Towards low energy and adaptable prosthetics through Spiking Networks

Nia Touko, supervised by Dr. Luca Manneschi

Department of Machine Learning, University Of Sheffield

Introduction & Motivation

Recent work into prosthetic devices shows the viability of a deep learning controller for classification of EMG signals. However, these models face two key challenges:

- High Power Consumption: Complex models are computationally expensive, leading to poor battery life.
- Performance Degradation: EMG signals are non-stationary and undergo domain shifts, causing stationary models to lose accuracy over time.

This project proposes a potential solution to this problem with an **S-LSTM Encoder with a GMM alignment based TTA Scheme.**

Methodology & Approach

Network Architecture

Previous work has shown the use of rate-coded LSTM networks to extract the features of EMG signals for similar tasks [2] due to their ability to capture long-term dependencies in sequential data. However, LSTM nodes have a complicated internal structure, resulting in a high computational cost [3].

One solution to this problem is to adopt a spiking neural network architecture for its low energy consumption [3]. By replacing the continuous activation functions within a standard LSTM with leaky-integrate-and-fire spiking neurons, an event-driven architecture is created [1].

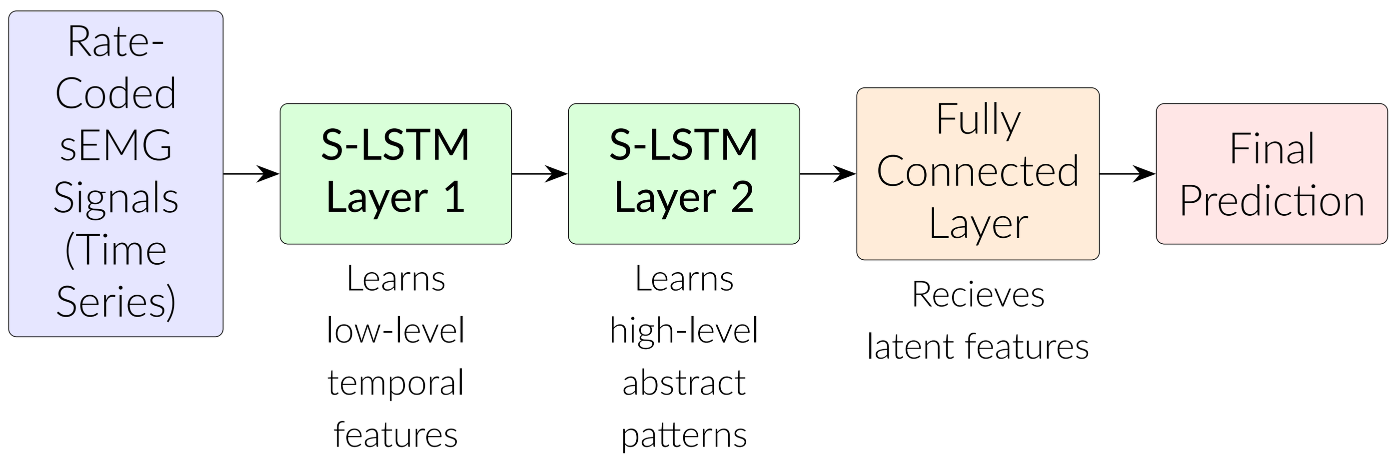


Figure 1. The dual-layered S-LSTM encoder architecture. The model processes rate-coded temporal signals through two sequential S-LSTM layers to extract hierarchical features, which are then passed to a fully connected layer for final classification.

Continual Learning Strategy

To mitigate the performance degradation of the model over time due to the domain shift of the sEMG signal pattern, a continual learning strategy was employed:

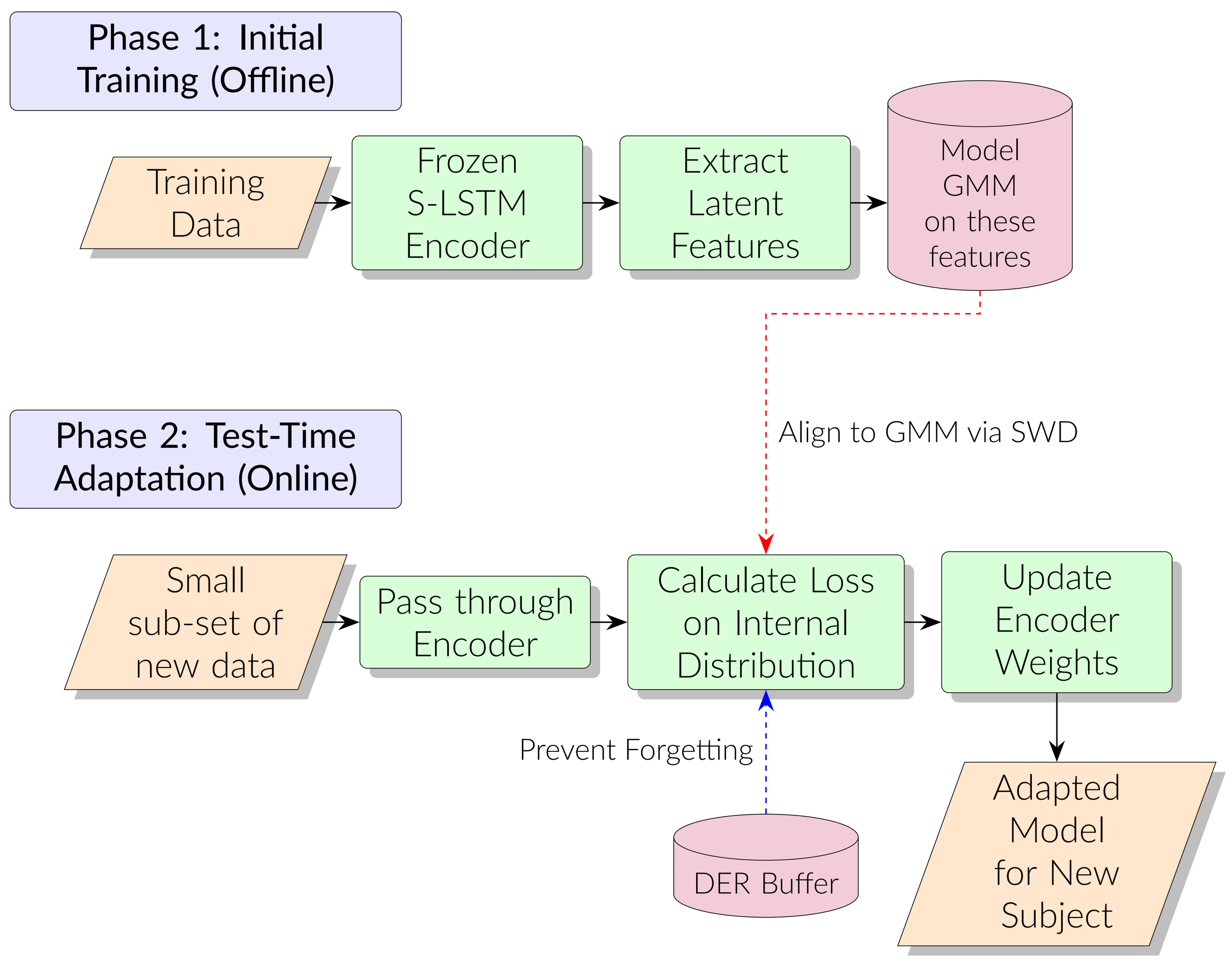
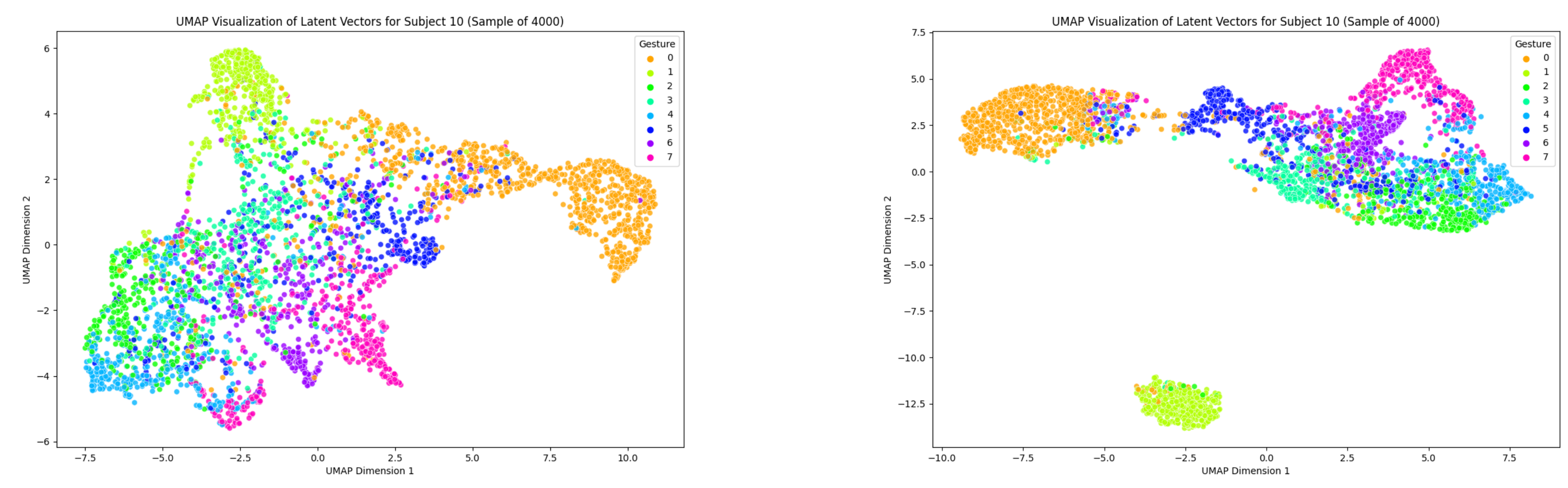


