Effect of Spoken Speech in Decoding Imagined Speech from Non-Invasive Human Brain Signals

Seo-Hyun Lee  
Dept. Brain and Cognitive Engineering  
Korea University  
Seoul, Republic of Korea  
seohyunlee@korea.ac.kr

Young-Eun Lee  
Dept. Brain and Cognitive Engineering  
Korea University  
Seoul, Republic of Korea  
ye_lee@korea.ac.kr

Soowon Kim  
Dept. Artificial Intelligence  
Korea University  
Seoul, Republic of Korea  
soowon_kim@korea.ac.kr

Byung-Kwan Ko  
Dept. Artificial Intelligence  
Korea University  
Seoul, Republic of Korea  
leaderbk525@korea.ac.kr

Seong-Whan Lee  
Dept. Artificial Intelligence  
Korea University  
Seoul, Republic of Korea  
sw.lee@korea.ac.kr

Abstract—Decoding imagined speech from human brain signals is a challenging and important issue that may enable human communication via brain signals. While imagined speech can be the paradigm for silent communication via brain signals, it is always hard to collect enough stable data to train the decoding model. Meanwhile, spoken speech data is relatively easy to obtain, implying the significance of utilizing spoken speech brain signals to decode imagined speech. In this paper, we performed a preliminary analysis to check whether it would be possible to utilize spoken speech electroencephalography data to decode imagined speech, by simply applying the pre-trained model with spoken speech brain signals to decode imagined speech brain signals. While the classification performance of imagined speech data solely used to train and validation was 30.5 ± 4.9 %, the transferred performance of spoken speech based classifier to imagined speech data was 26.8 ± 2.0 % with no significant difference found compared to the imagined speech based classifier (p = 0.0983, chi-square = 4.64). For more comprehensive analysis, we compared the result with the visual imagery dataset, which would naturally be less related to spoken speech compared to the imagined speech. As a result, visual imagery have shown solely trained performance of 31.8 ± 4.1 % and transferred performance of 26.3 ± 2.4 % which had shown significant statistical difference between each other (p = 0.022, chi-square = 7.64). Our results imply the potential of applying spoken speech to decode imagined speech, as well as their underlying common features.

Keywords—brain–computer interface, imagined speech, speech recognition, spoken speech, visual imagery

I. INTRODUCTION

Brain-computer interface (BCI) is a technology of converting user’s intention to an external output or action via decoding brain signals. It accompanies the imagery of the user, and the process of decoding user’s intention from the brain signals. BCI paradigms are the brain signals that the BCI system aims to decode, which consists of external stimulus or user’s spontaneous imagery including the user’s intention [1]. Exogenous BCI paradigms, such as event-related potential or steady-state evoked potential, have been actively invested, since it has shown effectiveness in conveying user’s intention in a relatively high speech and accuracy [2]–[4]. However, current research stream on BCI is highly focusing on the endogenous paradigms, such as motor imagery [5]–[7], imagined speech [8], or visual imagery [9], [10], since they do not require external stimuli, therefore, may be a more convenient way to convey user’s intention directly [11].

However, endogenous BCI paradigms yet hold limitations of low decoding performance, and inferior degree-of-freedom (DOI). In addition, it is relatively hard to acquire consistent brain signal data per each class, since it is not a stimulus-driven brain signals. Some users are known to be inefficient in endogenous BCI paradigms, therefore, may need the process of training the user beforehand. While endogenous BCI paradigms are strong in convenience and intuitiveness, limited amount of high-quality data and the lack of strong features have always been a challenging issue to be addressed.

Imagined speech is an emerging endogenous paradigm for intuitive BCI communication, which refers to the internal imagery of speech, without emitting vocal sound nor moving the mouth. It is easy to expand the DOI of imagined speech since there are various words or sentences to be decoded, therefore,
may be a strong BCI paradigm that can convey unconstrained intention of the user. However, it is relatively hard to collect imagined speech data compared to the exogenous paradigms or other strong paradigms, since it is hard to collect consistent imagery data to train the model from the user. Also, the main limitation of the endogenous paradigms are that the data collector cannot ensure if the user consistently imagined the exact right thing, or just had thought of something else, since we cannot check the imagined ground-truth by vision nor hearing.

