Multimodal Framework for Robot-Assisted Gait Rehabilitation: Brainwave Data Collection and Analysis

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1 Introduction

Stroke is a significant cause of mobility impairment, often resulting in long-term disability. Traditional rehabilitation approaches focus on restoring motor function, but advancements in robot-assisted rehabilitation provide new opportunities to enhance movement recovery. This research investigates brain-muscle interactions during robot-assisted walking in healthy individuals, with the long-term goal of applying these insights to improve rehabilitation for stroke patients. The study focuses on collecting and preprocessing electroencephalography (EEG) data for robust analysis of neural activity during walking with and without robotic assistance.

2 Experimental Setup

The setup follows a specific order: EMG sensors are placed first to capture muscle activity, followed by IMU sensors to monitor body movement, and then the EEG cap to track brain activity. The e-Walk exoskeleton is added when needed for specific tasks, allowing for natural movement data collection before introducing robotic assistance (1) [2].

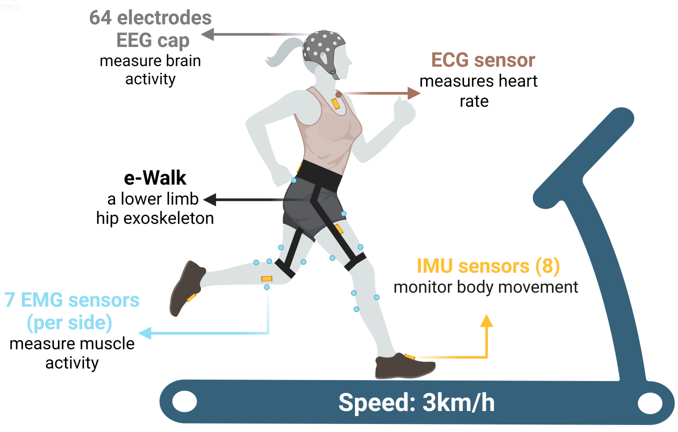


Figure 1: ***Experimental setup for a multimodal investigation of walking in neurologically intact humans.*** *The participant walks on a treadmill while wearing the e-Walk exoskeleton, equipped with wireless and portable sensors.*

- EEG setup.

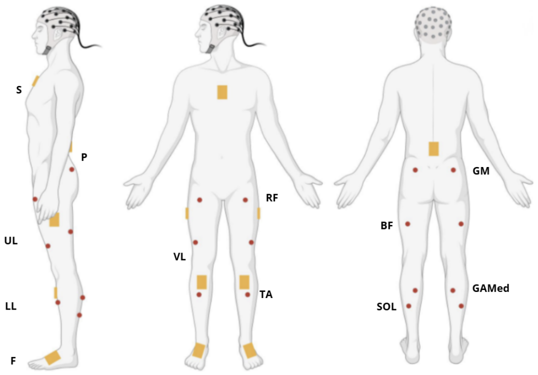
The process begins by cleaning the participant's scalp with alcohol to improve skin-electrode impedance and ensure optimal signal quality. Afterwards, the appropriate cap size (L, M, or S) is selected based on the participant's head circumference, and the cap is carefully placed following the extension of the 10-20 international system for optimal electrode positioning. For this setup, the reference electrode was positioned at CPz, and the ground electrode at Afz. Conductive gel is applied using syringes to ensure good contact between the scalp and electrodes. Finally, the electrodes are connected to the EEG amplifier, which is linked to the recording PC via a cable.

- EMG setup.

EMG sensors measured the electrical activity of muscles, providing insights into muscle during walking. The sensors were placed on key muscle groups such as the gluteus maximus (GM), rectus femoris (RF), biceps femoris (BF), vastus lateralis (VL), tibialis anterior (TA), gastrocnemius medialis (GAMed), and soleus (SOL) (Figure 2). These sensors captured detailed muscle activation patterns, revealing how muscles react and coordinate during both walking without assistance and exoskeleton-assisted walking tasks.

- IMU setup.

IMU sensors track the body's movement by capturing acceleration, orientation, and velocity through a combination of a magnetometer, accelerometer, and gyroscope. These sensors are placed on the pelvis (P), sternum (S), upper (UL) and lower legs (LL), and feet(F) to monitor gait dynamics (Figure 2). After placing the sensors, a calibration process is performed to correct for errors and biases, ensuring accurate data collection.



