Gait Phase Intent Decoding from Electroencephalography

Kazuma Hakushi, Zoelie Kim, Anika Awasthi, Devah Schaefers, Adan Sanchez, Larielys Nieves-Rivera
Software Division, Neurotech@Berkeley

Abstract

This project proposes a hybrid Temporal Convolutional Network (TCN) and Long Short-Term Memory (LSTM) pipeline to decode gait phase and ankle angle from 64-channel EEG data. Trained on each subject individually, the TCN outputs the gait phase probability, heel-strike probability, and a latent vector. The latent vector and cyclically encoded gait phase value are inputted into an LSTM which outputs the predicted angle at each timestep. In 6/8 of the subjects, the TCN successfully detects the heel-strike with a mean AUC of 0.924. Among these subjects, the architecture also achieves a mean accuracy of 72.8% in 4-class gait phase classification. Furthermore, a 0.735 mean R2 value is demonstrated in 5/8 of the subjects in predicting the right ankle angle. The inter-subject variability of these preliminary results indicate the necessity for further improvements. However, this model builds upon existing research to present a potential new model architecture for non-invasive, real-time BCI and prosthetic control systems.

Introduction & Literature Review

Brain-computer interfaces offer a solution for people with spinal cord injuries, stroke, and neuromuscular disorders who have lost the ability to walk. By reading movement intent from the brain, these devices have demonstrated the potential to trigger a prosthetic or exoskeleton in real time. Most BCI research uses invasive intracranial electrodes, limiting real-world applicability. We test whether non-invasive EEG can decode gait events to enable deployable BCIs in rehabilitation and neuroprosthetic applications.

- TCNs use dilated convolutions to capture patterns across multiple timescales, making them well-suited for gait decoding where fast heel-strike events and slower stride rhythms coexist in EEG signals (Altaheri et al., 2025).
- Most EEG-to-gait models predict joint angles at isolated time points and ignore gait-cycle structure. Fu et al. (2026) shows that encoding phase information into EEG representations improves continuous angle prediction (r = 0.70) across 50 subjects, supporting multi-task approaches that jointly decode gait events and kinematics.