Spoken speech refers to the natural speech that we use in the everyday life [12]. It is known that imagined speech brain signals resemble the features of spoken speech brain signals in some portion, therefore, holds potential to utilize spoken speech data to improve or enhance the imagined speech decoding performance. Unlike imagined speech, spoken speech data is relatively easy to be acquired, and are able to check whether the user performed the speech correctly, therefore, may be better to train the decoding model. Although spoken speech holds strength in data collection, decoding imagined speech is still the most crucial point in the field of BCI, since the first aim for BCI systems are to help patients who cannot move or talk [13].

In this paper, we explored the possibility of utilizing the spoken speech brain signal data to decode imagined speech electroencephalography (EEG). This is a preliminary study of simply applying the spoken speech-based trained model to the imagined speech EEG data, to find out the potential of transferring the robust model trained with spoken speech to imagined speech data with relatively weak features. We compared the results using the test set of imagined speech EEG with spoken speech based trained model to apply on the test set of imagined speech. Also, we compared the imagined speech result in the same method with the visual imagery dataset, to find out the difference between the two paradigms.

II. MATERIALS AND METHODS

A. Overall framework

As shown in the Figure [1], spoken speech data is relatively easy to obtain consistent and large number of trials, does not need to train the users since it is a natural speech that we perform in everyday life, and lastly, is has distinct brain features compared to imagined speech. However, it cannot coincide with the imagined speech, since the usage is only limited to the people who can speak out loud, and therefore, cannot establish silent communication only by brain signals. Therefore, our preliminary task was to utilize both strength of spoken speech and imagined speech, to further transfer the spoken speech based pre-trained model to the imagined speech EEG data.

B. Data Acquisition

1) Participants: Spoken speech, imagined speech, and visual imagery EEG dataset of 7 subjects were used in this.
TABLE I
PERFORMANCE OF DECODING IMAGINED SPEECH USING SPOKEN SPEECH BRAIN SIGNALS

|               | Imagined speech 10-fold cross validation | Spoken speech full trials | Spoken speech few trials |
|---------------|------------------------------------------|---------------------------|--------------------------|
| Subject 1     | 30.0                                     | 23.4                      | 23.0                     |
| Subject 2     | 35.6                                     | 26.6                      | 25.2                     |
| Subject 3     | 38.1                                     | 28.6                      | 29.1                     |
| Subject 4     | 28.7                                     | 29.5                      | 23.2                     |
| Subject 5     | 23.7                                     | 26.4                      | 31.4                     |
| Subject 6     | 27.3                                     | 25.9                      | 34.3                     |
| Subject 7     | 30.4                                     | 26.8                      | 28.0                     |
| AVG.          | 30.5                                     | 26.8                      | 28.0                     |
| STD.          | 4.9                                      | 2.0                       | 3.9                      |

TABLE II
PERFORMANCE OF DECODING VISUAL IMAGERY USING SPOKEN SPEECH BRAIN SIGNALS

|               | Imagined speech 10-fold cross validation | Spoken speech full trials | Spoken speech few trials |
|---------------|------------------------------------------|---------------------------|--------------------------|
| Subject 1     | 33.9                                     | 25.0                      | 24.5                     |
| Subject 2     | 25.3                                     | 24.1                      | 25.9                     |
| Subject 3     | 33.3                                     | 27.5                      | 31.8                     |
| Subject 4     | 33.4                                     | 29.1                      | 26.6                     |
| Subject 5     | 35.2                                     | 22.7                      | 23.2                     |
| Subject 6     | 26.4                                     | 28.0                      | 24.3                     |
| Subject 7     | 35.1                                     | 27.7                      | 22.7                     |
| AVG.          | 31.8                                     | 26.3                      | 25.6                     |
| STD.          | 4.1                                      | 2.4                       | 3.1                      |

study. The dataset were brought from the previous studies [1], [8], [14], [15]. The study was carried out in accordance with the Declaration of Helsinki. The experimental protocols were reviewed and approved by the Institutional Review Board at Korea University [KUIRB-2019-0143-01] and all subjects signed informed consent.

2) Experimental Setup: 64-channel EEG cap with active electrodes placement following the international 10-10 system were used for the recording. Reference and ground electrodes were set to FCz and FPz channels, respectively. EEG signals were recorded via Brain Vision/Recorder (BrainProduct GmbH, Germany) and operated by MatLab 2018a software.

3) Experimental Paradigm: Experimental paradigms are explained in detail in the previous studies [1], [8], [14]. The dataset of spoken speech, imagined speech, and visual imagery consists of the same words/phrases from the same participants. In this paper, 5-class words were selected from the dataset to test the transfer scenario as a preliminary study.

