Determining grasp selection from arm trajectories via deep learning to enable functional hand movement in tetraplegia

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Group: 8

2024.4.7

仿生设计与学习实验室
Bionic Design & Learning Lab

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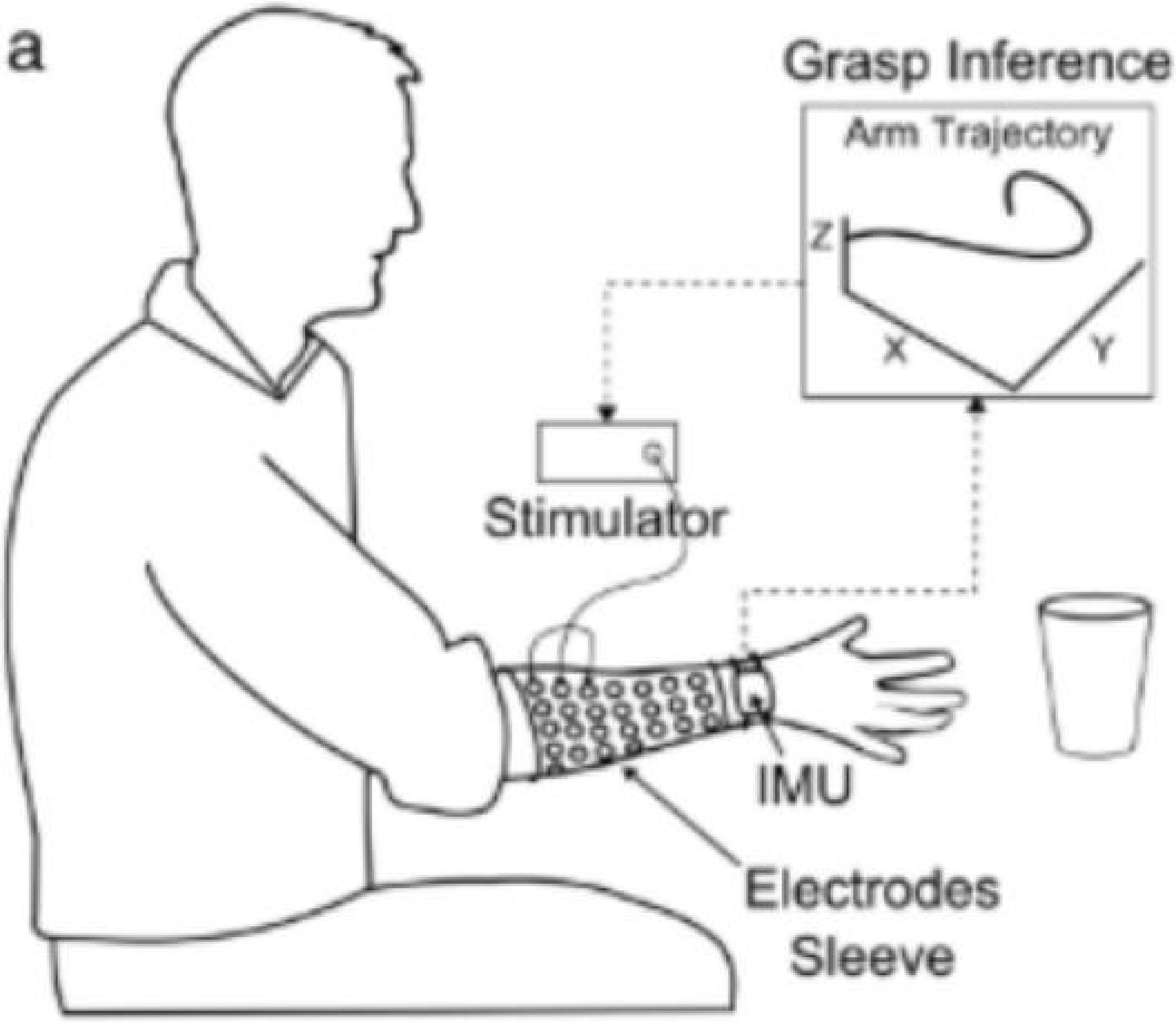
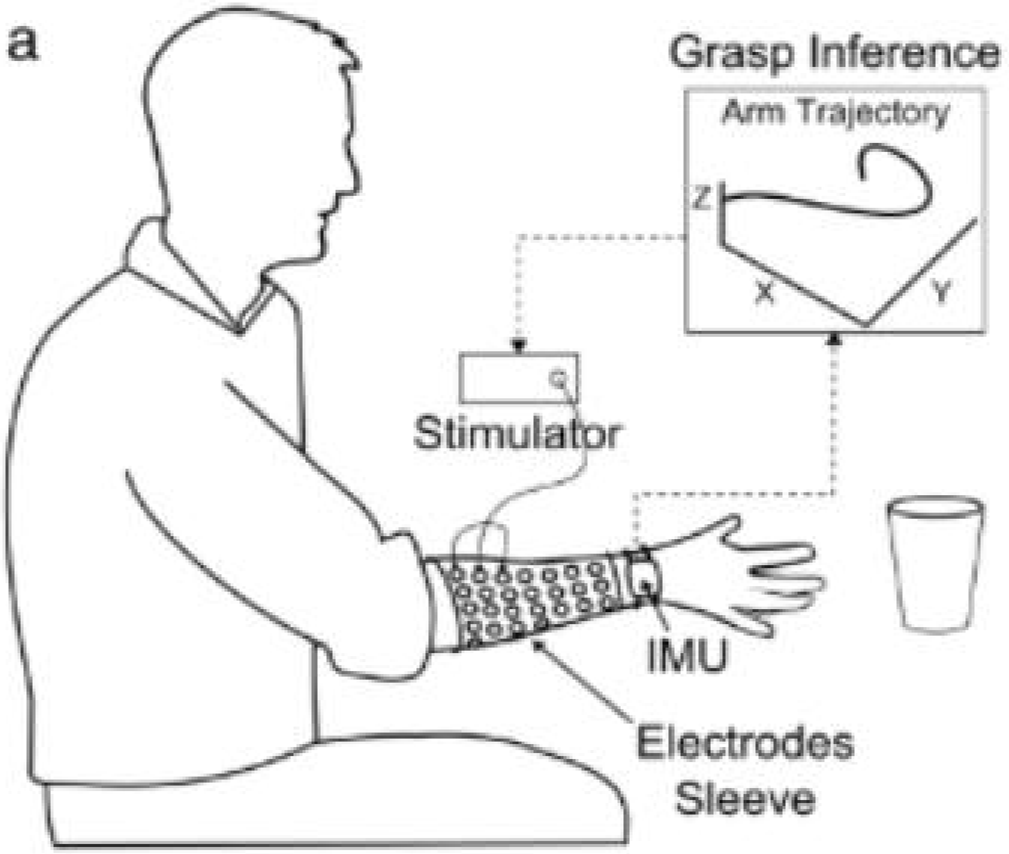

