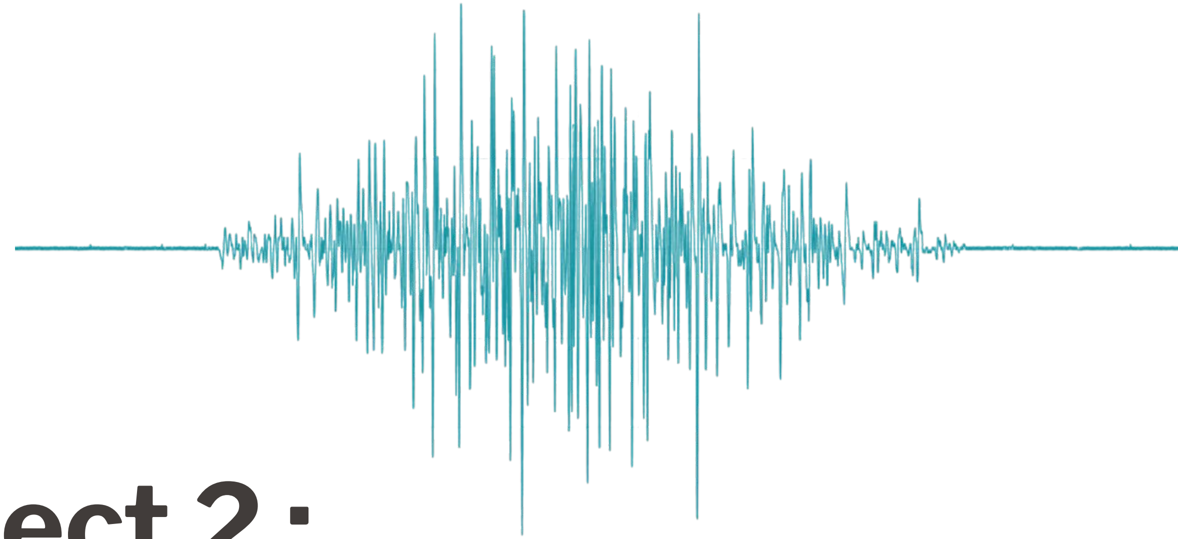
EPFL



Mini-Project 2 : EMG Signal Analysis

NX-421- Neural Signals and Signal Processing
Profs. Van de Ville, Micera

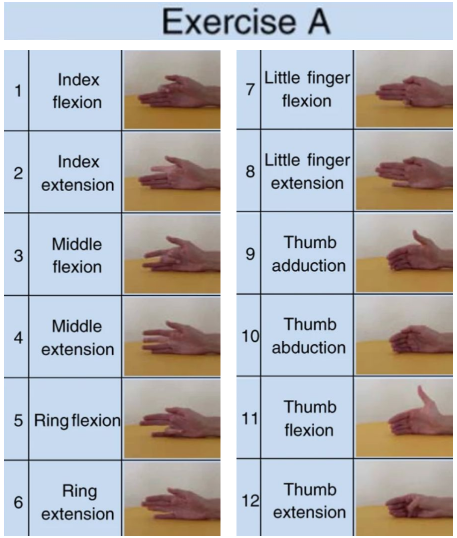
Group P:
Khushi Singh
Heliya Shakeri
Angana Mondal
Pamela Van Den Enden Uribe
Arnault Dominic Philippe Stähli

MOTIVATION

To build a movement intention decoder using sEMG and glove EMG data for prosthetics and assistive devices