C. EEG Data Classification

1) Imagined speech decoding: 10-fold cross validation was performed using 90 % of randomly selected imagined speech data as a training set and the remaining 10 % as a test set. This was set as the baseline performance to compare with the performance of spoken speech based transferred classifier. Support vector machine (SVM) classifier was trained with common spatial pattern (CSP) feature in all three modes of classification, including the following subsections.

2) Imagined speech decoding with spoken speech dataset: The model trained with spoken speech dataset was transferred to the imagined speech data. Weights for the CSP filters were first trained with spoken speech EEG and applied to the imagined speech data. We tested in two different sets of spoken speech dataset, as one was a model trained with full spoken speech trials (88 trials per class) and another was the model trained with only a small number of spoken speech trials (10 trials per class).

3) Visual imagery decoding with spoken speech dataset: Comparing the performance with visual imagery dataset was performed to check the viability of transferring spoken speech brain signals to imagined speech brain signals. As same as above, the model trained with spoken speech dataset was transferred to the visual imagery data. Weights for the CSP filters were first trained with spoken speech EEG and applied to the visual imagery data.

D. Statistical Analysis

For the statistical analysis, we performed Kruskal–Wallis one-way analysis of variance (ANOVA) test to compare the classification accuracy of the baseline performance of non-transferred 10-fold cross validation, spoken speech based transferred result of full trials, and few trials. Paired t-test was performed as a post-hoc test. Significance level was set to 0.05.

III. RESULTS AND DISCUSSION

A. Imagined Speech Decoding

As shown in the Table 1, the averaged classification performance of imagined speech data solely used to train and validation was $30.5 \pm 4.9 \%$, and the transferred performance of spoken speech based classifier to imagined speech data was $26.8 \pm 2.0 \%$. The spoken speech based transferred result trained with only few spoken speech trials were 28.0
± 3.9%. Based on the statistical analysis, there was no significant difference found between the imagined speech 10-fold cross validation result with the spoken speech based transferred result (p = 0.0983, chi-square = 4.64). The result exhibits comparable performance of the transferred model, which implies the potential of applying spoken speech dataset to decode imagined speech. Since spoken speech data is much simpler and easier to acquire, if comparable result could be acquired, it would be more efficient to train and transfer the model with large spoken speech dataset.

B. Visual Imagery Decoding

For more comprehensive analysis, we compared the result with the visual imagery dataset, which would naturally be less related to spoken speech compared to the imagined speech [16]. As shown in Table 2, visual imagery have shown solely trained performance of 31.8 ± 4.1% and transferred performance of 26.3 ± 2.4% which had significant statistical difference between each other (p = 0.022, chi-square = 7.64). Since there was statistically significant difference only for the case of visual imagery (Figure 2), this result confirms that there may be common features between the two speech-related paradigms.

IV. CONCLUSION

Our result implies that the potential of applying spoken speech to decode imagined speech, as well as their underlying common features. Since we have just simply transferred the pre-trained model to a different dataset, such method as fine tuning would further improve the result. For the future work, we would apply deep learning model to pre-train the model with spoken speech dataset, and freeze and fine tune the model with small amount of imagined speech data for better results [17]–[20].

