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# Deep learning-based electroencephalic decoding of coherence and direction of the random dot kinematogram

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*Introduction:* EEG-based mind-reading under covert attention shifts is an essential research topic in brain-machine interfaces (BMI) [1]. Specifically, identifying electrophysiological signatures underlying motion direction perception of moving stimuli with varying motion coherence is crucial for understanding human attentional mechanisms and coherent motion processing [2]. Despite its significance, few studies have explored this area, highlighting the need for further research [3]. This study aimed to determine whether coherence levels and motion direction could be decoded above chance levels using the random dot kinematogram (RDK) task and EEGNet, a deep learning model [4].

*Material, Methods and Results:* Participants performed a behavioral task that required identifying the direction of coherently moving dots among randomly moving ones under three coherence levels (25%, 50%, and 75%) and two directions (left and right). EEG data were recorded from 25 participants (mean age: 23.8, 16 female) using 63 channels. Ocular artifacts were removed using independent component analysis (ICA), and EEG data were segmented from stimulus onset to 1-second post-stimulus. Artifact-contaminated trials were excluded from further analyses. Data were split 4:1 for training and testing, with 5-fold cross-validation to optimize model parameters. Trained over 500 iterations in a cross-participant setting, the EEGNet model classified coherence (3 classes), direction (2 classes), and combined conditions (6 classes). It achieved accuracies of 0.61 for coherence decoding, 0.77 for direction decoding, and 0.41 for combined classification—all above chance levels (Figure 1A). Additionally, the model achieved AUC values of 0.77, 0.84, and 0.69, respectively (Figure 1B).

*Conclusion:* This study demonstrated the feasibility of decoding coherent and directed motion perception using EEG signals. The findings highlight the potential of deep learning-based EEG decoding approaches to advance our understanding of human motion integration. However, despite these promising results, the model's performance is currently insufficient for practical applications. Future research will focus on improving decoding accuracy and analyzing decoded EEG components to gain deeper insights into the underlying neural mechanisms.

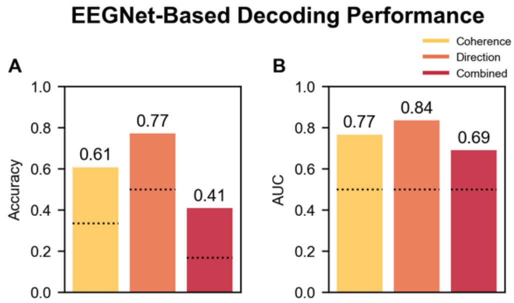


Figure 1: *(A) Accuracies and (B) AUCs of EEGNet-based decoding performance for coherence, direction, and combined classification. The dotted lines indicate the chance level of decoding performance.*

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