI), which was overlaid on a $2\text{ mm} \times 2\text{ mm} \times 2\text{ mm}$ voxel grid. FSL cluster command on the ROI was used to calculate the location of the voxel with maximum intensity and respective intensity value. It also calculated the location of the weighted average of all the voxel intensities presented in the ROI (equivalent to the center of mass). The location of the maximum intensity voxel might be subject to noise. Therefore, the weighted average voxel location was used instead to represent the source activity location. The results from the voxel analysis

were presented in MRI voxel coordinates as well as MNI coordinates (in mm) for group analysis.

3 Results

The source reconstruction showed a bilateral activity in the primary motor cortex region for the majority of the participants. After using the left primary motor region mask and the weighted average to calculate the locations of individual fingers within participants mathematically, the weighted average finger locations across participants was calculated. The average 3D voxel location of the individual fingers (for $n = 10$) after removing the outliers using visual inspection is shown in Fig. 2 as well as Table 1. The total span for the four fingers in the primary motor area (M1) can be calculated using the 3D distance and was found to be 5.5662 mm. The distances between centers of mass are shown in Table 2. The p value ($p < 0.01$) statistics confirmed the calculated distance between finger locations to be significant.

4 Discussion

We have previously reported Yong et al. [11] that our finger sensor device was successful in detecting 31 different finger actions on healthy participants and 2–24 actions in people suffering from stroke using Support Vector Machine (SVM) with Radial Basis Function kernel (RBF) to solve multiclass classification. This can be helpful in automatic labeling of the MEG data before analysis. Previous findings by Li et al. [1] showed our device does not interfere with the MEG data collection and provides a high SNR. The activations in the primary motor cortex region of the brain were clearly observable, and time–frequency analysis in sensor space showed clear beta suppression during the tapping period.

The motor activity related to one hand is expected to be a result of neural activity in the contralateral regions of the brain. Due to bilateral activation in the majority of the participants and activations in other regions of the brain, the primary motor region activations were filtered using the M1 left side atlas provided in fslviewer. It can be seen from Fig. 2 and Table 1 that the average locations of the individual finger areas follow the somatotopic order established in [12] except the pinky finger. Note that the ring and pinky finger locations do not follow the somatotopic order strictly but do lie within the error range. While pressing on the chambers, the small finger and ring finger movements were highly correlated as compared to other fingers, and this may also contribute to the mixing of the two finger components. Also, it was difficult separating

Fig. 2 The location of individual fingers within M1 in Coronal, Axial and Sagittal slice respectively: *Red* (index), *Green* (middle), *Blue* (ring) and *Yellow* (pinky). (Color figure online)

Table 1 Average location of fingers in participants

Finger	MRI coordinates (vox)			SD	MNI(in mm)		
	x	y	z		x	y	z
Index finger	59.56	52.31	63.52	2.9384	−27.12	−23.38	53.02
Middle finger	58.47	51.77	63.96	2.4997	−24.94	−24.46	53.92
Ring finger	57.51	51.31	64.40	2.8433	−22.24	−25.38	54.80
Pinky	58.08	51.51	64.18	2.1808	−24.16	−24.98	54.36

Table 2 3D distance between centers of individual fingers

Index-middle	Index-ring	Index-pinky	Middle-ring	Middle-pinky	Ring-pinky
2.5940 mm	5.5662 mm	3.6218 mm	2.98 mm	1.0356 mm	2.0100 mm

individual movements. Because there were only four force measurements, computing ICA components were not helpful. The ICA components were arbitrarily ordered for each participant resulting in some ambiguity to individual component labeling, though signal morphology could be used to match components. Moreover, the ICA presented a few components as entirely negative, which did not make physical sense. It is expected that future versions of our device will have more force chambers, which may better enable the use of ICA to isolate independent digit or movement components.

The individual finger locations are not discrete in the cortex with regions overlapping at the boundaries [13, 14]. If only the first three digits were used, the finger spans shown in Table 2 agrees with the values in the literature using high-resolution fMRI at 3T [14]. Also, the finger locations were slightly distal from the skull and almost close to the white matter. These discrepancies could be a result of the lower spatial resolution of the MEG and our choice of voxel resolution.

For future analysis, the individual finger components could be separated by further subdividing the 21 s finger-

tapping block into different taps. For one tap period, a simultaneous tap in the adjoining or adjacent chamber could be ignored or validated based on a particular threshold or by using machine-learning algorithms. This approach may result in a more sophisticated regressor design, which could be used to generate contrasts between rest and tap states. A device with more than four chambers could also be designed to collect a more detailed set of motion/force data. The use of machine learning algorithms or potentially ICA could be used to eliminate the involuntary correlated finger movements from the data.

5 Conclusion

It has been previously shown that our finger sensor does not interfere with MEG data collection [1]. The current study used the force data from our finger sensor during MEG imaging of a series of right-handed finger movements to show activations in the M1 region. The additional information from the finger sensor was useful in identifying a rough location of individual digits. This was possibly due

to the isolation of individual finger data using the ADC channels and could not be done using the MEG data alone. The slight discrepancies in somatotopy observed could be a result of the mixing of individual finger components. In future, designing a device with more chambers and using machine-learning algorithms or ICA could provide better regressors for the GLM. The movement data from this simple finger sensor can potentially enable a means to study complex sensorimotor functions. This prototype may also offer the foundation for a new therapeutic tool to examine neural correlates of finger flexions during recovery of motor function for patients with acquired brain injury.

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Compliance with ethical standards

Conflict of interest None of the authors had any commercial relationship that might result in a conflict of interest.

Human and animal rights The subject participation was voluntary and the ethics REB 2012s0527 for the study were submitted prior to and approved by REB at SFU under the declaration of Helsinki.

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