a
Grasp Inference
Arm Trajectory
Z
X
Y
Stimulator
IMU
Electrodes
Sleeve

Problem Setting

- Problem Formulation: The study focuses on predicting the **grasping intentions** of individuals with spinal cord injuries by analyzing their **arm movement trajectories** towards target objects in **three-dimensional space**, using deep learning algorithms, and realizing hand movements through neuromuscular stimulation.
- Key Definitions and Notations: Arm movement data collected by **Inertial Measurement Unit (IMU)** are used as **input** to identify motion trajectories through **Dynamic Time Warping (DTW)** and **Long Short-Term Memory (LSTM) networks**, culminating in grasping actions executed by a **neuromuscular stimulation device**.



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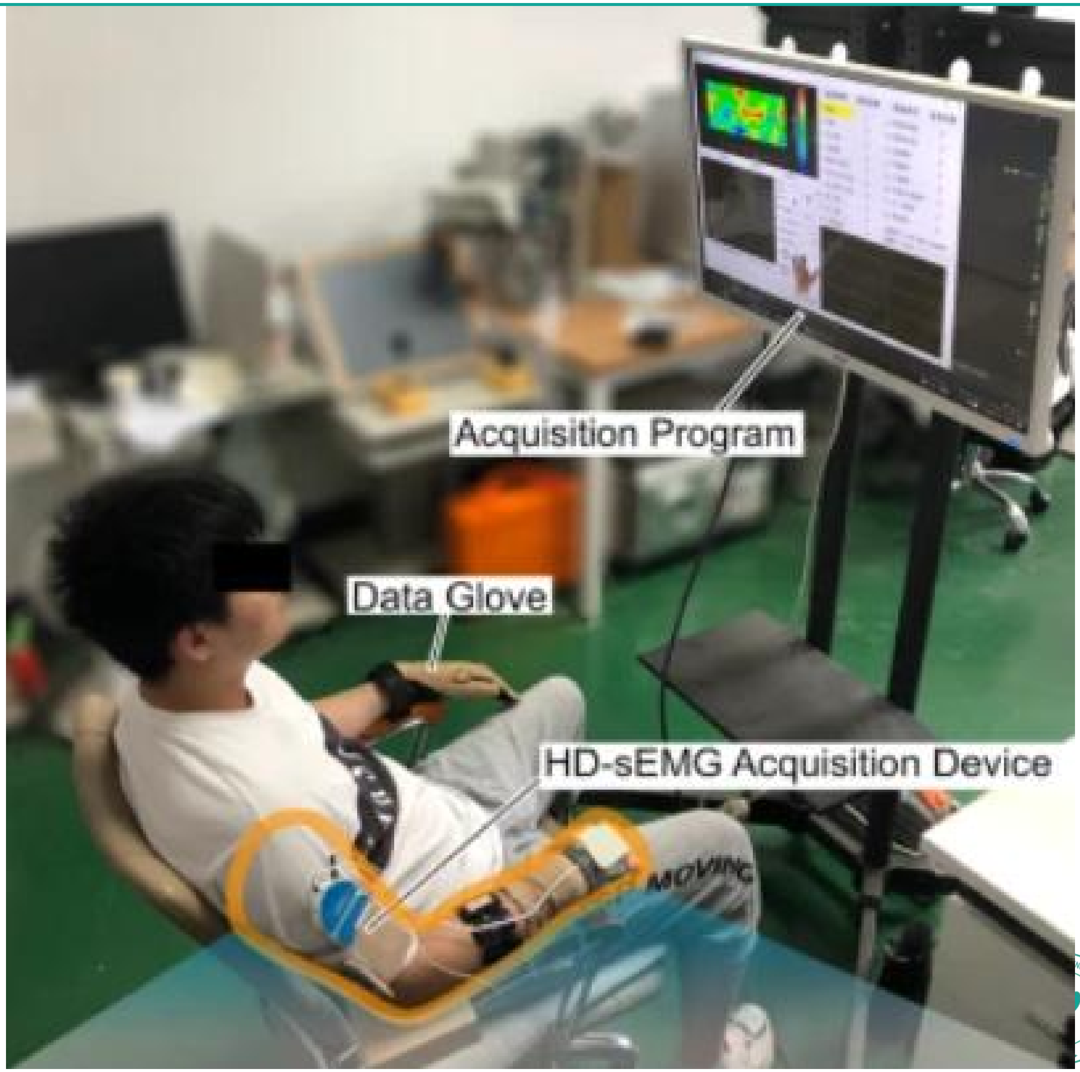
Motivation and Main Problem

- Description: The study addresses how to utilize functional hand movements in individuals with tetraplegia by analyzing **arm movement trajectories** combined with **deep learning** and **neuromuscular stimulation** technologies.
- ML: Key to solving this problem is the use of deep learning algorithms, specifically **Long Short-Term Memory (LSTM) networks**, to process and classify complex motion trajectory data.
- Key Insight: Utilizing arm movement trajectory information collected by **wearable devices (IMU)** and deep learning through LSTM models can effectively predict and identify different types of **grasps**, thus controlling neuromuscular stimulation devices to achieve functional hand movements.

