GAIT PATTERN ANALYSIS USING EMG via MACHINE LEARNING FOR OPTIMIZING LOWER LIMB EXOSKELETON USAGE

SUBMITTED AS PART OF FINAL PROJECT
ME 6250 : WEARABLE ROBOTICS
NORTHEASTERN UNIVERSITY BOSTON

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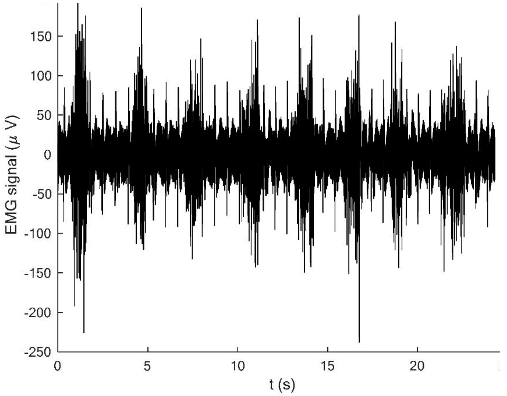


Introduction and Motivation

Exoskeleton Devices : Enhanced Mobility, Clinical Rehabilitation, Musculoskeletal Training
EMG : Physiological signals signifying muscle activation of the muscles.

Abstract : Make **machine learning models** understand the distinct and underlying **features of sEMG** signals from lower limb muscles, in **time and frequency domain**, further use **binary classification models** to assess if the gait is normal or abnormal, to estimate the need for **exoskeleton assistance**.

MOTIVATION : Understanding muscle synergy and **narrowing down recovery time for lower limb rehabilitation** using exoskeletons, by **targeted assistance to muscles** associated with knee mechanics.

Previous studies have shown that integrating **EMG** into **exoskeleton-based rehabilitation** improves recovery efficiency, particularly in conditions like:

- **Post-surgical rehabilitation** (e.g., ACL repair): Targeting knee extensors like RF and VM.
- **Neurological impairments** (e.g., stroke, spinal cord injury): Restoring coordination between knee flexors and extensors (BF/ST vs. RF/VM).
- **Age-related muscle decline**: Enhancing muscle reactivation to prevent atrophy.

Hypothesis

Learning patterns of muscle activation (via **EMG**) using **ML** and providing closed-loop **exoskeleton** assistance could be beneficial in :

- Encouraging volitional control
- Fall prevention
- Track progress of recovery post therapy during rehab.
- Providing flexibility for diverse conditions

Phantom Neuro Gets $6M to Help Amputees Control Robotic Limbs

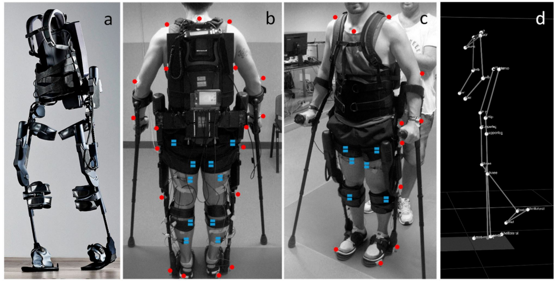
The startup is developing an implantable sensor that translates the body's electrical signals into intended movements.

https://phantomneuro.com/

Related Prior Work

Exoskeleton for Gait Rehabilitation: Effects of Assistance, Mechanical Structure, and Walking Aids on Muscle Activations

Highlight : Proved distinct muscle activation patterns between exo-assisted and unassisted walking modes.
Limitations : Temporal Analysis of Walking, missing dynamic transitions which are ADLs, no ML/AI used.



