From Sound to Sensation: Machine Learning Unravels the Influence of Auditory Cues on Body Representation

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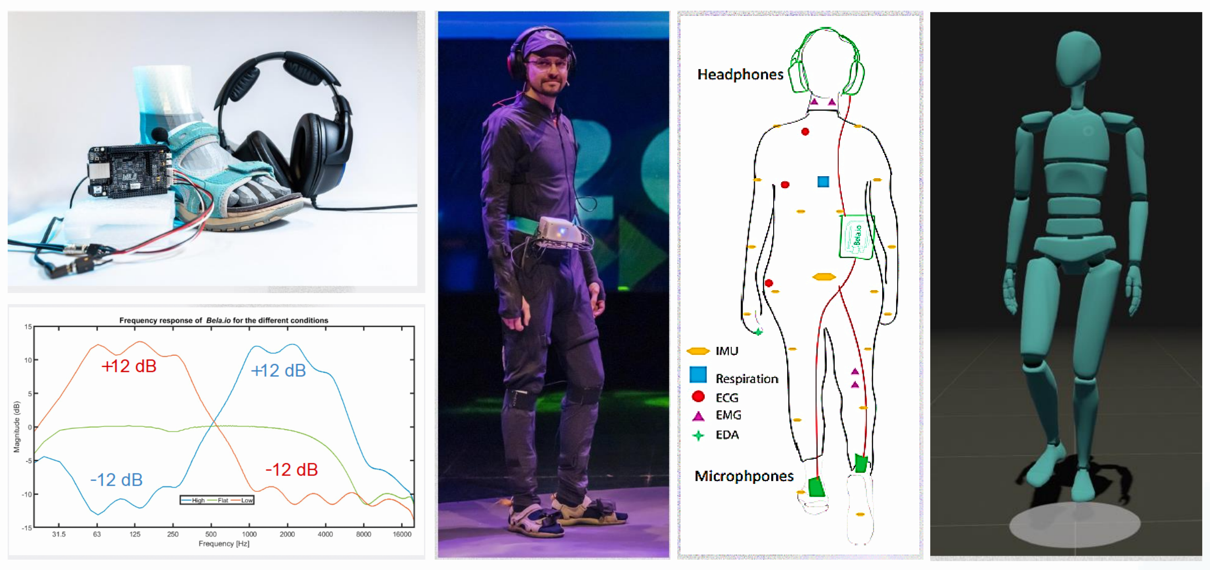


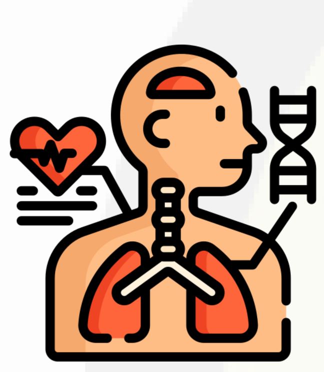
INTRODUCTION

- **Objective:** Explore the impact of auditory illusions combined with multisensory and sensorimotor cues, on perceptions of body weight [1, 2].
- **Participants:** 104 individuals wearing motion capture suits and wearable sensors.
- **Methodology Highlights:**
  - Walking trials with auditory feedback.
  - Use of low and high-pass filters to modulate footstep sounds.
- **Measurements:** Various scales and tasks to assess body perception.
- **Analysis:** Utilization of Machine Learning algorithms for data interpretation.

[1] Tajadura-Jiménez, A., et al. (2015). *As light as your footsteps: altering walking sounds to change perceived body weight, emotional state and gait.* In CHI'15, 2943-2952
[2] Tajadura-Jiménez, A., et al. (2019). *As light as you aspire to be: Changing body perception with sound to support physical activity.* In CHI'19, pp. 1-14