Context / Related Work / Limitations of Prior Work

- Context / Related Work: Previous studies have attempted to restore or augment hand movements in individuals with tetraplegia using surface electromyography (sEMG) signals or brain-computer interface technologies.
- Limitations of Prior Work: Past works may have limitations in the accuracy, real-time performance of user intent recognition, and the portability and usability of the system.
- **INCONVENIENT !!!**



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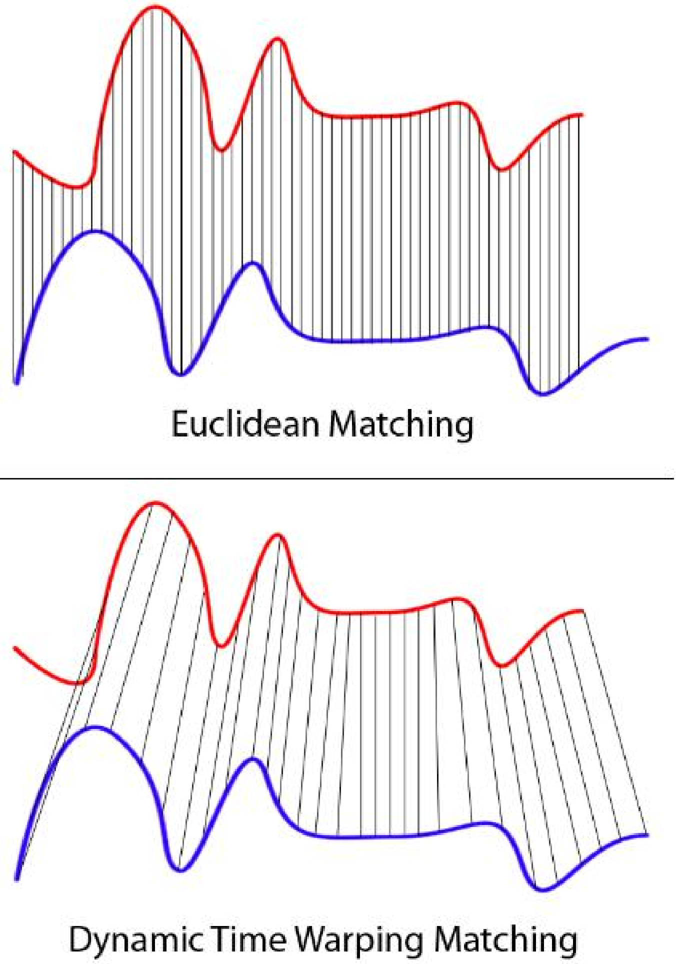
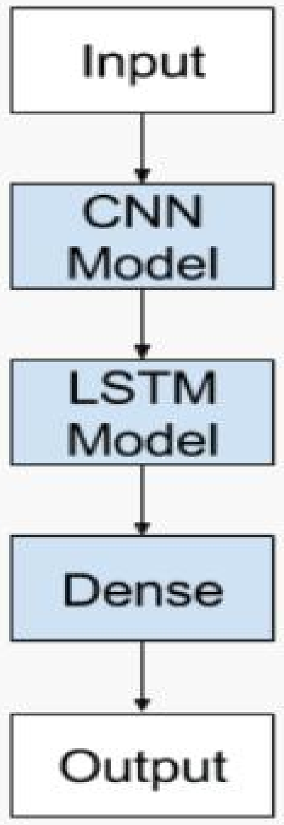
Proposed Approach / Algorithm / Method

- Proposed Method: The framework employs an **LSTM** network and **DTW** to analyze **time-series data**, with the optimization objective being to maximize the accuracy of motion trajectory classification.
- Core Technical Innovations: The integration of the LSTM deep learning model and DTW with neuromuscular stimulation technology allows for **high-accuracy motion trajectory recognition** and real-time control of hand movements.
- DTW ->





Convolutional Neural Network Long Short-Term Memory Network Architecture

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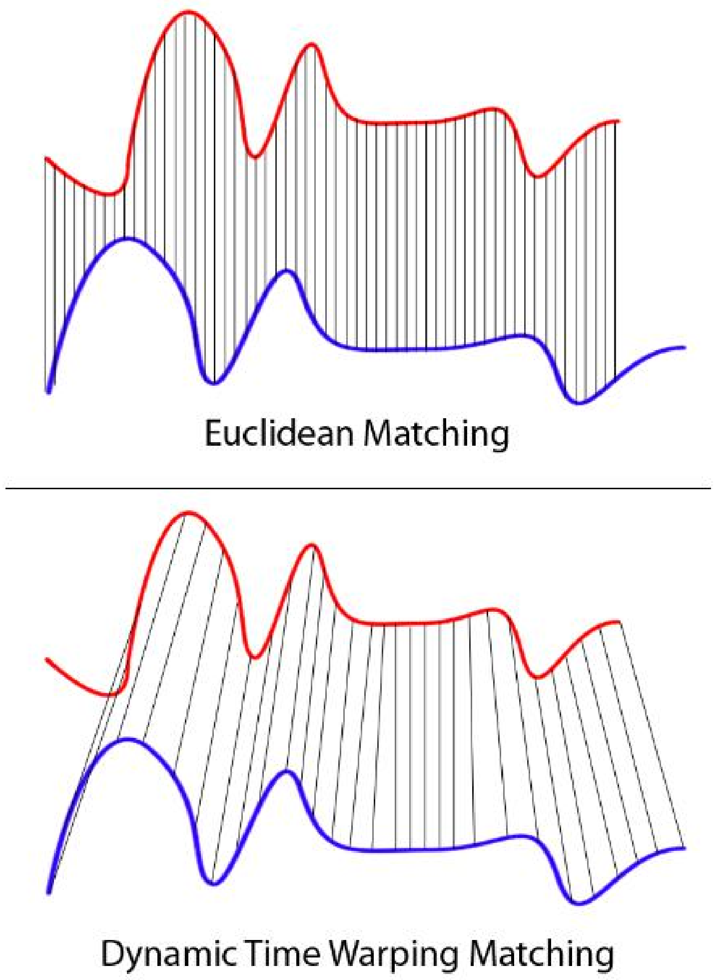
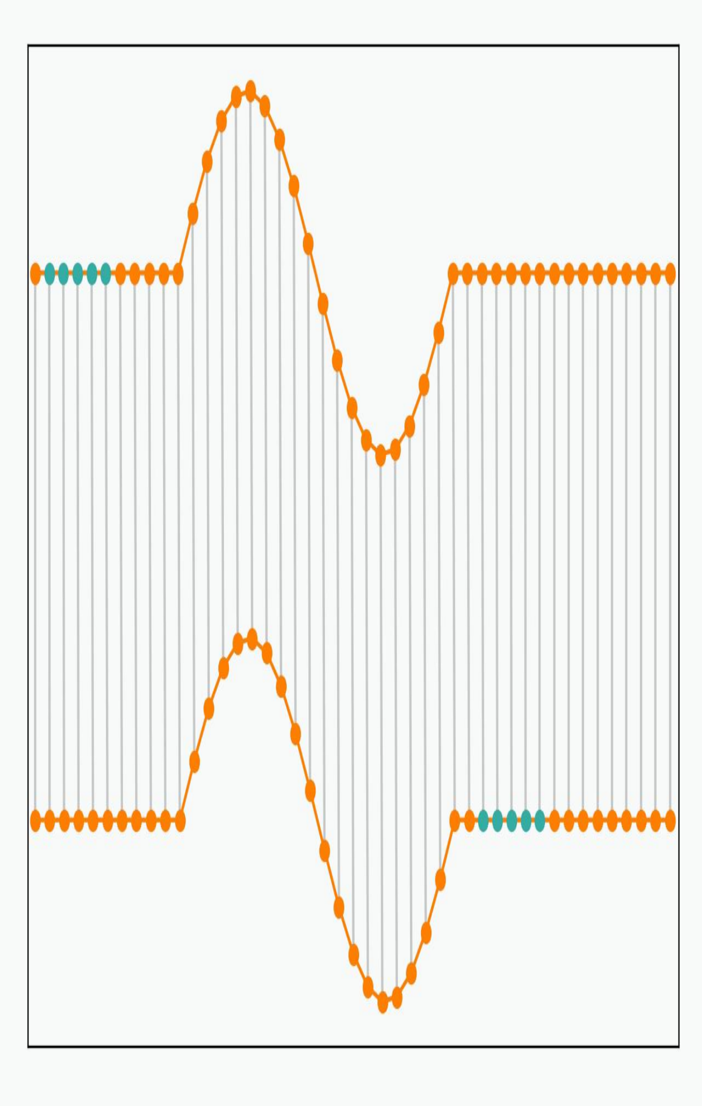
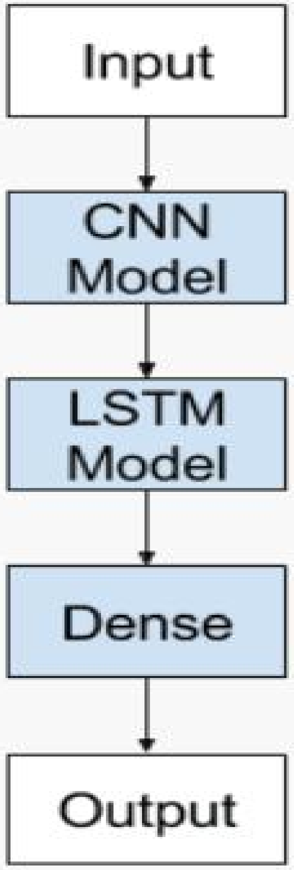
Proposed Approach / Algorithm / Method