Model Architecture

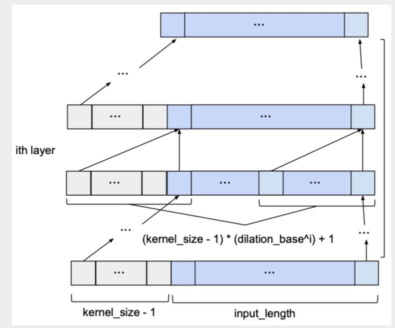
Preprocessing

Raw EEG

Band pass filtering
Notch filtering
Normalization
Walking detection

Stage 1: TCN - Gait Phase + Latent Vector

TCN



Phase Logit

Heel Strike Probability

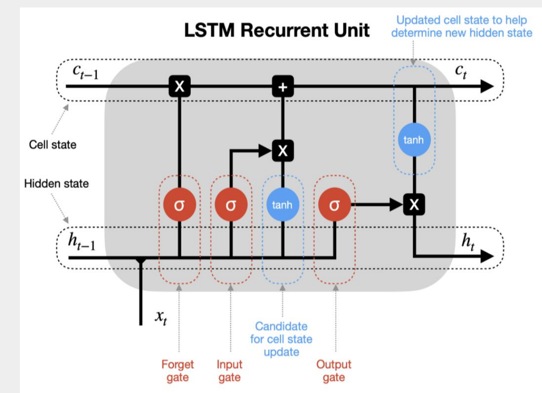
Latent Vector

Stage 2: LSTM - Angle Prediction

Cyclic Encoding

Sin phase
Cosine phase

LSTM