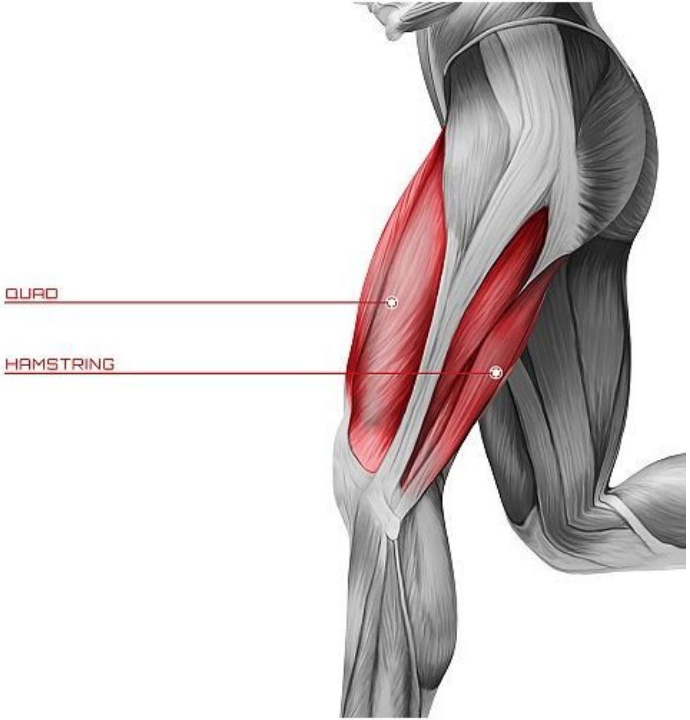
Excerpts from the above paper

When comparing the different assistance modalities (Figure 5), we found that the temporal patterns of activations did not change with the different assistive modalities, i.e., for all the muscles, the shape of the envelopes were highly similar; however, significant differences were observed in terms of level of muscle activations.

Specifically, small or negligible differences were found for the distal lower limb muscles (TA, GM, SOL), while higher and significant differences were found in the other muscles (GLM, BF, ST, RF, VM).

https://eksobionics.com/

Overview of Lower Limb Muscles Chosen in this project



Biceps Femoris (BF)
Core Functionality : A part of the hamstrings, assists in hip extension and knee flexion.
Targeted Support : Knee flexion in activities like climbing or walking uphill.

Semitendinosus (ST)
Core Functionality : Part of the hamstrings, this muscle assists in knee flexion, hip extension, and medial rotation of the thigh.
Targeted Support : Medial stabilization in the exoskeleton design ensures natural gait movement patterns.

Rectus Femoris (RF)
Core Functionality : A part of the quadriceps, assists in knee extension and hip flexion.
Targeted Support : Standing up from a seated position.

Vastus Medialis (VM)
Core Functionality : Another quadriceps muscle crucial for knee extension.
Targeted Support : Knee joint alignment during dynamic movements.

Overview of EMG Dataset

Aim : To collect EMG data of ADLs, eg. gait, sitting and standing for mapping EMG

Device Used : MWX8 by Biometrics
Type of EMG : Surface (Raw)
No. of Channels : 4 [BF, RF, VM, ST]
Sampling Frequency : 1kHz
Additional Data : Knee Goniometer (1) (Not used in project)

Test Subjects :
22 male subjects, 11 with different knee abnormalities previously diagnosed by a professional.

Data used in the project : Raw EMG signals of Gait

Sanchez, O. & Sotelo, J. (2014). EMG dataset in Lower Limb [Dataset]. UCI Machine Learning Repository. https://doi.org/10.24432/C5ZW3P.

Proposed Methodology - Muscle Wise Approach

EMG Signal Collection + Pre Processing → Feature Extraction Time, Frequency, TFD → Binary Classification Feature based ML Based

Signal Pre Processing :
Normalization - MVC
Filtering - Band Pass Filter and Notch Filter
Rectification - For Envelope Extraction
Smoothing - To create an Envelope

Feature Extraction : Sliding Window Approach
Time Domain : 11
Frequency Domain : 6
Time-Frequency Domain (Discrete Wavelet Transform) : 3