Convolutional Neural Network Long Short-Term Memory Network Architecture

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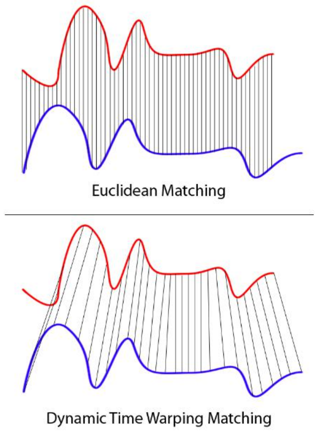
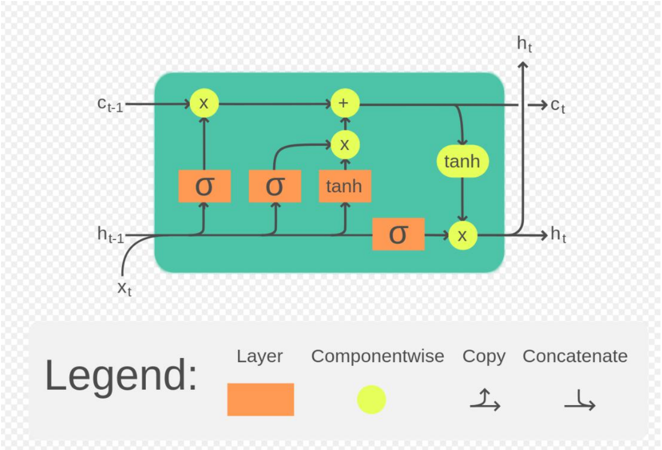
Theory

- Theory Assumptions: It's assumed that grasping intentions can be accurately predicted through arm movement trajectories, and these trajectories can be effectively identified by deep learning algorithms.
- Theory Basis and References: The study is grounded in previous theories on Long Short-Term Memory (LSTM) networks for processing time-series data, further applied to the classification of motion trajectories. See paper "LSTM: A Search Space Odyssey,"