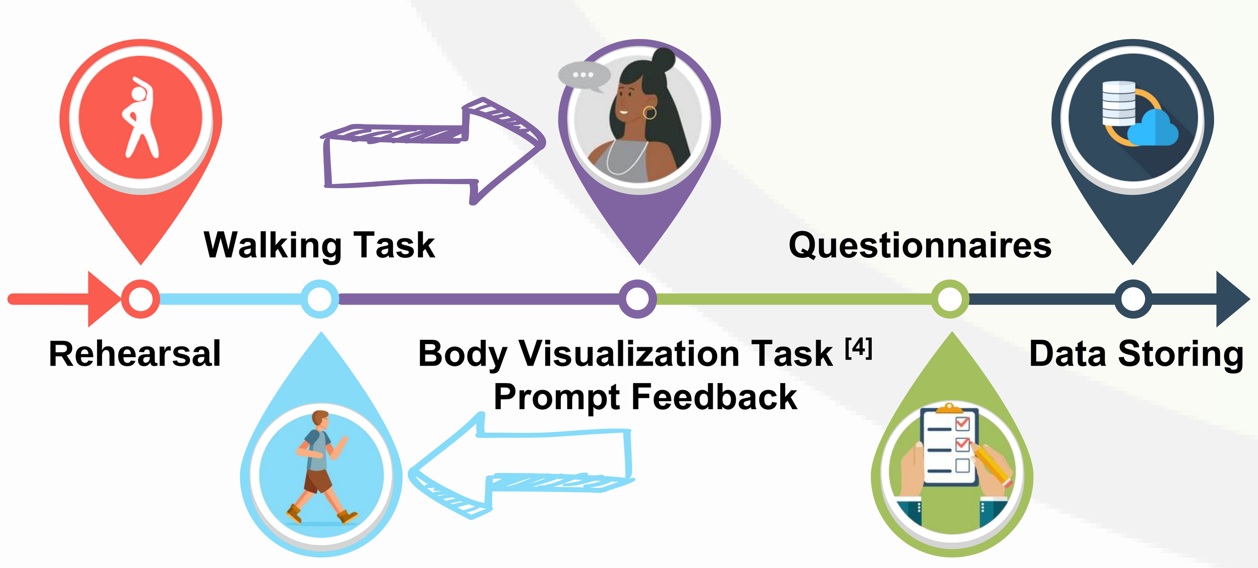
DATA COLLECTION

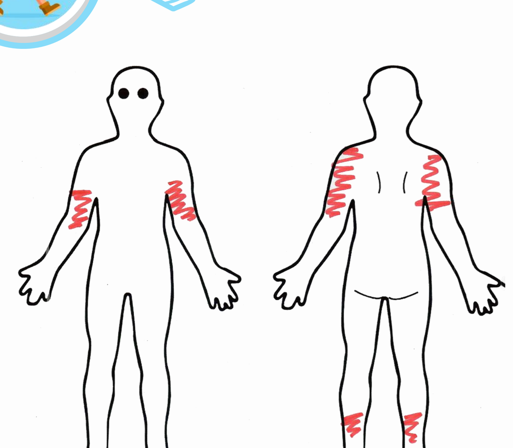
- **Walking Trials:** 10-meter trail, with 6 repetitions



EMG
ECG
IMU
Respiration
Accelerometer
EDA

- **Auditory Feedback[1]:**
  - Footstep sounds via headphones
  - Low and high-pass filters
- **Measurements:**
  - Perceived body weight (1 = Light, 7 = Heavy)
  - Avatar Task and Body Maps [3]



