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Magnetometers vs Gradiometers for Neural Speech Decoding

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***Abstract*— Neural speech decoding aims at providing natural rate communication assistance to patients with locked-in state (e.g. due to amyotrophic lateral sclerosis, ALS) in contrast to the traditional brain-computer interface (BCI) spellers which are slow. Recent studies have shown that Magnetoencephalography (MEG) is a suitable neuroimaging modality to study neural speech decoding considering its excellent temporal resolution that can characterize the fast dynamics of speech. Gradiometers have been the preferred choice for sensor space analysis with MEG, due to their efficacy in noise suppression over magnetometers. However, recent development of optically pumped magnetometers (OPM) based wearable-MEG devices have shown great potential in future BCI applications, yet, no prior study has evaluated the performance of magnetometers in neural speech decoding. In this study, we decoded imagined and spoken speech from the MEG signals of seven healthy participants and compared the performance of magnetometers and gradiometers. Experimental results indicated that magnetometers also have the potential for neural speech decoding, although the performance was significantly lower than that obtained with gradiometers. Further, we implemented a wavelet based denoising strategy that improved the performance of both magnetometers and gradiometers significantly. These findings reconfirm that gradiometers are preferable in MEG based decoding analysis but also provide the possibility towards the use of magnetometers (or OPMs) for the development of the next-generation speech-BCIs.**

I. INTRODUCTION

Neurodegenerative disorders such as amyotrophic lateral sclerosis (ALS) may cause locked-in syndrome where the patients are completely paralyzed but remain cognitively aware. The brain may be the only source of communication for these patients. Brain-computer interface (BCI) spellers can help these patients communicate to a level but the communication rate of these devices is very slow (under 10 words/min) [1]. Neural speech decoding paradigm on the other hand attempts to decode speech directly from the brain and holds promise towards real-time communication assistance (about 200 words/min), thereby, improving the quality of life for these neurologically impaired patients.

Neural speech decoding has been investigated either non-invasively with electroencephalography (EEG) [2]–[5] and magnetoencephalography (MEG) [6]–[9] or invasively with electrocorticography (ECoG) [10]–[12] to find neural patterns corresponding to different speech representations (phonemes/syllables/words/phrases). To our opinion, MEG has advantages over the other neuroimaging modalities, i.e., being non-invasive in contrast to ECoG and the magnetic fields recorded with MEG being less distorted compared to the electric fields recorded via EEG since the cerebrospinal fluid, skull, and skin have different electrical conductivities but similar magnetic permeability. MEG has an excellent temporal resolution ($\sim 1\,\mathrm{ms}$) and adequate spatial resolution ($\sim 5\,\mathrm{mm}$) [13], making it suitable to study the fast and spatially distributed dynamics of cognitive speech processing. Moreover, MEG signals have been proven effective in various speech studies including investigations of MEG oscillations during speech production [14], [15] and understanding real-time temporal patterns of neural activations of speech-motor coordination [16]–[18], providing supporting evidence towards the use of MEG signals for speech decoding.

MEG measures magnetic fields from the brain with highly sensitive magnetometers and gradiometers. Gradiometers consist of two opposite wound coils that are sensitive to the spatial gradient of magnetic fields whereas the magnetometers consist of a single superconducting coil that directly measures the magnetic fields from deeper sources. Due to the differential nature of the gradiometers, environmental noise has the same effect on both coils and becomes canceled out but magnetometers pick up that noise, thereby, acquiring low SNR signals. Due to this superiority in noise suppression, gradiometers have been the preferred choice for sensor space analysis with MEG [19]. However, this raises the question: with proper denoising, whether magnetometers have the potential for speech-BCI applications? In this study, we used SQUID magnetometers to decode five imagined and spoken phrases and compared their performance with gradiometers. In addition, acknowledging the fact that magnetometers are noisy and might perform poorer than gradiometers, we used wavelet denoising prior to decoding. To our knowledge, this is the first study to investigate the efficacy of magnetometers (vs gradiometers) in neural speech decoding.

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Fig. 1. The MEG unit with a subject

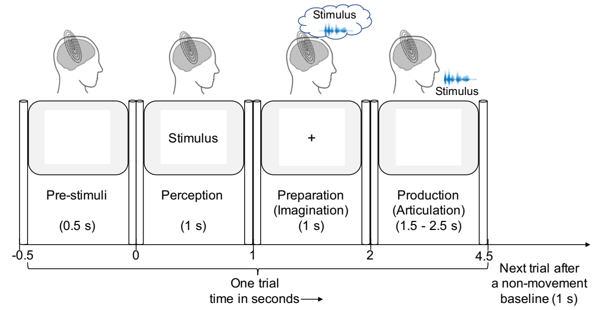

Fig. 2. The time-locked experimental protocol, where subjects imagine and overtly articulate the visual speech stimuli.