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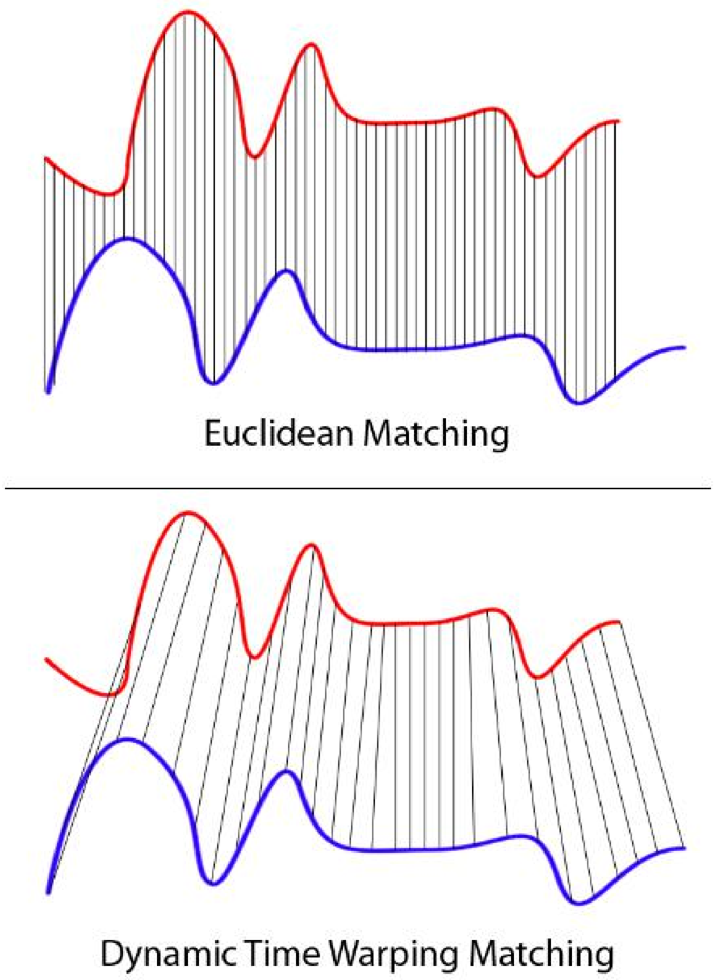
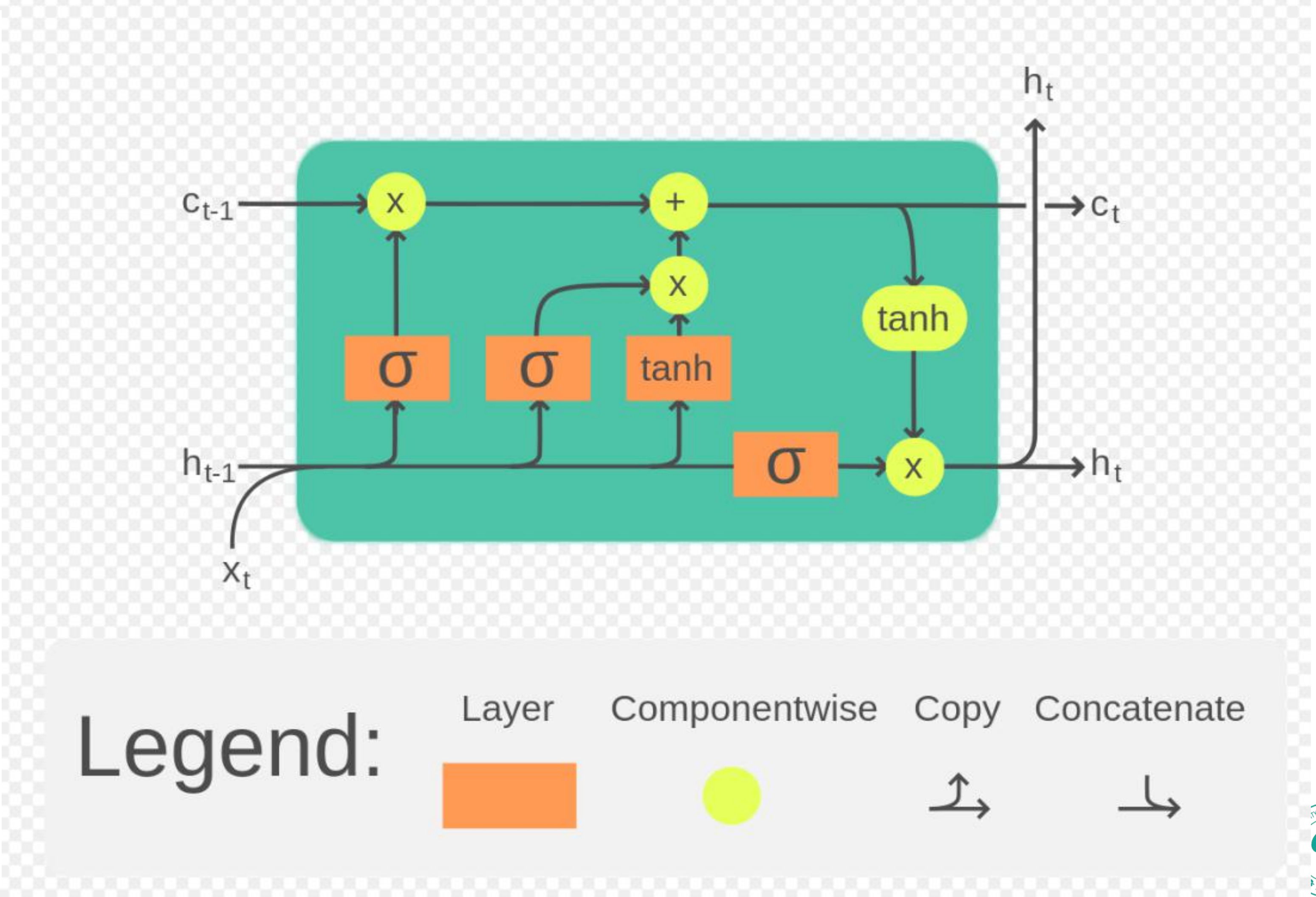
Theory





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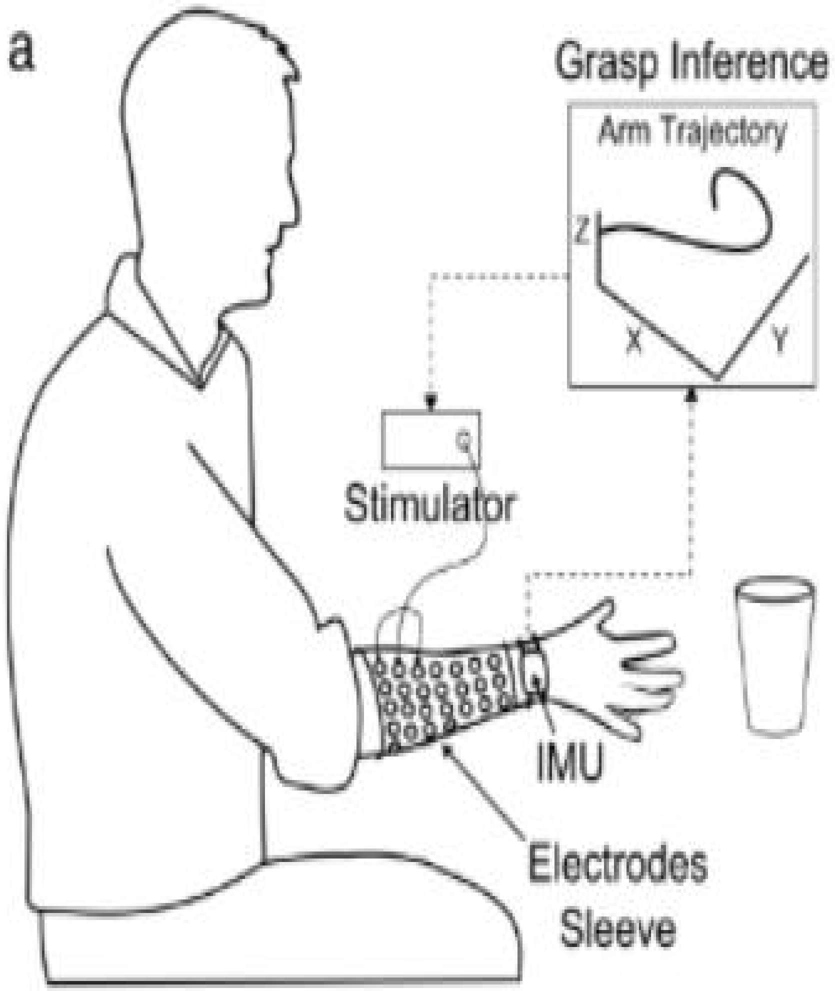
Experimental Setup

- Experimental Setup: Arm movement trajectories towards specific targets in three-dimensional space were collected from individuals with spinal cord injuries using inertial sensors.
- Domains: The study was conducted in individuals with spinal cord injuries, utilizing data from natural and arbitrary arm movement trajectories.
- Baselines: Compared with traditional neuromuscular stimulation control methods and previous deep learning approaches.
- Scientific Hypotheses Tested: Validated that integrating arm movement trajectory information with deep learning improves the accuracy and real-time performance of grasping intention recognition.