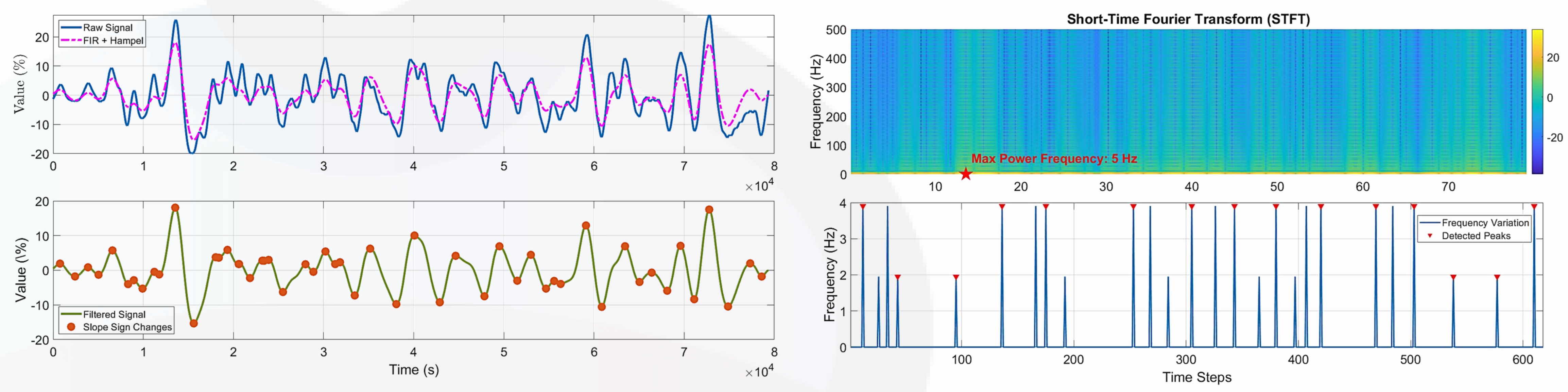


[3] Turmo Vidal, L., et al. (2023). *Towards Advancing Body Maps as Research Tool for Interaction Design.* In TEI'23, 1-14
[4] Available online: https://bodyvisualizer.com/

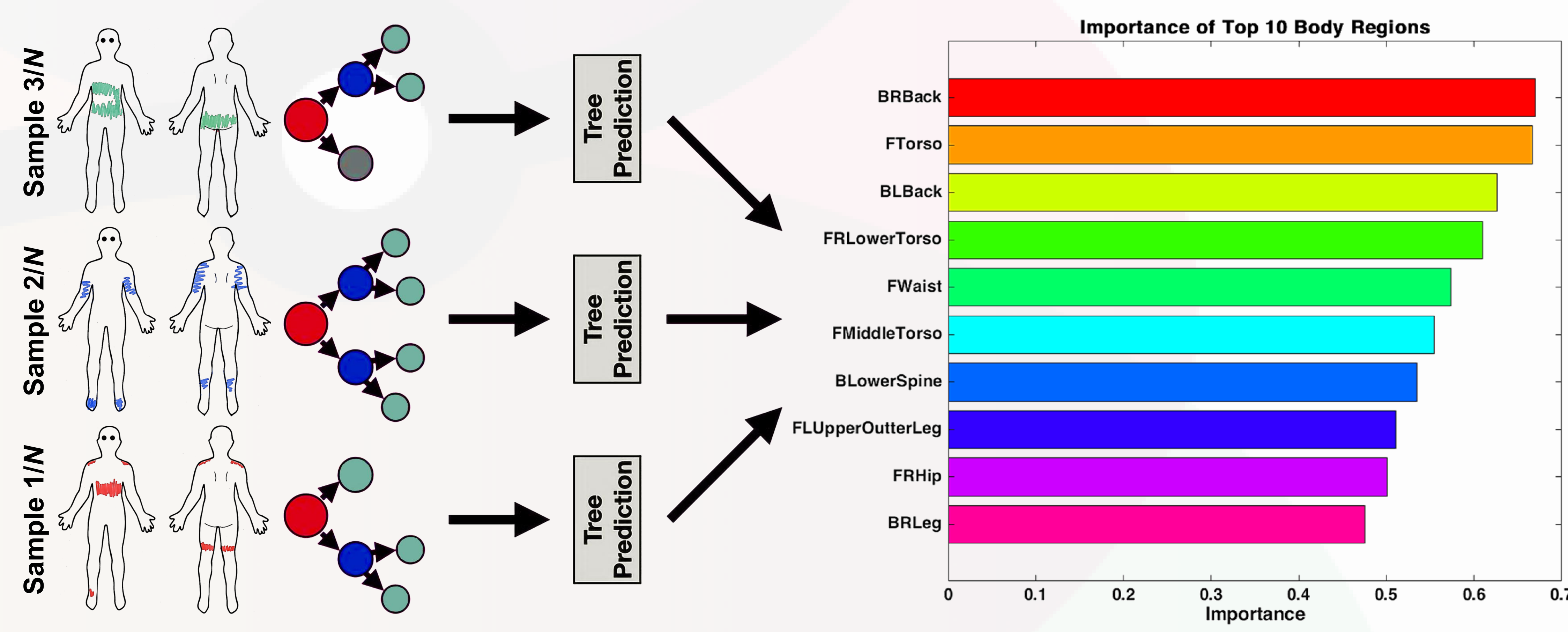
1. **High Frequency:** Amplified higher bands (1–4 kHz) by 12 dB, attenuated lower bands (83–250 Hz) by 12 dB.
2. **Low Frequency:** Amplified lower bands (83–250 Hz) by 12 dB, attenuated higher bands (1–4 kHz) by 12 dB.
3. **Control:** No frequency adjustments.

