

# Predicting Joint Movement Trajectories from the ECoG Signal Patterns of Apes\*

Chanjin Park

Department of Computer Science  
Yonsei University, Graduate School  
Wonju, Korea  
cjpark04@yonsei.ac.kr

Jungwoo Lee

Department of Computer Science  
Yonsei University, Graduate School  
Wonju, Korea  
jw.lee@yonsei.ac.kr

Seungmin Hyun

Department of Computer Science  
Yonsei University, Graduate School  
Wonju, Korea  
smhyun@yonsei.ac.kr

Ho-Jin Jung

Division of Software  
Yonsei University, Mirae Campus  
Wonju, Korea  
hojinj@yonsei.ac.kr

Han Ul Yoon

Division of Software  
Yonsei University, Mirae Campus  
Wonju, Korea  
huyoon@yonsei.ac.kr

**Abstract**—Due to a strong heterogeneity between two signals, it is often a challenging problem to obtain an analytical model between brain signals and joint movements. This paper proposes an approach to predicting joint movement from electrocorticography via a convolutional neural network. First, spectrogram images were obtained in sequence from the measured ECoG of an ape by sliding a time-window. Next, the corresponding joint movement of the ape was extracted from video recording by applying DeepLabCut. Finally, the spectrogram images and the joint movement were utilized as an input and a desired output to train the convolutional neural network, respectively. The result showed the feasibility of the proposed approach to model a relationship between the electrocorticography and the joint movements.

**Index Terms**—electrocorticography, joint movement prediction, convolutional neural network, event-related potential.

## I. INTRODUCTION

According to the conceptual model of motor coordination, a muscle movement is generated by modularized brain signals which is called muscle synergy [1]. There exist two common types of brain signals according to measuring locations: electroencephalography (EEG) and electrocorticography (ECoG). The former can be obtained from the scalp above the cranium; in contrast, the later is measured from the subcranial cerebral cortex.

Compared to EEG signal, ECoG signal has the advantageous characteristic of which it is more robust against external noise or disturbance caused by the shield lever of a signal line, motion artifact, etc. Accordingly, studies have been done to decode a joint movement and human behavior from the ECoG signal. T. Pistohl et al. decoded ECoG data by applying a linear discriminant analysis and classified human grasping behaviors successfully [2]. Wang et al. reported that the walking states and step rates could be decoded from ECoG signal [3].

\*This work was partially supported by the Alchemist Project Program (Grant No. RS-2024-00423702) and the Technology Innovation Program (Grant No. 00418941) funded by the Ministry of Trade, Industry & Energy (MOTIE, Korea).

Establishing a mathematical model representing a relationship between brain signal and kinematic data, i.e., ECoG and joint movement, has been a challenging problem due to a strong heterogeneity between two signals [4]. This facts give us an insight as well as underlying rationale for employing a neural network (NN), a universal function approximator, to model the relationship between those two. The NN-based approaches to mitigate aforementioned problem can be exemplified with disseminated studies in [5] and [6] in which the finger trajectory and the gait direction anticipations were decoded from the brain signals, respectively.

In this paper, we propose an NN-based approach to predict joint movement trajectories from the ECoG signal of apes. We note that this study belongs to a larger class of the problem of designing a physiological transformer architecture to decode kinematic information from brain signals. The rest of paper is organized as follows: Sec. II introduces our methods to establish a methodology to predict joint movement trajectories from the ECoG signal. The results and discussion are followed in Sec. III. Sec. IV will be the conclusion of this paper.

## II. METHODS

### A. Utilizing Event-Related Potentials as Features to Predict the Joint Movement

Fig. 1 shows the example of event-related potentials (ERPs) in a spectrogram (time-frequency plot) according to the measured ECoG. By investigating the spectrogram, the two different types of ERP can be detected: event-related synchronization (ERS) and event-related desynchronization (ERD). The ERS and the ERD indicate the event-related and frequency-band specific power increase and decrease, respectively [7]. The ERS and the ERD are marked in Fig. 1.