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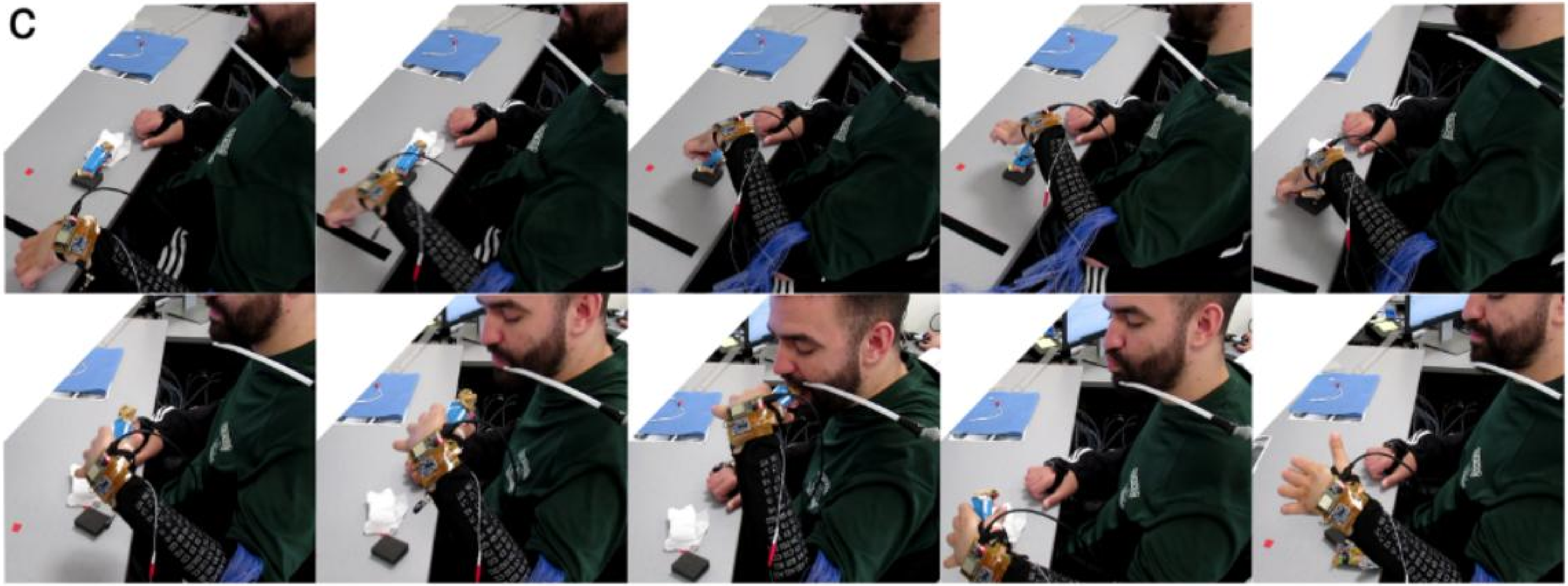
Experimental Setup



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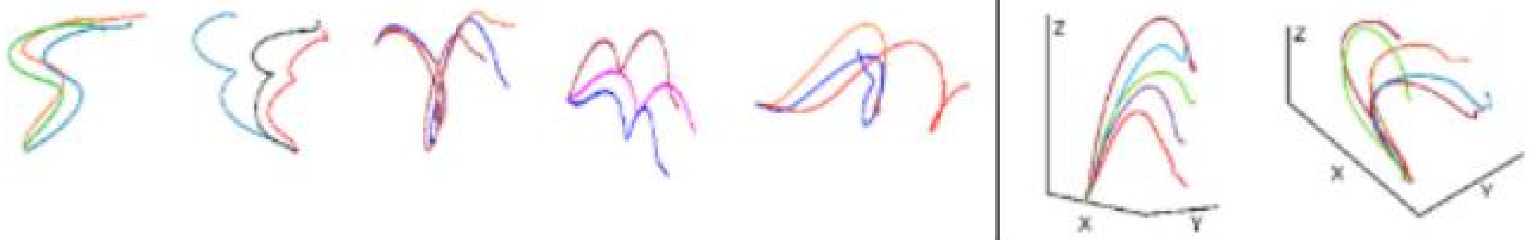
Experimental Setup

Table 1 Number of valid 2D and 3D arm trajectories from two participants with tetraplegia, used for training and testing machine learning algorithms. The trajectories are further categorized into arbitrary and natural reaching trajectories in 2D and 3D space



	Arbitrary Trajectories					Natural Reaching	
Classes	s	ε	γ	m	Corkscrew	Pen-reach	Bottle-reach
Participant							
1	60	65	22	20	21	28	15
2	25	23	-	-	16	15	17
Total	85	88	22	20	37	43	32