REFERENCES

[1] S.-H. Lee, M. Lee, J.-H. Jeong, and S.-W. Lee, “Towards an EEG-based intuitive BCI communication system using imagined speech and visual imagery,” in Conf. Proc. IEEE, Int. Conf. Syst. Man Cybern. (SMC), 2019, pp. 4409–4414.
[2] D.-O. Won, H.-J. Hwang, D.-M. Kim, K.-R. Müller, and S.-W. Lee, “Motion-based rapid serial visual presentation for gaze-independent brain-computer interfaces,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 26, no. 2, pp. 334–343, Aug. 2017.
[3] M. Lee, B. Baird, O. Gosseries, J. O. Nieminen, M. Boly, B. R. Postle, G. Tononi, and S.-W. Lee, “Connectivity differences between consciousness and unconsciousness in non-rapid eye movement sleep: a tms–eeg study,” Sci. Rep., vol. 9, no. 1, pp. 1–9, 2019.
[4] M.-H. Lee, J. Williamson, D.-O. Won, S. Fazli, and S.-W. Lee, “A high performance spelling system based on eeg-eog signals with visual feedback,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 26, no. 7, pp. 1443–1459, May 2018.
[5] J.-H. Jeong, N.-S. Kwak, C. Guan, and S.-W. Lee, “Decoding movement-related cortical potentials based on subject-dependent and section-wise spectral filtering,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 28, no. 3, pp. 687–698, 2020.
[6] H.-I. Suk, S. Fazli, J. Mehrt, K.-R. Müller, and S.-W. Lee, “Predicting bci subject performance using probabilistic spatio-temporal filters,” PloS one, vol. 9, no. 2, p. e87056, 2014.
[7] J.-H. Jeong, K.-H. Shim, D.-J. Kim, and S.-W. Lee, “Brain-controlled robotic arm system based on multi-directional cnn-bilstm network using eeg signals,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 28, no. 5, pp. 1226–1238, Mar. 2020.
[8] S.-H. Lee, M. Lee, and S.-W. Lee, “Neural decoding of imagined speech and visual imagery as intuitive paradigms for BCI communication,” IEEE Trans. Neural Syst. Rehabil. Eng., Dec. 2020.
[9] T. Sousa, C. Amaral, J. Andrade, G. Pires, U. J. Nunes, and M. Castelo-Branco, “Pure visual imagery as a potential approach to achieve three classes of control for implementation of bci in non-motor disorders,” J. Neural Eng., vol. 14, no. 4, p. 046026, 2017.
[10] S.-H. Lee, M. Lee, and S.-W. Lee, “Spatio-temporal dynamics of visual imagery for intuitive brain-computer interface,” in Proc. Int. Winter Conf. Brain-Computer Interface (BCI), 2020, pp. 1–5.
[11] S.-H. Lee, Y.-E. Lee, and S.-W. Lee, “Toward imagined speech based smart communication system: Potential applications on metaverse conditions,” in 2022 10th International Winter Conference on Brain-Computer Interface (BCI), 2022, pp. 1–4.
[12] K. Meng, S.-H. Lee, F. Goodarzy, S. Vgrin, M. J. Cook, S.-W. Lee, and D. B. Grayden, “Evidence of onset and sustained neural responses to isolated phonemes from intracranial recordings in a voice-based cursor control task,” Proc. Interspeech 2022, pp. 4063–4067, 2022.
[13] Y. Zhang, H. Zhang, X. Chen, S.-W. Lee, and D. Shen, “Hybrid high-order functional connectivity networks using resting-state functional mri for mild cognitive impairment diagnosis,” Sci. Rep., vol. 7, no. 1, pp. 1–15, 2017.
[14] S.-H. Lee, M. Lee, and S.-W. Lee, “EEG representations of spatial and temporal features in imagined speech and overt speech,” in Proc. Asian Conf. Pattern Recognit. (ACPR), 2019, pp. 387–400.
[15] J.-H. Jeong, J.-H. Cho, Y.-E. Lee, S.-H. Lee, G.-H. Shin, Y.-S. Kweon, J. d. R. Millán, K.-R. Müller, and S.-W. Lee, “2020 international brain–computer interface competition: A review,” Front. Hum. Neurosci., vol. 16, p. 989300, 2022.
[16] S.-H. Lee, M. Lee, and S.-W. Lee, “Functional connectivity of imagined speech and visual imagery based on spectral dynamics,” in Proc. Int. Winter Conf. Brain-Computer Interface (BCI), 2021, pp. 1–6.
[17] K.-H. Thung, P.-T. Yap, E. Adeli, S.-W. Lee, D. Shen, A. D. N. Initiative et al., “Conversion and time-to-conversion predictions of mild cognitive impairment using low-rank affinity pursuit denoising and matrix completion,” Med. Image Anal., vol. 45, pp. 68–82, 2018.
[18] K.-T. Kim, C. Guan, and S.-W. Lee, “A subject-transfer framework based on single-trial emg analysis using convolutional neural networks,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 28, no. 1, pp. 94–103, 2019.
[19] O.-Y. Kwon, M.-H. Lee, C. Guan, and S.-W. Lee, “Subject-independent brain–computer interfaces based on deep convolutional neural networks,” IEEE Trans. Neural Netw. Learn. Syst., vol. 31, no. 10, pp. 3839–3852, 2019.
[20] Y.-E. Lee and S.-H. Lee, “Eeg-transformer: Self-attention from transformer architecture for decoding eeg of imagined speech,” in 2022 10th International Winter Conference on Brain-Computer Interface (BCI). IEEE, 2022, pp. 1–4.