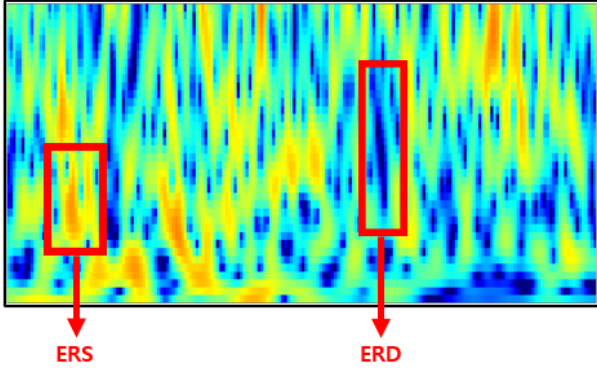


Fig. 1. The example of event-related potentials (ERPs) in a spectrogram according to the measured ECoG: event-related synchronization (ERS) and event-related desynchronization (ERD).

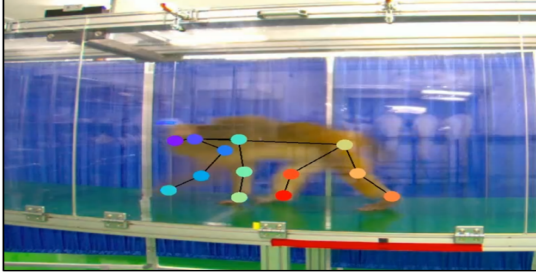


Fig. 2. An example of the extracted ape's skeleton from the recorded video using DeepLabCut.

### B. Extracting Skeleton Data by DeepLabCut and Calculating Joint Angles

Fig. 2 depicts an example of the extracted ape's skeleton from the recorded video using DeepLabCut (v3.0, DeepLabCut Team, Cambridge, MA) [8]. Afterward, 10-joint angles were calculated from the extracted skeleton which will be utilized as a target output to train a neural network in below.

### C. Predicting the Joint Movement via the CNN

Fig. 3 presents the processes and corresponding data flows between subfunctional blocks through our proposed approach. First, a sagittal-view video as well as ECoG signal were measured simultaneously during 6 seconds by using a video camcorder and a ECoG sensor while the ape is walking. A sampling frequency was set to 512Hz. By following the procedure introduced in Sec. II-B, apes' joint angles were obtained. Next, from the ape's ECoG signal data, a spectrogram image of  $2486 \times 560$  (time steps  $\times$  frequency) is obtained; especially, the frequency band of our most interest was 3Hz~40Hz containing  $\mu$ -wave (8Hz~12Hz) and  $\beta$ -wave (13Hz~30Hz) which is related to motor-learning behaviors. Lastly, a convolutional neural network (CNN) followed by a fully connected layers played a key role to infer the ape's joint movement based on the spectrogram of the ECoG signal. The procedure was as follows:

- 1) The spectrogram image was sliced by the sliding window ( $8 \times 560$ ) along a time line and then the sliced image was utilized as the input of the CNN.
- 2) The pre-calculated 10 joint angles were utilized as the target output of the CNN
- 3) Given the sliced spectrogram image, the CNN was trained in order to predict the target output

We note that the ECoG data was augmented 10 times by applying amplitude adjusted fourier transform (AAFT) [9].

## III. RESULTS AND DISCUSSION

Fig. 4 shows the prediction result of the joint movement with the ECoG and the video recording for 5 seconds. From Fig. 4, horizontal and vertical axes represent time and an ape's 10-joint angles. The solid and the dotted lines represent the predicted joint angles and the ground truth value, respectively. In addition, the reconstructed ape's skeletons with respect to specific time frames are displayed at the bottom. The average cross-correlation between the ground truth and the predicted values for all joint angles is 0.85. Consequently, by applying our proposed approach, the ape's joint angle could be predicted from the ECoG signal and video recordings.

## IV. CONCLUSION

Throughout this paper, we proposed an approach to predict joint movement trajectories from the ECoG signal and video recording of apes. Due to the strong heterogeneity between brain signals and kinematic data, we proposed NN-based approach, which played a role of an universal function approximator, to model a relationship between the two signal. The prediction results showed the feasibility of the proposed NN-based approach. For the future works, various NN-based approaches will be applied and evaluated, which include an embedding techniques to map brain signal onto a latent space, transformer-based architecture, and so on.