Angle Prediction

Training

Stage 1: TCN - Classification Training

Train TCN Layers
Freeze LSTM layers
Loss: Cross Entropy

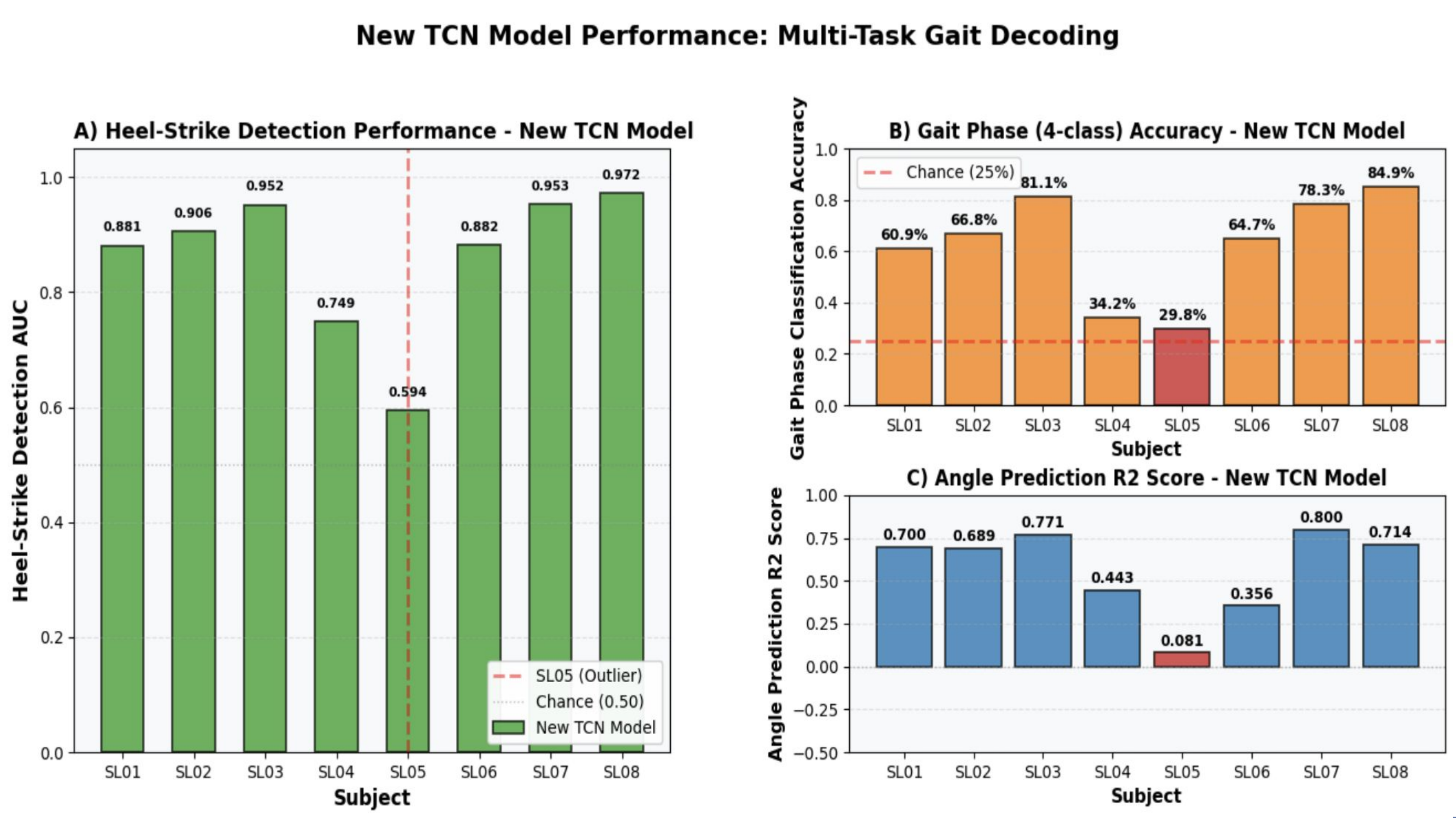
Stage 2: LSTM - Regression Training

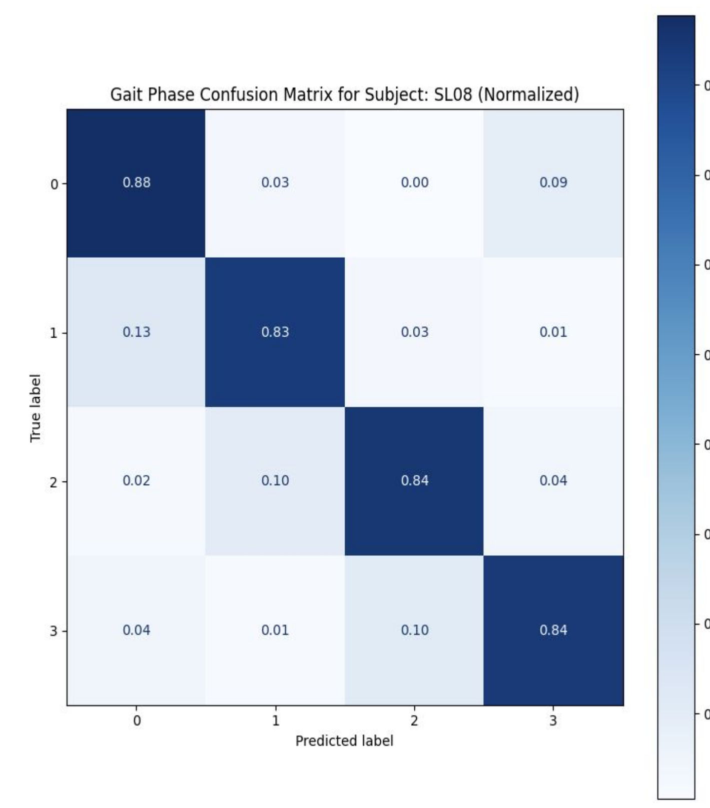
Freeze TCN Layers
Train LSTM layers
Loss: Huber

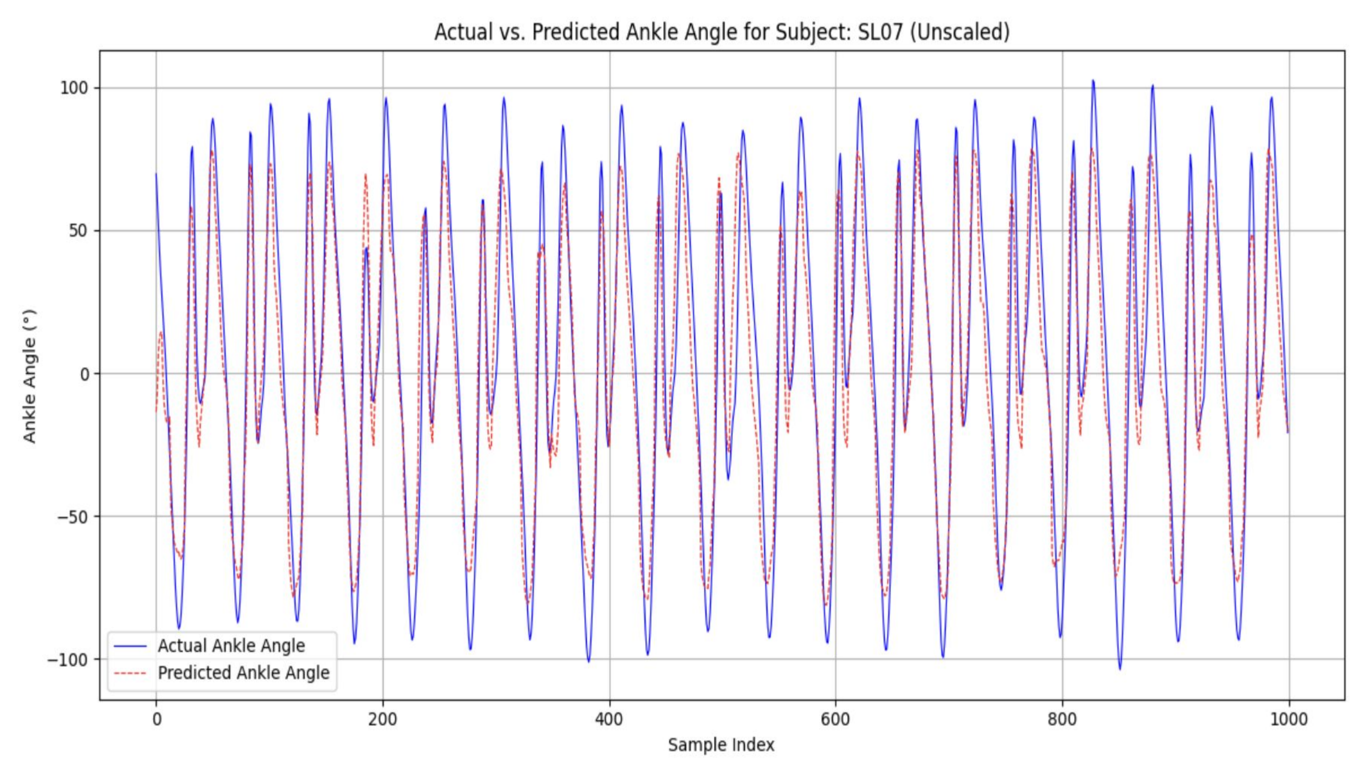
Stage 3: TCN + LSTM - Full Model Fine-Tuning