Figure 2. The continual learning mechanism. In Phase 1, a reference Gaussian Mixture Model (GMM) is created from the training data. In Phase 2, the model adapts to new data by minimizing a combined loss function that aligns the internal distribution to the GMM whilst preventing catastrophic forgetting through a Dark Experience Replay (DER).

Experimental Setup

- The Ninapro DB6 dataset [4] was picked to validate and train the model.
- The model was trained on 70% **of the data in** 7 **of the sessions.**
- The remaining 3 sessions were used for inter-session testing.
- One example of each gesture from the current unseen session was used as input for the continual learning strategy.

Results and analysis



(a) Base Model (b) Contrastive Loss Element

Figure 3. UMAP plots of the latent features of the networks. A contrastive loss function was implemented during training to improve feature separation.

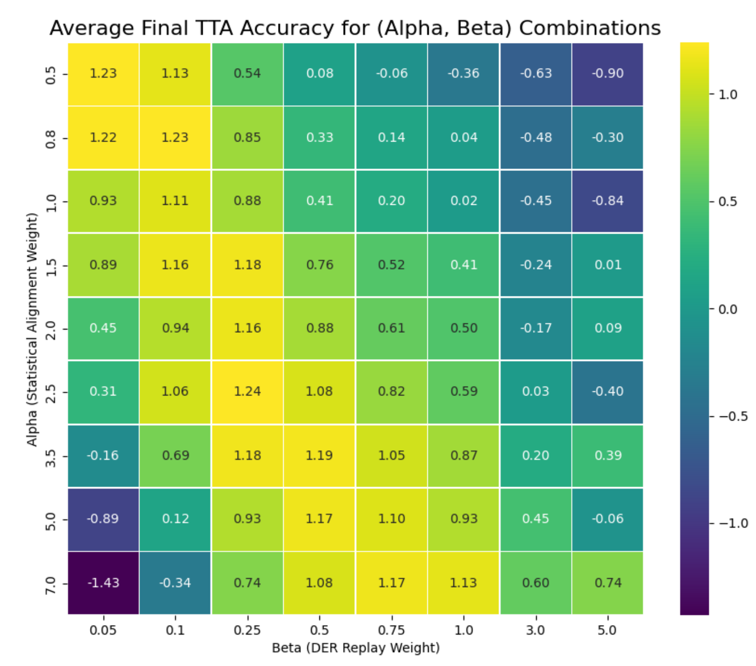


Figure 4. Heatmap to find the weights of the GMM and DER loss functions.

The heatmap shows the final percentage increase over the base performance on average across all sessions. From this heatmap, an alpha value of 1 and a beta value of 0.1 was selected. An important note is that the performance is most optimal when **the alpha value is approximately 10 times the beta value**. A simulation of each session was then run, resulting in the following plot of the TTA improvement.