## REFERENCES

- [1] Safavynia et al., "Muscle synergies: implications for clinical evaluation and rehabilitation of movement," Topics in spinal cord injury rehabilitation, 17.1, pp.16-24, 2011.
- [2] T. Pistohl et al., "Decoding natural grasp types from human ecog," NeuroImage, vol. 59, pp.248-260, July, 2011.
- [3] P. Wang et al., "Decoding of the walking states and step rates from cortical electrocorticogram signals," arXiv preprint, arXiv:2104.07062, 2021
- [4] Y. Qi et al., "Dynamic ensemble bayesian filter for robust control of a human brain-machine interface," IEEE Transactions on Biomedical Engineering, vol. 69, no. 12, pp. 3825-3835, 2022.
- [5] Z. Xie, O. Schwartz, and A. Prasad, "Decoding of finger trajectory from ECoG using deep learning," Journal of neural engineering, vol. 15, no. 3, P. 036009, 2018.
- [6] Y. Vaghei, E. Park, and S. Arzanpour, "Decoding brain signals to classify gait direction anticipation," in Proc. of the 44th Annual Int'l Conf. of the IEEE Engineering in Medicine & Biology Society (EMBC), 2022
- [7] K. Nakayashiki et al. "Modulation of event-related desynchronization during kinematic and kinetic hand movements," Journal of Neuroengineering and Rehabilitation, vol. 11, pp. 1-9, 2014.
- [8] N. Mathis et al., "Deeplabcut: markerless pose estimation of user-defined body parts with deep learning," Nature Neuroscience, vol. 21, pp. 1281-1289, August, 2018.
- [9] J. Theiler et al., "Testing for nonlinearity in time series: the method of surrogate data," Physica D: Nonlinear Phenomena, vol. 58, no. 1-4, pp. 77-94, 1992.