Binary Classification : KNN, DT, RF, SVM

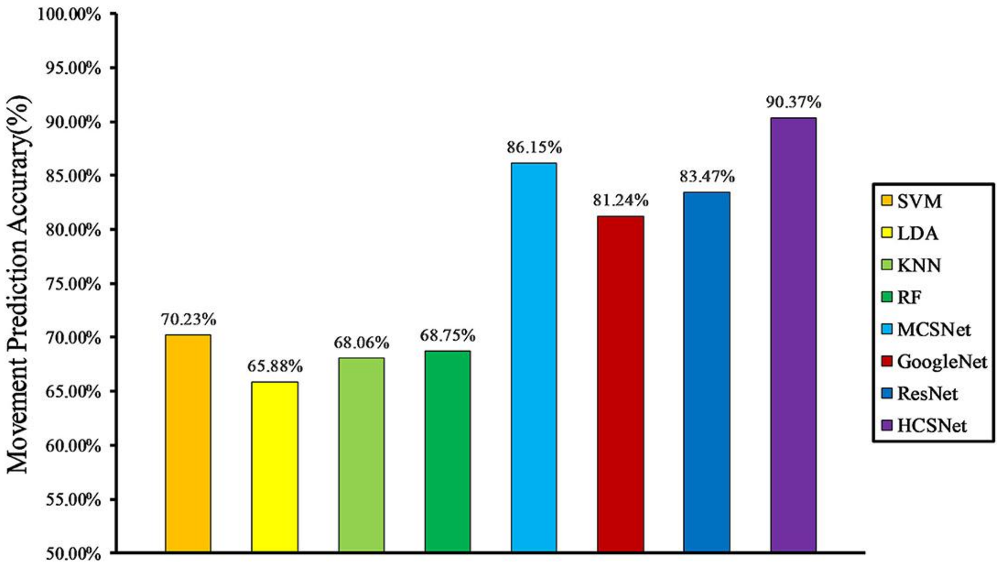
Tools used in the project

Signal Conversion (Python)

Analysis (MATLAB)

Signal Visualization (Audacity)

Comparable Results - Prior Work



Highlight : Uses hand-crafted features extracted from EMG signals for lower limb movement prediction
Limitations : Not suitable for real time assistance since it uses CNN (computational complexity)

Excerpts from the paper

An sEMG-Based Human-Exoskeleton Interface Fusing Convolutional Neural Networks With Hand-Crafted Features

Results -

"It can be seen that the hand-crafted features-based lower-limb movement prediction models have poor performance in the cross-subject situation, with an **average accuracy rate of about 70%.**"

Data Split -

"For within-subject, we divide the data of the same subject according to a ratio of 7:3 and then use **70% of the data to train the model** for that subject. **Four-fold cross-validation** is used to avoid the phenomenon of model overfitting."

Note : The muscles used in this study are rectus femoris, vastus lateralis, tibialis anterior, biceps femoris, and lateral gastrocnemius

```
train_ratio = 0.727;
k_folds = 4;
knn_neighbors = 5;
svm_kernel = 'linear';
svm_box_constraint = 1;
svm_gamma = 1;
rf_num_trees = 100;
rf_min_leaf_size = 1;
dt_max_splits = 20;
```

Best Results - Project

Classifier	Feature Type	Mean Accuracy
KNN	TD	62.5
KNN	FD	75
KNN	Wavelet	62.5
SVM	TD	93.75
SVM	FD	68.75
SVM	Wavelet	75
Random Forest	TD	81.25
Random Forest	FD	56.25
Random Forest	Wavelet	62.5
Decision Tree	TD	62.5
Decision Tree	FD	43.75
Decision Tree	Wavelet	75

Biceps Femoris

Classifier	Feature Type	Mean Accuracy
KNN	TD	68.75
KNN	FD	56.25
KNN	Wavelet	56.25
SVM	TD	62.5
SVM	FD	56.25
SVM	Wavelet	56.25
Random Forest	TD	56.25
Random Forest	FD	68.75
Random Forest	Wavelet	62.5
Decision Tree	TD	43.75
Decision Tree	FD	62.5
Decision Tree	Wavelet	50

Semitendinosus

Classifier	Feature Type	Mean Accuracy
KNN	TD	68.75
KNN	FD	62.5
KNN	Wavelet	56.25
SVM	TD	62.5
SVM	FD	68.75
SVM	Wavelet	56.25
Random Forest	TD	81.25
Random Forest	FD	75
Random Forest	Wavelet	50
Decision Tree	TD	68.75
Decision Tree	FD	87.5
Decision Tree	Wavelet	56.25