Experimental Results

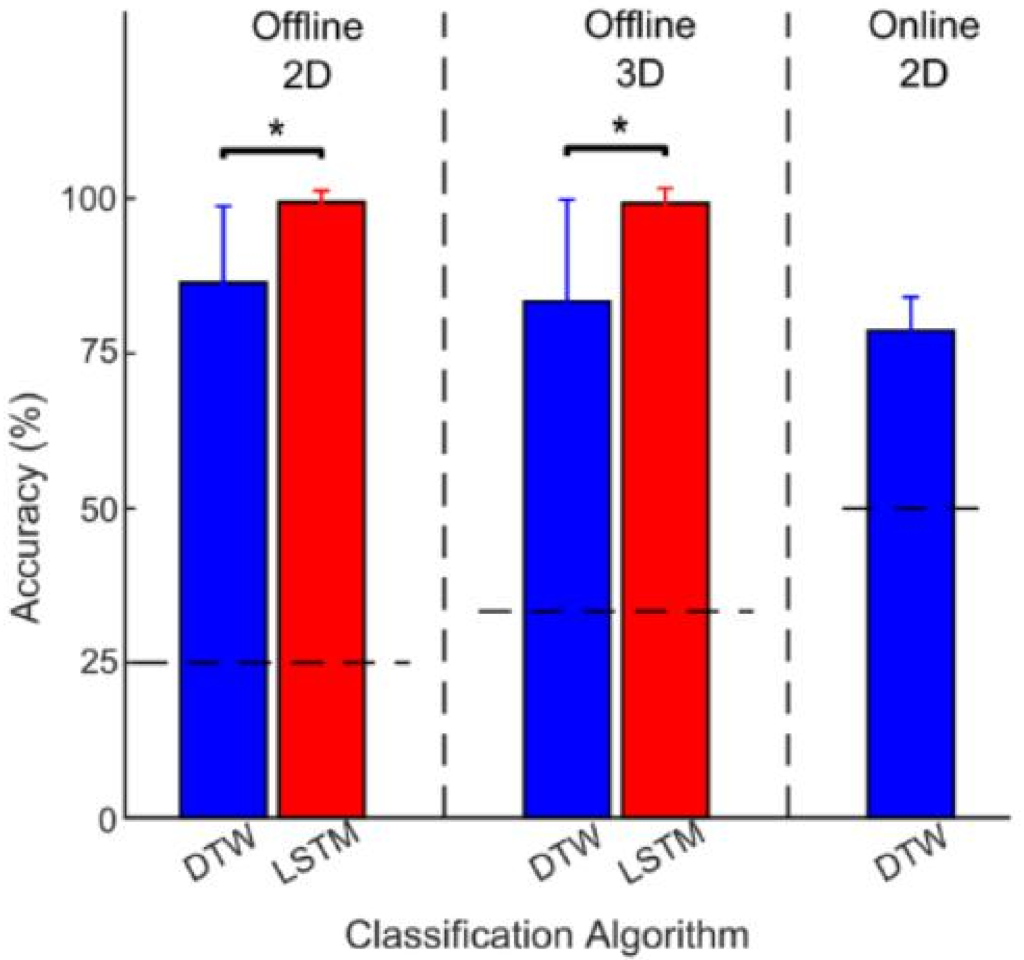


Fig. 2 Bar graphs comparing classification accuracies (Mean ± SD) using two machine learning algorithms: DTW and LSTM. Performance was evaluated using both offline (2D & 3D) and online (2D only) arm trajectories. Statistical significance threshold was set at $p < 0.05$. The horizontal dashed lines represents the chance level (= 1/number of classes) under each comparison

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Experimental Results

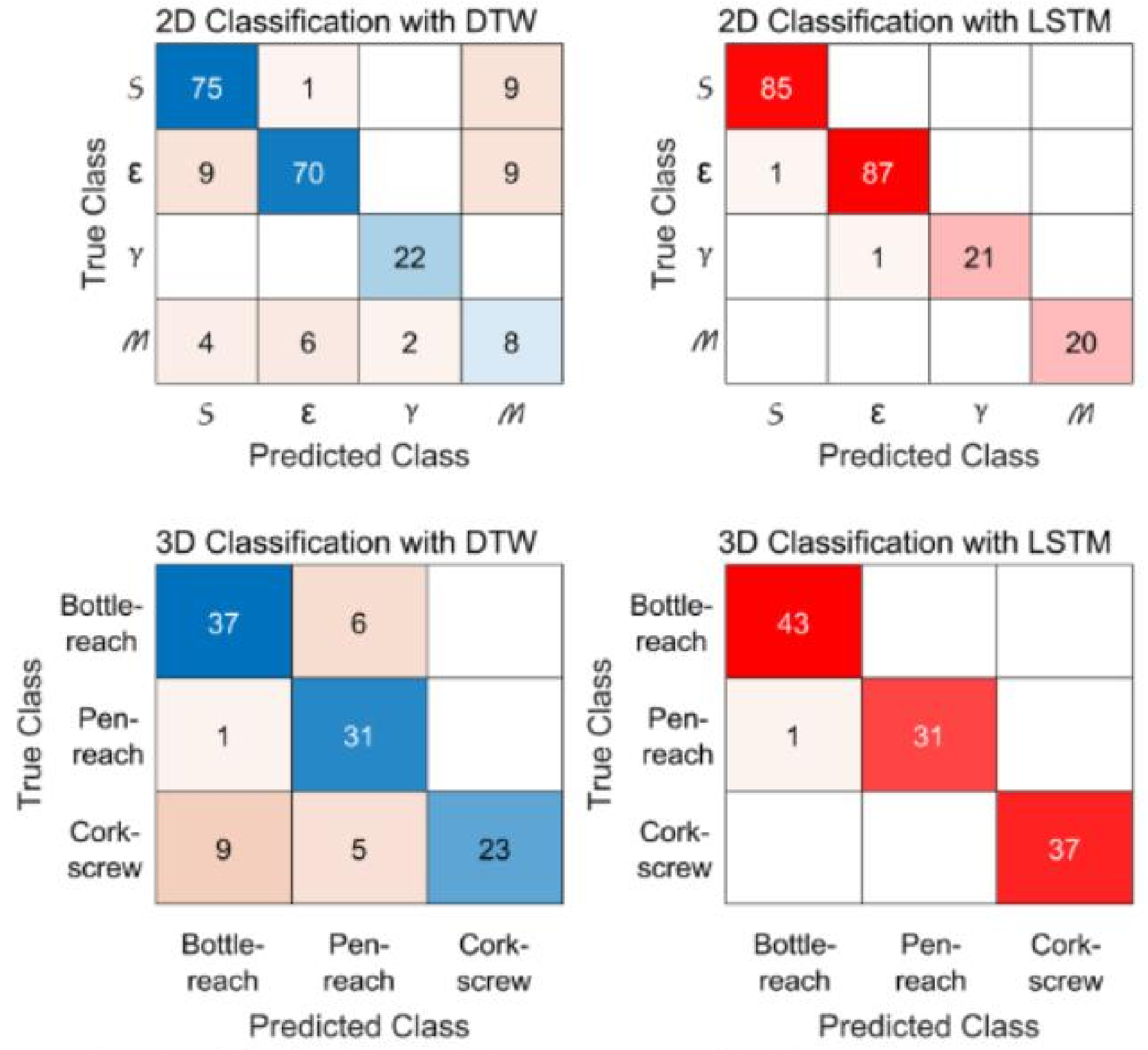

Fig. 3 Confusion matrices illustrating DTW and LSTM-based classifier performance for 2D & 3D trajectories