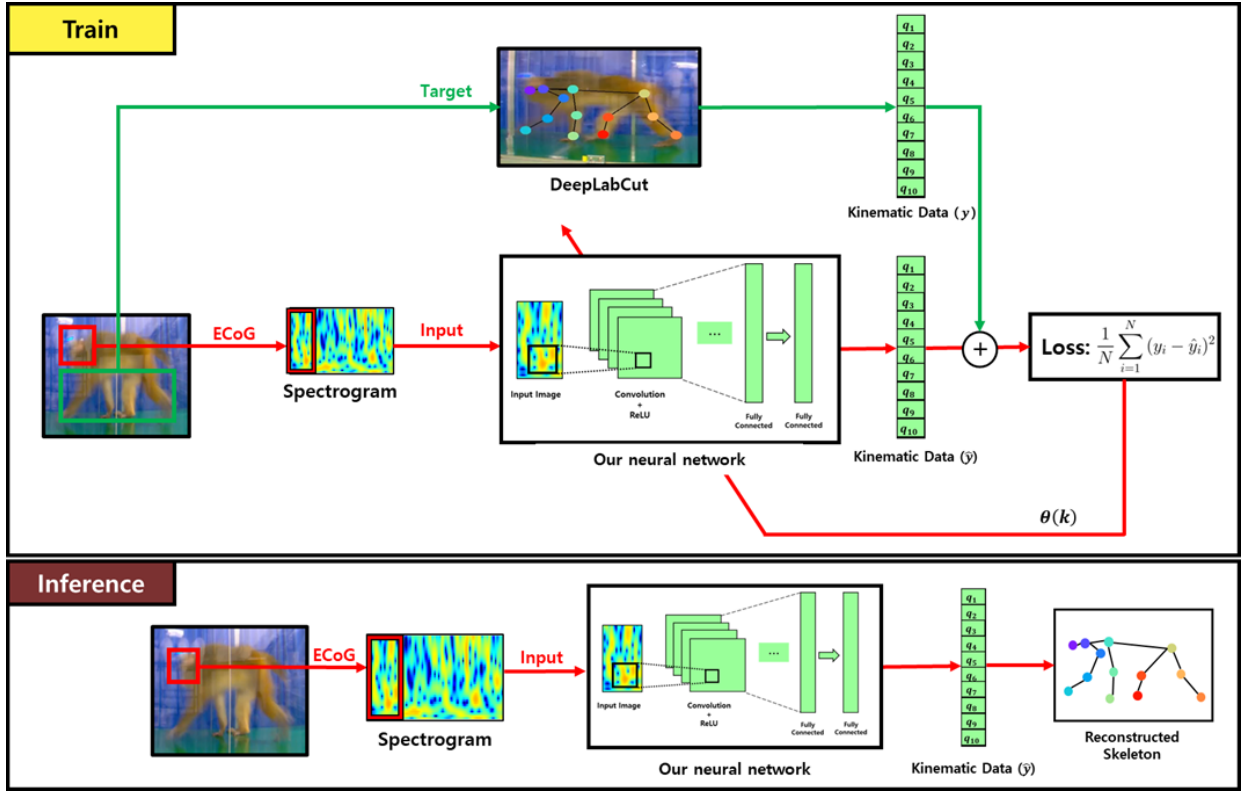


Fig. 3. The processes and corresponding data flows between subfunctional blocks through our proposed approach.

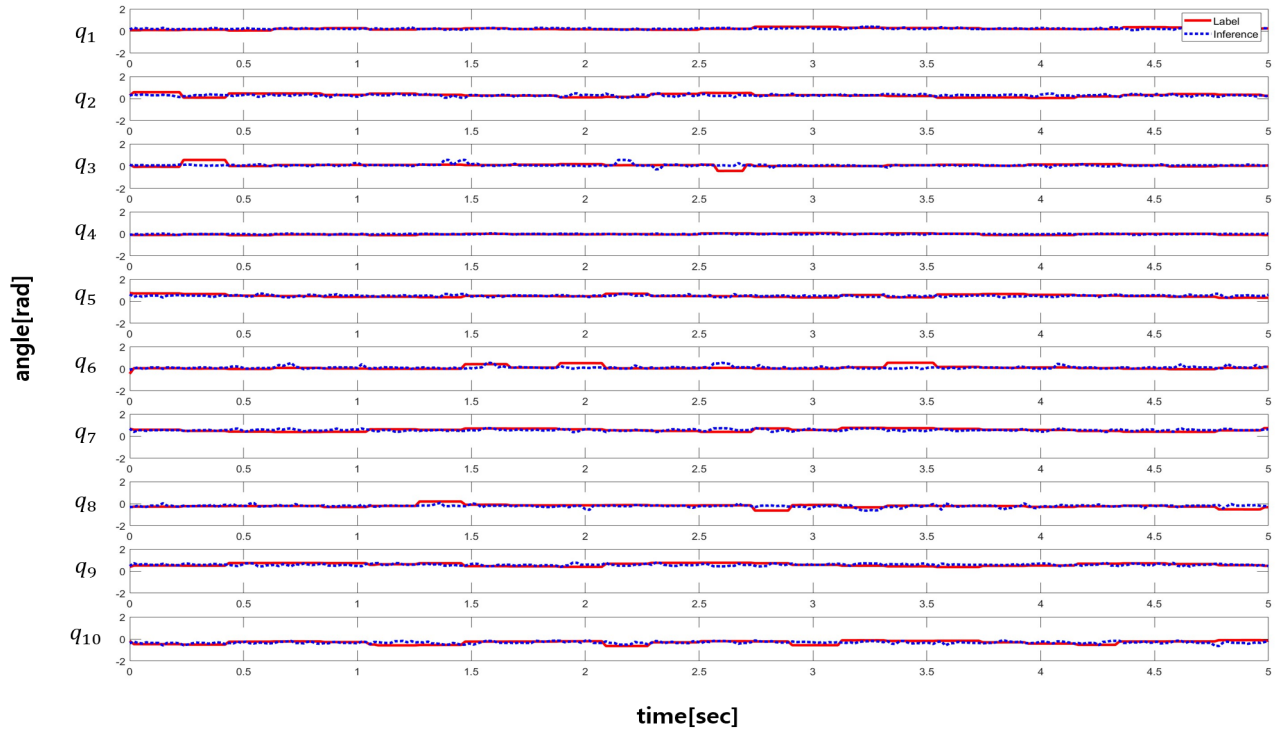


Fig. 4. The prediction result of the joint movement with the ECoG and the video recording for 5 seconds.