II. Data Collection

We used two identical 306 channel Elekta Neuromag MEG machines (MEGIN, LCC) for data collection, one situated at the Dell Children's Medical Center, Austin, TX and the other at Cook Children's Medical Center, Fort Worth, TX (Figure 1). The machines consist of 204 gradiometers and 102 magnetometers and are housed inside a magnetic shielded room (MSR) to discard external magnetic interference. Seven healthy subjects (3 females and 4 males; age=41 $\pm$ 14 years) participated in the study with informed consent in accordance with the ethical committee of the participating institutions. Subjects were seated comfortably within the MEG unit with their arms resting on a platform and their head inside the MEG dewar. Visual stimuli were generated by a computer running the STIM2 software (Compumedics, Ltd.), and presented via a DLP projector onto a screen situated at 90 cm from the machine. Two pairs of bipolar EEG electrodes were used to record the electrocardiogram (ECG) and electrooculogram (EOG) signals. Jaw movement was recorded via a custom-built air bladder with a pressure sensor attached to the chin. Voice was recorded with a standard built-in microphone. Both voice and movement signals were recorded simultaneously with MEG signals.

The experiment was designed as a time-locked protocol with four stages in a trial (Figure 2). Five commonly used phrases were selected as the stimuli of the experiment namely *1. "Do you understand me", 2. "That's perfect", 3. "How are you", 4. "Good-bye", and 5. "I need help"*. The first stage of a trial was 'Pre-stimuli' (0.5 s) where the subjects were at rest. Then a phrase out of the 5 stimuli was displayed on the screen in the second stage of 'Perception' (1 s) in pseudo-randomized order. In the third stage ('Imagination'/'Preparation') a fixation cross was shown on the screen heralding the subjects to imagine and prepare to speak the shown stimuli for 1 s. Then the subjects overtly spoke the phrase at their natural speaking rate in the final stage of 'Production'/'Articulation' ($1.5 - 2.5$ s). We designed both the imagination and the production task in the same trial acknowledging the difficulty in verifying the behavioral compliance of imagined speech production [20]. This 4-stage task was repeated for 100 trials for each stimulus with a $1 - 1.5$ s of non-movement baseline period between successive trials.

The MEG data were recorded with a 4 kHz sampling frequency with an online filter of $0.3 - 1330$ Hz and then low pass filtered to 250 Hz with a 4^{th} order Butterworth filter and resampled to 1 kHz. Power line noise (60 Hz) and harmonics were removed with a 2^{nd} order IIR notch filter. The continuous MEG signals were epoched into trials centered on stimulus onset. Via thorough visual inspection, trials containing high amplitude artifacts and trials in which the subject did not comply with the paradigm timing e.g., 'subject spoke before the cue to articulate', were discarded with an average of 25% rejection rate. Flat and noisy channels were also removed from the analysis.

III. Methods

A. Decoding

We used linear discriminant analysis (LDA) for classification of the preprocessed gradiometer and magnetometer signals corresponding to the 5 phrases. LDA is a supervised machine learning classifier that computes the directions ('linear discriminants') that maximize the separation between multiple classes [21]. In our previous decoding studies with gradiometer signals, we found that LDA performs equivalently to support vector machines and multilayer perceptron classifiers [14] and better than naive Bayes, decision trees, ensembles, and k-nearest neighbor classifiers specifically to the data used in this study [22]. Moreover, considering the relatively fast training procedure and few hyperparameter tuning for this decoder, we chose LDA as our choice of decoder. We extracted the root mean square (RMS) features from the MEG signals to train the decoder as RMS features have been proven effective in MEG and EEG based decoding analyses [16], [23], [24]. The feature dimension was about 204 for gradiometers and 102 for magnetometers. The hyperparameters (alpha and beta parameters of the Dirichlet distribution) of the classifier were tuned for each subject and each task (imagination and production) with Bayesian optimization. We performed a subject-dependent decoding analysis considering the huge cognitive variance across subjects [25]. We used 5-fold cross-validation for classification and report the cross-validation accuracy.