Rectus Femoris

Classifier	Feature Type	Mean Accuracy
KNN	TD	75
KNN	FD	56.25
KNN	Wavelet	68.75
SVM	TD	75
SVM	FD	75
SVM	Wavelet	81.25
Random Forest	TD	75
Random Forest	FD	56.25
Random Forest	Wavelet	68.75
Decision Tree	TD	75
Decision Tree	FD	62.5
Decision Tree	Wavelet	75

Vastus Medialis

Best Results - Project

Biceps Femoris

Classifier	Feature Type	Mean Accuracy	Mean Precision	Mean Recall	Mean F1
KNN	TD	62.5	62.5	62.5	62.5
KNN	FD	75	79.1666666666667	75	76.9736842105263
KNN	Wavelet	62.5	66.6666666666667	62.5	64.4736842105263
SVM	TD	93.75	95.8333333333333	93.75	94.7368421052632
SVM	FD	68.75	75	68.75	71.7105263157895
SVM	Wavelet	75	79.1666666666667	75	76.9736842105263
Random Forest	TD	81.25	87.5	81.25	84.2105263157895
Random Forest	FD	56.25	54.1666666666667	56.25	55
Random Forest	Wavelet	62.5	66.6666666666667	62.5	64.4736842105263
Decision Tree	TD	62.5	66.6666666666667	62.5	64.4736842105263
Decision Tree	FD	43.75	41.6666666666667	43.75	42.5
Decision Tree	Wavelet	75	79.1666666666667	75	76.9736842105263

Overall Feature Type Performance:

- TD features generally outperform FD and Wavelet features.
- Random Forest and SVM are more consistent across metrics.

Overall Classifier Performance:

- SVM and Random Forest tend to achieve the highest scores, especially when paired with TD features.

Future Scope of Work

- Explore light weight deep learning models for real time adaptive systems
- Gait Phase Estimation by learning movement patterns, with additional sensors (IMU/Goniometer/Pressure Sensors)
- Explore time-frequency representations to capture subtle variations in gait patterns through wavelet analysis and entropy measures
- Extension of research to multiple muscles

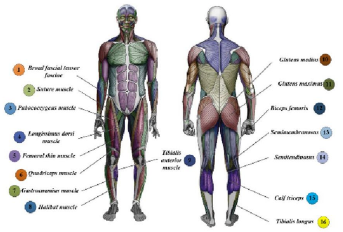
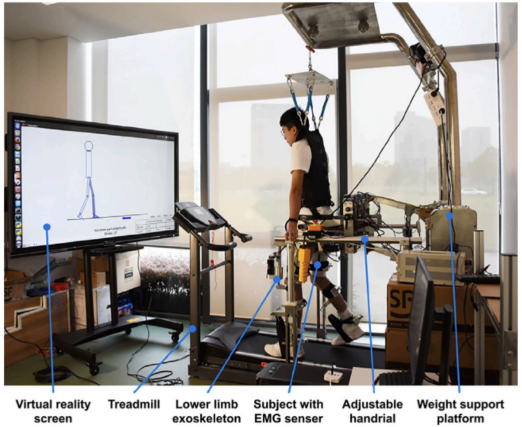


Fig. 1 Location of sensor attachment

Ref



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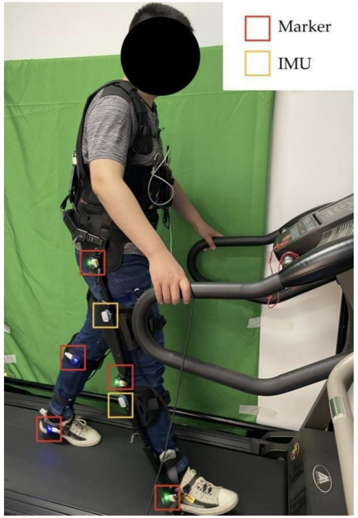

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Thank You !