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Experimental Results

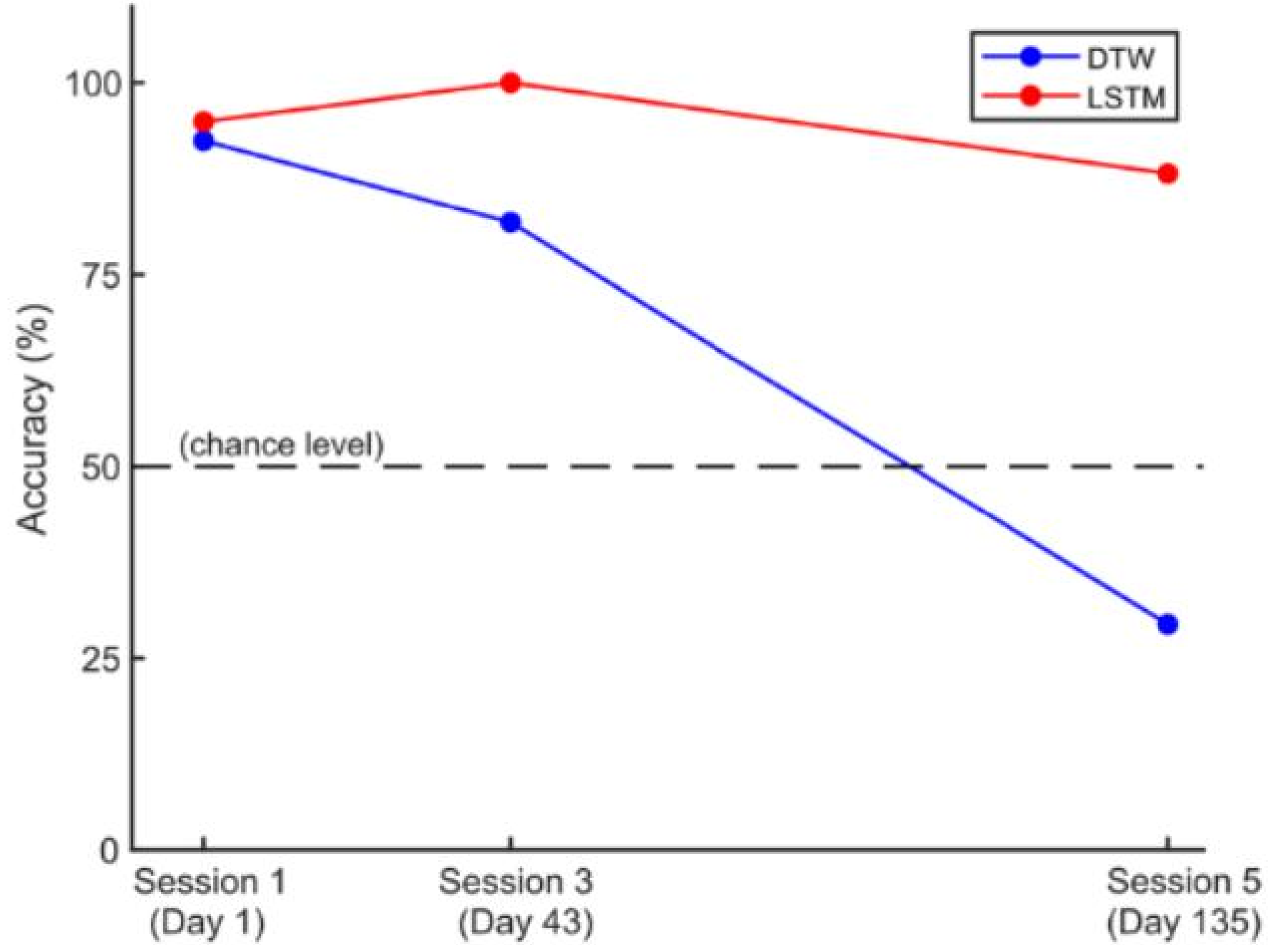

Fig. 4 Comparison of LSTM vs. DTW performance across multiple sessions. In this example, data recorded for two 2D trajectories $\mathcal{S}$ and $\mathcal{E}$ over three sessions were used for analysis

Discussion of Results

- Conclusions: Demonstrated the **feasibility** and **effectiveness** of using arm movement trajectory information combined with deep learning methods to restore functional hand movements in individuals with tetraplegia.
- Insights Gained from Experiments: Deep learning, especially **LSTM networks**, is extremely **effective** in recognizing complex motion trajectories and improving the **accuracy** and real-time performance of neuromuscular stimulation device control.

Limitations

- Limitations: LSTM -> Neuron Network -> **Large dataset requirement**

- Although the LSTM model performs well, it requires a **high volume** and **quality** of data, potentially necessitating extensive training data to maintain accuracy and real-time performance.

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Future Work

What interesting questions does it raise for future work?

- Multiple IMUs (more physical meanings)

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Extended Readings

- Bhagat N, King K, Ramdeo R, Stein A, Bouton C. Determining grasp selection from arm trajectories via deep learning to enable functional hand movement in tetraplegia. Bioelectronic Medicine. 2020 Dec;6:1-8.
- Yu Y, Si X, Hu C, Zhang J. A review of recurrent neural networks: LSTM cells and network architectures. Neural computation. 2019 Jul 1;31(7):1235-70.
- Staudemeyer RC, Morris ER. Understanding LSTM--a tutorial into long short-term memory recurrent neural networks. arXiv preprint arXiv:1909.09586. 2019 Sep 12.

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Summary

- Problem Discussed: How to realize functional hand movements in individuals with tetraplegia through analyzing arm movement trajectories and deep learning.
- Why It's Important and Hard: This issue is significant for enhancing the quality of life for individuals with tetraplegia, with technical challenges including accurate trajectory recognition and real-time performance.
- Key Limitation of Prior Work: Previous methods might not have fully utilized arm movement information, or lacked in real-time performance and accuracy.
- Key Insight(s) of the Proposed Work: Utilizing deep learning, particularly LSTM models, can effectively identify arm movement trajectories and control neuromuscular stimulation devices to achieve intended actions.
- What Was Demonstrated by This Insight: Showed the feasibility and effectiveness of using arm movement trajectory information combined with deep learning to restore functional hand movements in individuals with tetraplegia.

Thank you for listening!

Group 8