Unfreeze all Parameters
Train on full model
Total Loss: Cross Entropy + Huber

Results







Conclusion & Future Directions

Our results demonstrate that TCNs and LSTMs could be suited for gait decoding as they capture the multi-scale temporal dependencies inherent in EEG signals that simpler linear models often miss. For most of the tested subjects, the model is able to identify heel-strike, gait phases, and ankle angle measure, proposing a non-invasive approach to real-time BCI control in robotic exoskeletons and neuroprosthetics. However, the observed inter-subject variability highlights the need for more robust decoding techniques. We propose training on more data and testing other temporal architectures such as sequence transducers and state space models for improved latent space estimation. Implementing more advanced EEG preprocessing such as spectral decomposition through Wavelet transform or ICA could also enhance feature extraction. Future iterations will also explore ways to integrate multi-task learning to simultaneously decode multi-joint kinematics, including knee and hip as well as model generalizability across subjects. Moreover, investigating the underlying reasons for subject-specific performance drops could provide critical insight to potential biases from our training data or architecture, allowing us to develop a universal gait-decoding pipeline.

References

Altaheri, H., Karray, F., & Karimi, A. H. (2025). Temporal convolutional transformer for EEG based motor imagery decoding. Scientific Reports, 15, 32959.
Dr. Dhanya NM. (2025, June 9). Improving Time Series Prediction Models Using Cyclic Features Encoding in Neural Networks. Medium. https://medium.com/@dhanyahari07/improving-time-series-prediction-models-using-cyclic-features-encoding-in-neural-networks-0eebef307fc2
Fu, X., Jiang, W., Liu, R., Müller-Putz, G. R., & Guan, C. (2026). EEG-to-Gait Decoding via Phase-Aware Representation Learning. arXiv preprint arXiv:2506.22488.
He, Y., Luu, T. P., Nathan, K., Nakagome, S., & Contreras-Vidal, J. L. (2018). A mobile brain-body imaging dataset recorded during treadmill walking with a brain-computer interface. Scientific Data, 5, 180074.
Lässig, F. (2021, July 6). Temporal Convolutional Networks and Forecasting. Unit8. https://unit8.com /resources/temporal-convolutional-networks-and-forecasting/
Olah, C. (2015, August 27). Understanding LSTM Networks. colah's blog. https://colah.github.io/ posts/2015-08-Understanding-LSTMs/
Rakhmatulin, I., Dao, M.-S., Nassibi, A., & Mandic, D. (2024). Exploring Convolutional Neural Network Architectures for EEG Feature Extraction. Sensors, 24(3), 877.