DATA ANALYSIS

1. **Noise Removal:** (1) FIR filters for noise removal, (2) Hampel filter for outlier identification.
2. **Feature Extraction:** (1) Time domain, (2) Frequency domain, (3) Time-Frequency domain

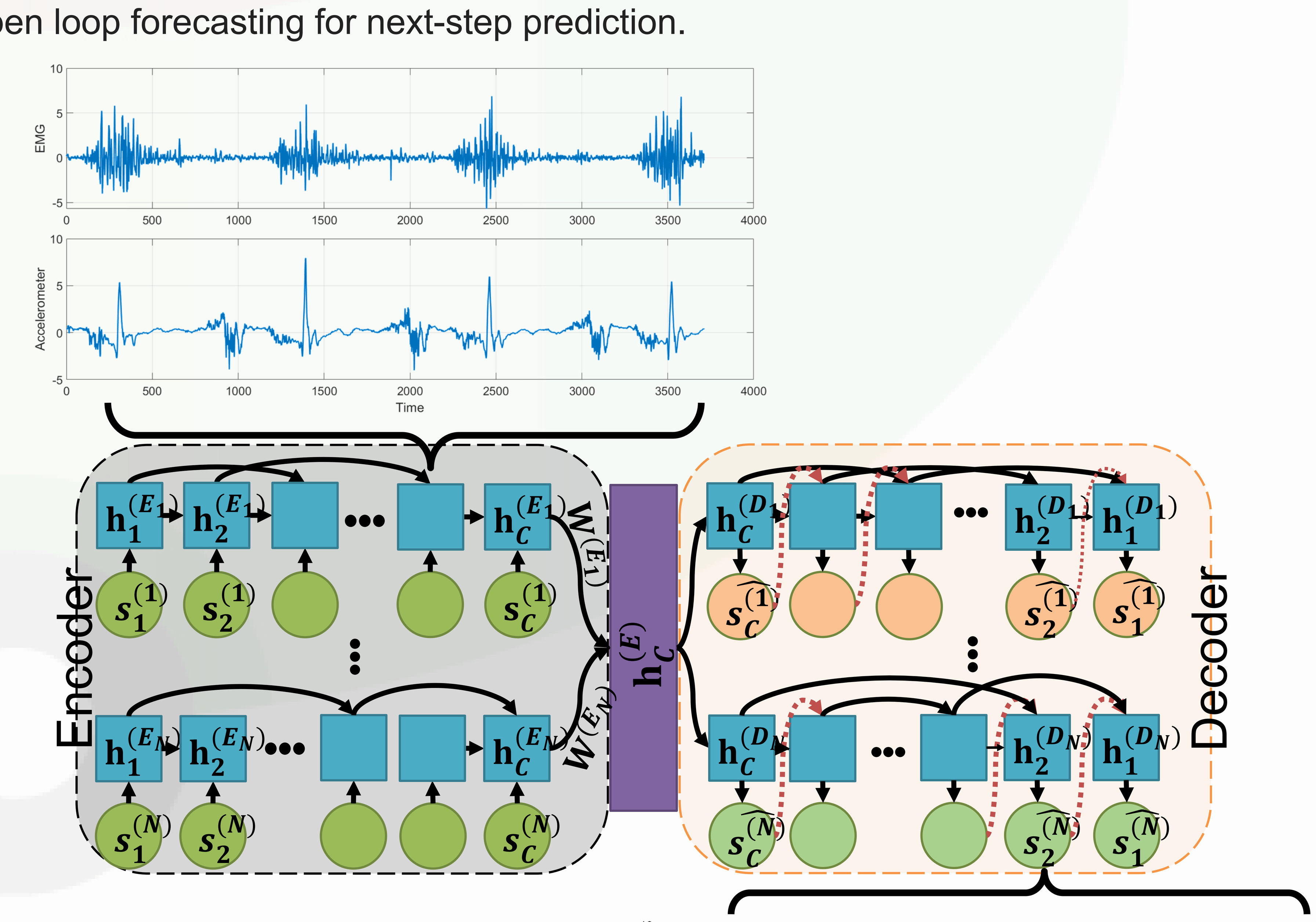


3. **Body Map (BM) Transformation:** Each **BM** partitioned into 136 regions and transformed into a matrix.
4. **Ensemble Decision Trees:** This ML method was trained on all BMs (N = 104 × 6) to Identify the 10 most important regions across all auditory conditions.

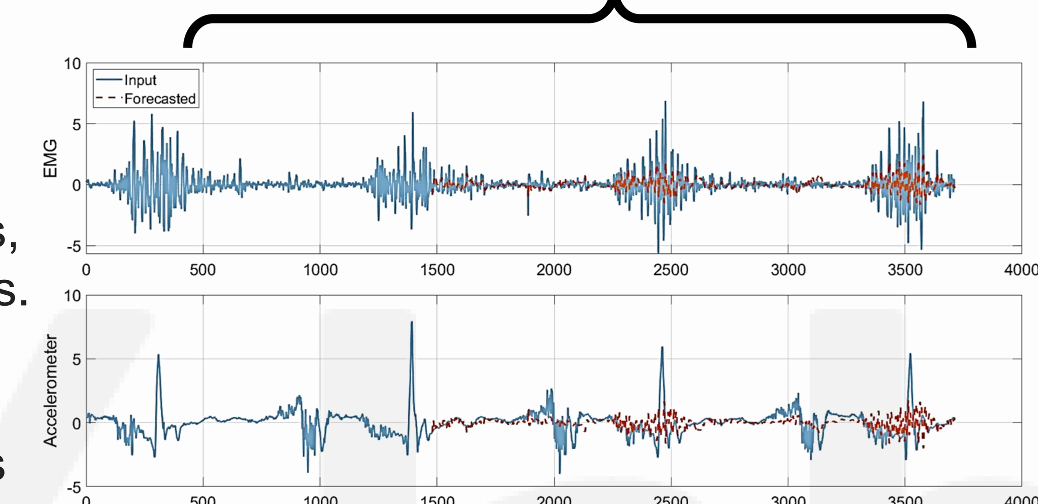


REAL-TIME PREDICTION WITH DEEP AUTOENCODERS

- **Objective:** Real-time prediction of perceived weights using deep autoencoders and bidirectional GRUs.
- **Method:** Simultaneous processing of six signals for comprehensive data analysis.
- **Unique Feature:** Open loop forecasting for next-step prediction.



- **Primarily Findings & Significance:**
  1) Advanced feature extraction techniques (e.g., STFT) analysis provide deep insights into physiological signals, enabling better ML models to make accurate predictions.
  2) The deep learning approach excels in forecasting physiological signals, paving the way for real-time body representation analysis and innovative health strategies for people with body representation disorders.



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