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Using a Long Short-Term Memory Neural Network for Generation of Control Signals from μECoG Data

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Introduction: Neural decoding studies highlight significant advancements in brain-computer interfaces (BCIs) for predicting motor intentions and controlling assistive technologies. Studies have demonstrated the robustness of using field potentials recorded from intraparenchymal BCIs as control signals for communication and motor prostheses [1, 2, 3]. We have similarly demonstrated that local field potentials recorded from epicortical micro-electrocorticography (µECoG) BCIs can be decoded using Machine Learning (ML) algorithms, and serve as control signals for speech and motor prostheses [4,5]. µECoG offers a good balance between invasiveness, signal quality, and longevity, making it a viable choice for real-time neural control systems. Artificial Intelligence (AI) algorithms are currently being utilized for decoding behavioral states from cortical activity [6]. Despite its potential, challenges remain in translating µECoG data into accurate control signals suitable for real-world applications. This work investigates these challenges by implementing AI algorithms, specifically Long Short-Term Memory (LSTM) networks, on µECoG neural signals recorded during motor tasks. LSTM networks were selected due to their ability to model temporal dependencies in time-series data. The study aims to evaluate the AI model's ability to generalize and preserve temporal dependencies, which are critical for practical deployment in assistive technologies.

Material, Methods and Results: The µECoG signals were recorded from a patient performing reaching movements toward multiple targets, with 16-channel grids implanted over the hand and arm regions of the primary motor cortex [5]. Common Average Referencing (CAR), comb filters, and low-pass filters were applied to clean the data, remove noise and artifacts, prior to extracting the features from the data for training the model. Model evaluation included scenarios where the X,Y positions of the mouse were predicted using interpolated data i.e., where temporal relationships are not maintained; and extrapolated data i.e., temporal relationships are maintained, in order to understand the temporal dependencies in the algorithm and its ability to provide a generalized solution.

Initial results demonstrated an accuracy of over 90% in predicting movement trajectories and classifying motor intentions within a single experimental session using interpolated data. This high accuracy was based on shuffled data, which does not accurately model real-world conditions. Subsequent investigations compared interpolated data (LSTM with shuffled data) and extrapolated data (LSTM with unshuffled data separated in time) to better assess generalization. Preliminary findings indicated that while the LSTM model performs well with interpolated data, the performance was reduced to approximately 70% accuracy when handling extrapolated data, highlighting challenges in capturing temporal dependencies effectively and utilizing AI models in real-time applications.

Conclusion: Our findings show that LSTM networks perform well with interpolated data but struggle to generalize when temporal relationships are preserved i.e., with extrapolated data. This highlights a critical limitation for real-world applications and aligns with existing research emphasizing the need for models that handle sequential neural data effectively.

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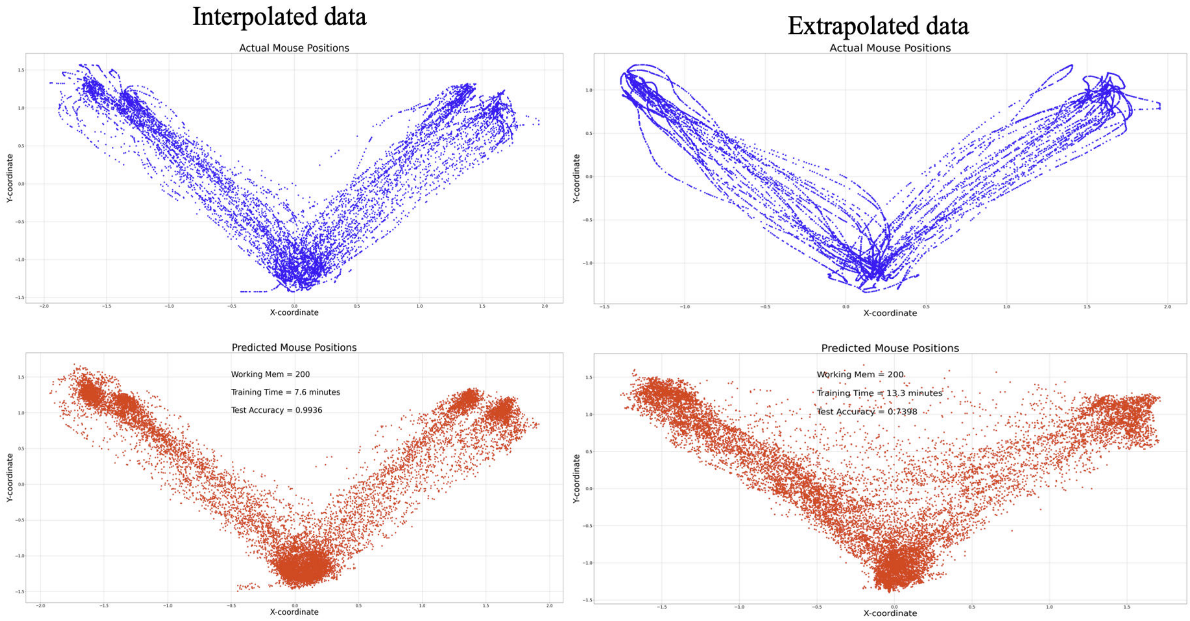

Figure 1: A comparison plot in which the first one shows the predicted vs actual mouse positions of the interpolated data and the second one shows the same for extrapolated data.

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