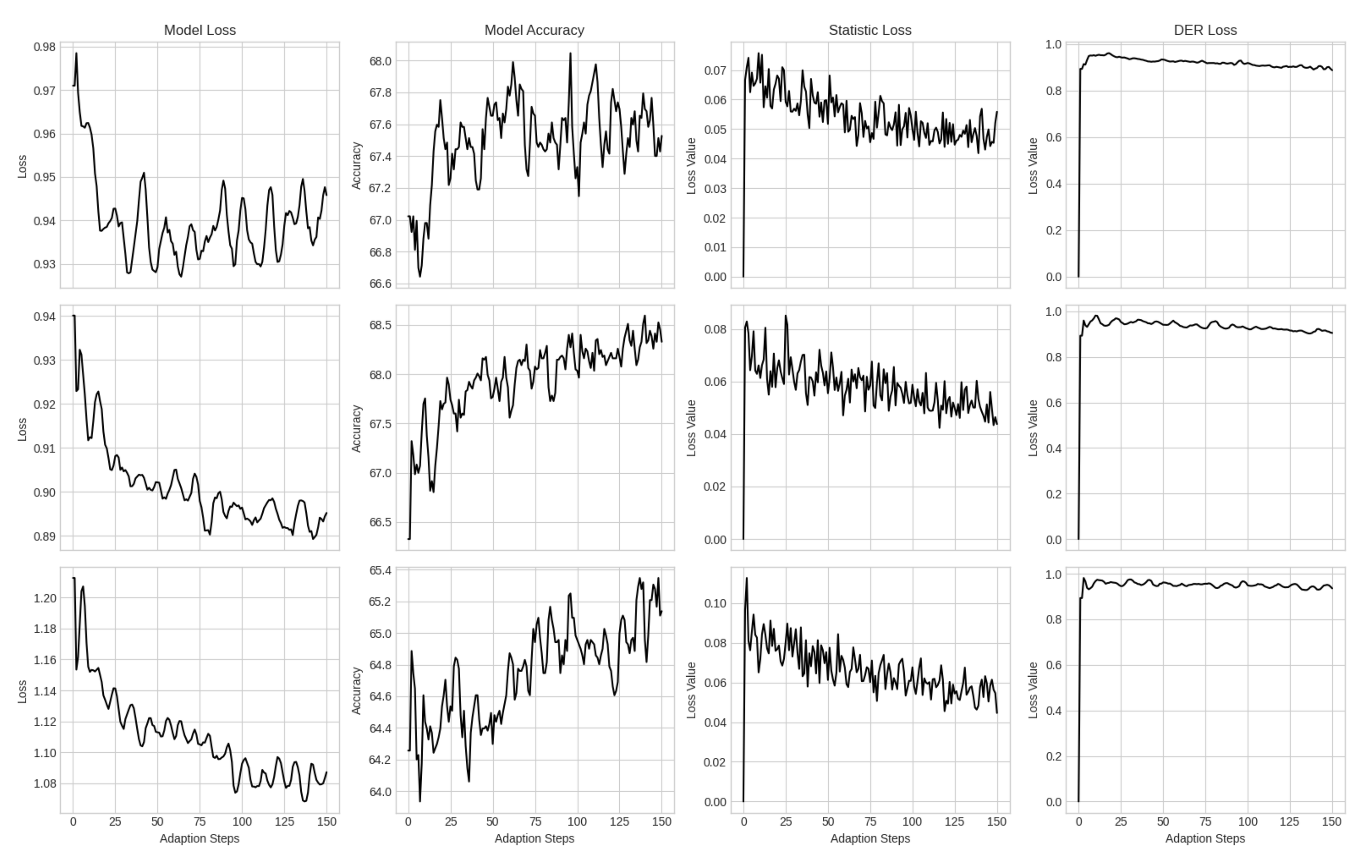


Figure 5. TTA Results on subject 2 of the dataset from baseline performance (where the graph starts). Each row is an unseen session. In order, they are sessions 8,9, and 10 from the dataset

Conclusion & Future Work

The simulations demonstrate the viability of using an S-LSTM encoder with a GMM alignment-based TTA scheme for a low-powered controller for transradial prosthetics. The basic model had a **training average accuracy of** 78.2%. The proposed TTA system resulted in an average increase of the baseline testing performance of 1.694% on a notoriously difficult dataset. This adaptation allowed the model to recover and **retain** 78.4% **of its original training accuracy**, demonstrating effective mitigation of domain shift. Future work will include evaluating the solution's ability to adapt to the multi-subject case, and refining the adaptation process with investigation into meta-learning and prototypical approaches.

References

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ntouko1@sheffield.ac.uk