Sensor Type	Brand	Sampling frequency
EEG	ANT Neuro	1 kHz
EMG	Noraxon	2 kHz
IMU	Xsens (MTw Awinda)	100 Hz

Figure 2: ***Sensor Placement and Specifications.*** *On the left, the placement of EEG, EMG, and IMU sensors on the participant's body is displayed. On the right, the table provides the sensors' specifications. The order of frequencies reflects the different bandwidths of the signals each device measures: EMG captures fast muscle activity, EEG records brain signals, and IMU measures slower body movements.*

3 Experimental Protocol

The experiment involved five young adults performing the following tasks :

1. **Resting State Standing**
   Participants stand still with their eyes open and closed for 2 minutes each, both at the beginning of the experiment and after completing all walking tasks. This allows for the collection of baseline EEG and EMG data before movement and comparison of neural activity.

2. **Walking without the Exoskeleton**
   Participants walk for 6 minutes without robotic assistance. This serves as the control condition, allowing comparison between assisted and unassisted walking.

3. **Exoskeleton Familiarization and Walking Conditions**

Figure 3: ***Front and side view of the exoskeleton***

Participants are familiarized with the exoskeleton (Figure 3) for 9 minutes before walking under three randomized conditions to ensure unbiased and reliable results. This helps prevent order effects, such as task fatigue or learning patterns, ensuring each task's results remained independent of the others. The walking conditions include:

- Transparent mode: Walking without assistance for 6 minutes.
- Low robotic assistance: Walking with 80 % exoskeleton support for 6 minutes.
- High robotic assistance: Walking with 100 % exoskeleton support for 6 minutes.

Data is collected using all sensor types during each task.

4 Data Collection and Preprocessing Pipeline

After conducting the experiments, the collected EEG data was preprocessed using MATLAB and EEGlab to ensure high-quality signals for analysis.

4.1 MATLAB Preprocessing Steps

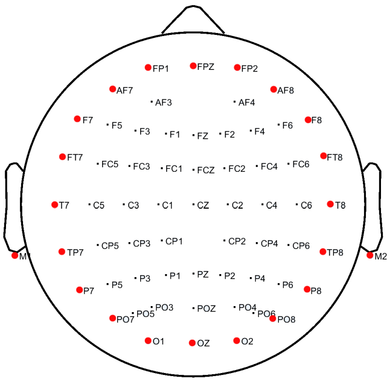
1. **Band-pass and Notch Filtering**
   A 1-60 Hz band-pass filter with a 6th-order Butterworth filter was applied to remove noise outside the range of interest. Additionally, a 50 Hz notch filter eliminated power line noise.

2. **Removal of the EOG Channel**
   The EOG channel, used to detect eye movements, is part of the standard montage but was not acquired during the experiment. Since the electrode for EOG is typically placed on the face near the eyes, it was removed due to the specific setup constraints.

4.2 EEGlab Preprocessing Steps

The pre-processing pipeline was developed in EEGlab, a widely used toolbox for EEG data analysis [1]. Below are the detailed steps followed in the pipeline:

1. **Remove Noisy Data**



Outer circumference electrodes were excluded a priori, as these channels tend to capture more muscular artifacts. Additionally, bad portions of data from the 41 remaining channels, particularly at the beginning and end of the recordings, were removed to ensure cleaner and more reliable brain signals for analysis.

2. **Perform Independent Component Analysis (ICA)**

Independent Component Analysis (ICA) is a computational method used to decompose EEG signals into independent components (Figure 4). In this study, ICA was applied specifically to isolate and remove ocular artifacts, such as eye movements and blinks, which can interfere with the analysis of neural signals. By separating these non-neural components from the brain activity, ICA improved the clarity of the EEG data, ensuring a cleaner representation of neural signals during the walking tasks.

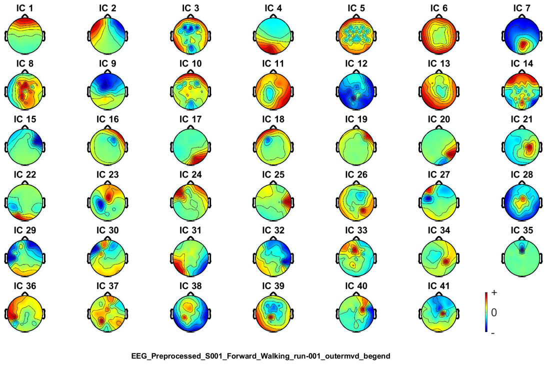


Figure 4: ***Scalp Topographies.*** *The figure shows scalp topographies for the 41 ICs resulting from the application of ICA on the EEG data. IC1 corresponds to the eye blink while IC2 represents lateral eye movement.*