B. Wavelet Denoising

Since magnetometers have low SNR compared to gradiometers, we also investigated wavelet denoising and its impact on decoding. Wavelets express a signal as a linear combination of a distinct set of functions, obtained by shifting and scaling a single function (mother wavelet) [26]. Wavelets decompose the signal in such a way that in each level the signal disintegrates into two components (details and approximation) such that the detail component carries the high-frequency element whereas the approximation component contains the low-frequency oscillations. Wavelets have been a popular approach to denoise neural signals [27], especially, in the case of MEG, the Daubechies (db4) wavelet has been proven very effective for denoising [6], [24], [28]. Hence, here, we used db-4 discrete wavelet transform to denoise the MEG signals. Please note, although the motivation behind using wavelets was to denoise the noisy magnetometers, for a fair comparison, we performed wavelet analysis on both gradiometer and magnetometer signals. We optimized the level of decomposition from a range of levels between $1-7$ and selected the optimal level for a subject based on the best validation accuracy.

IV. Results and Discussions

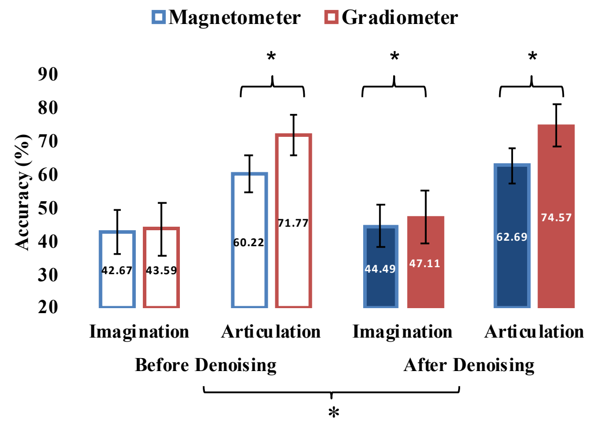

Fig. 3. Comparison of decoding performances between magnetometers and gradiometers, * denotes statistical significance with $p < 0.05$, error bars indicate standard error

Figure 3 shows the comparison of the decoding accuracy between magnetometers and gradiometers for imagination and production (articulation) tasks. With magnetometers, prior to denoising, the decoding accuracy for imagination was $42.67\% \pm 6.7\%$ and for production, it was $60.22\% \pm 5.62\%$, both significantly higher than the theoretical chance level (20%) for a 5-class classification. The decoding performances with gradiometers for decoding spoken phrases were statistically significantly higher (1-tail paired t-test) than the magnetometers with an accuracy of $71.77\% \pm 5.96\%$. This reconfirms the previous literature recommending gradiometers for sensor space analysis with MEG [29], [30]. For decoding imagined phrases, the accuracy was $43.59\% \pm 7.73\%$ with gradiometers but not significantly higher than magnetometers. It is interesting to observe a significantly higher performance of gradiometers during production than imagination. This might be because of the differential design of gradiometers that is advantageous in suppressing the movement artifacts during production.

Our results show that that neural speech decoding is possible with the magnetometer sensors of SQUID-MEG. Optically pumped magnetometers (OPMs) offer a new method for MEG measurements [31]–[34]. The OPMs sensing mechanism happens above room temperature, hence sensor-source gap is minimized and signal-to-noise ratio is maximized. Furthermore, the design of OPM-MEG systems may include synthetic gradiometers or reference sensors which can be used to cancel out the inhibiting effect of environmental interference [35] enhancing the decoding accuracy of the overall BCI system. With this success of magnetometers in speech decoding, we anticipate the potential usefulness of the OPM technology in future speech-synthesizing BCI systems. It should be noted that magnetometers have been shown to perform equivalently to gradiometers in the source space after proper denoising considering their ability to record deeper neuromagnetic activity compared to gradiometers [29], [36]. In this work, we are more focused on the sensor space analysis as decoding has to be in real-time. After wavelet denoising, the average decoding accuracy with magnetometers increases about 2% for both imagination and production which was significant across 7 subjects (1-tail paired t-test, $p < 0.05$). However, the accuracy also significantly improves for gradiometer based decoding analysis with a 3% increment. This further illustrates that the gradiometers should be the default choice for SQUID-MEG analysis in sensor space. It would be interesting to combine both gradiometers and magnetometers to perform decoding which is in the scope of our future work. Also, the efficacy of wavelet denoising in decoding was evident.

V. Conclusions

In this study, we compared the decoding performance of magnetometers and gradiometers in sensor space for decoding 5 imagined and spoken phrases. Experimental results indicated that magnetometers can be used to decode covert and overt speech significantly higher than chance level. Gradiometers performed significantly better than magnetometers reconfirming the previous literature supporting the preferred use of gradiometers in sensor space analysis of SQUID-MEG data. In addition, the efficacy of wavelets in denoising MEG signals was demonstrated with an average of $2-3\%$ improvement in decoding accuracy.

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