3. **Fix Bad Channels**

Noisy or malfunctioning EEG channels were identified using statistical methods such as Kurtosis, which helps detect irregularities in the signal by identifying outliers. Rather than removing these channels, they were interpolated using spherical

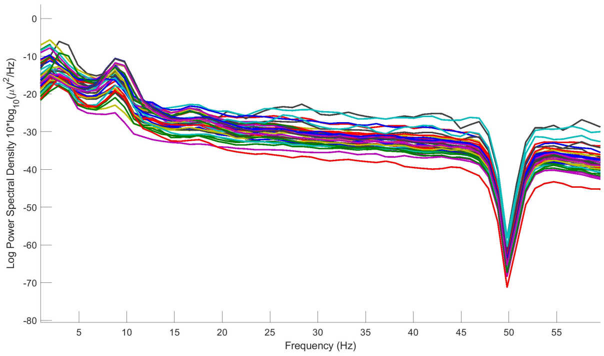


Figure 5: *Power Spectral Density (PSD) of EEG data showing the typical log-linear decrease in power with frequency. The noticeable drop at 50 Hz confirms the effect of the previously applied notch filter to eliminate power line interference.*

interpolation with data from neighboring channels to preserve the integrity of the dataset. This approach ensures that potentially relevant data is not lost, while also preventing the noise from these bad channels from affecting the overall analysis. By filling gaps with interpolated values, we maintained a complete and consistent dataset for further processing.

4. **Re-reference to Common Average Reference (CAR)**

$$V_i^{CAR}(t) = V_i(t) - \frac{1}{41}\sum_{j=1}^{41} V_j(t) \tag{1}$$

The EEG signals were re-referenced using the Common Average Reference (CAR) technique (1). This method subtracts the average signal from all channels to reduce noise common across channels, such as electrical interference, while preserving unique brain activity. This improves the clarity and quality of the EEG data for further analysis.

5 Results

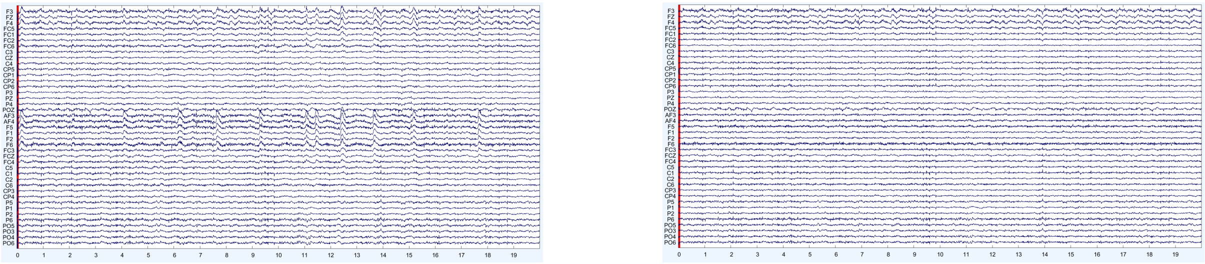


Figure 6: ***EEG signals across 41 channels, before (left) and after (right) preprocessing.*** *The left plot shows raw EEG data with visible spikes from eye blinks, particularly in the frontal channels (e.g. F6, AF3, AF4), along with high-frequency noise. The right plot shows cleaner data after preprocessing, with reduced artifacts and noise.*

The preprocessing pipeline was applied to EEG data collected from five participants, with two datasets processed by myself and three by my teammate, a master's student. This pipeline was used for the walking task without exoskeleton assistance and the three tasks with the exoskeleton. The results shown here correspond to my recording during the Transparent mode condition, demonstrating the reduction in noise and artifacts after preprocessing (Figure 6).

6 Conclusion

This research provides valuable insights for future studies on brain-muscle coordination during robot-assisted rehabilitation. The preprocessing pipeline developed in this study ensures clean, analyzable data, which will be crucial for understanding the neural mechanisms underlying assisted walking. Further steps will involve segmenting the EEG data by gait cycles and rejecting artifacts using a threshold-based approach. Event-Related Spectral Perturbation (ERSP) will also be analyzed to understand how neural activity changes with varying levels of robotic assistance [3]. Ultimately, this research could inform rehabilitation strategies for stroke patients, helping to enhance motor recovery through robotic assistance.

7 Acknowledgments

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8 References

9 References

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