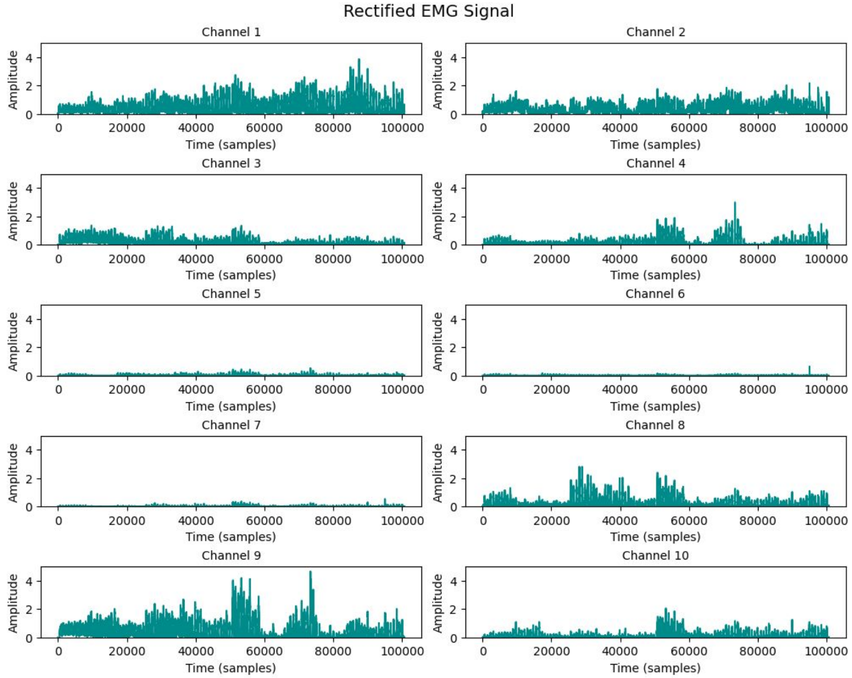
PART 1

SINGLE SUBJECT CLASSIFICATION



NinaPro Dataset 1 - Subject 2

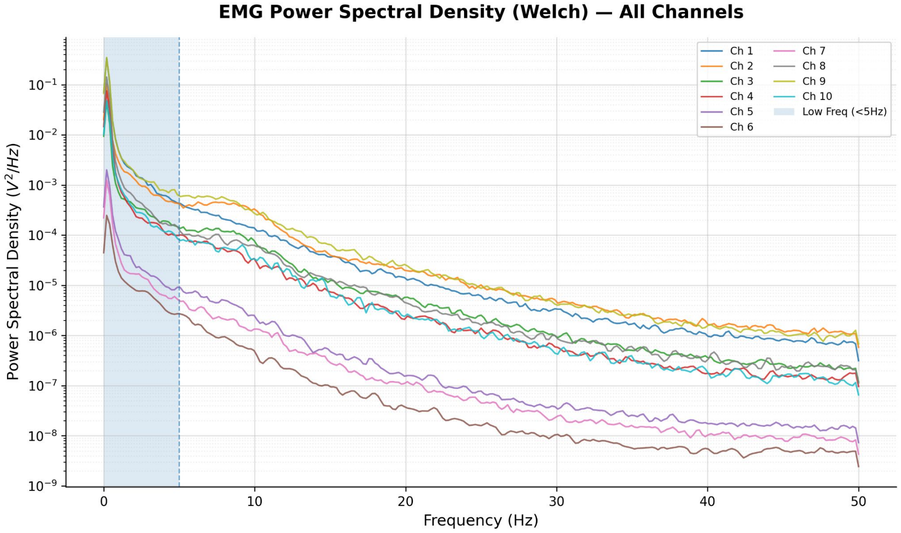
Amplitude vs Time



We observe that all signals are positive.

- Data appears to already be **rectified**.

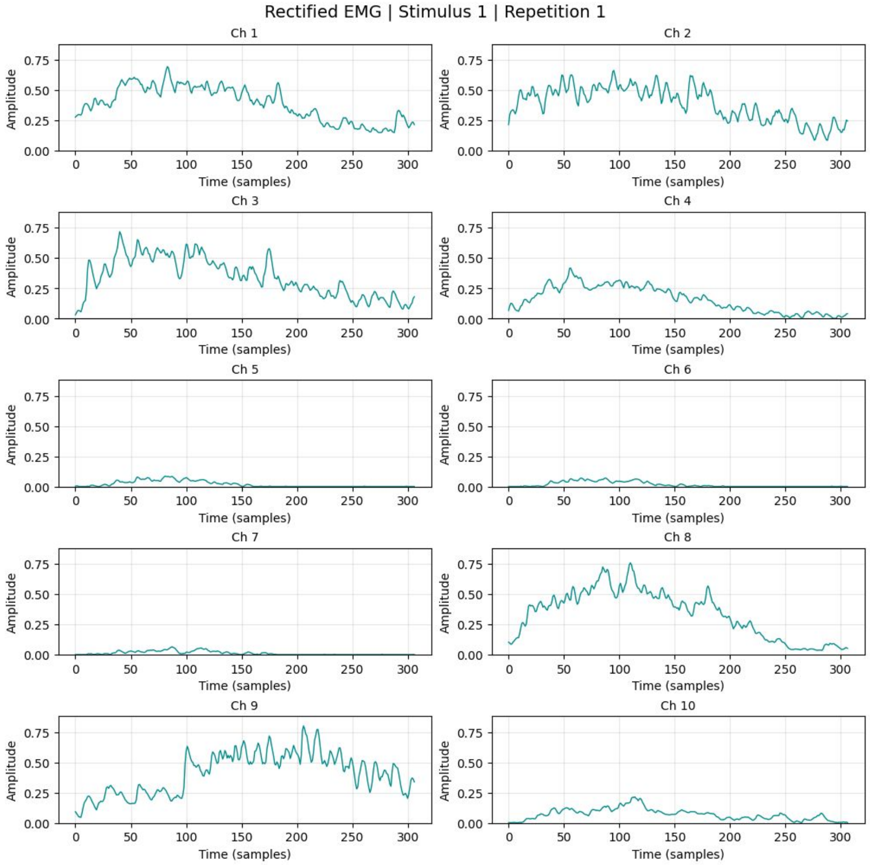
PSD vs Frequency



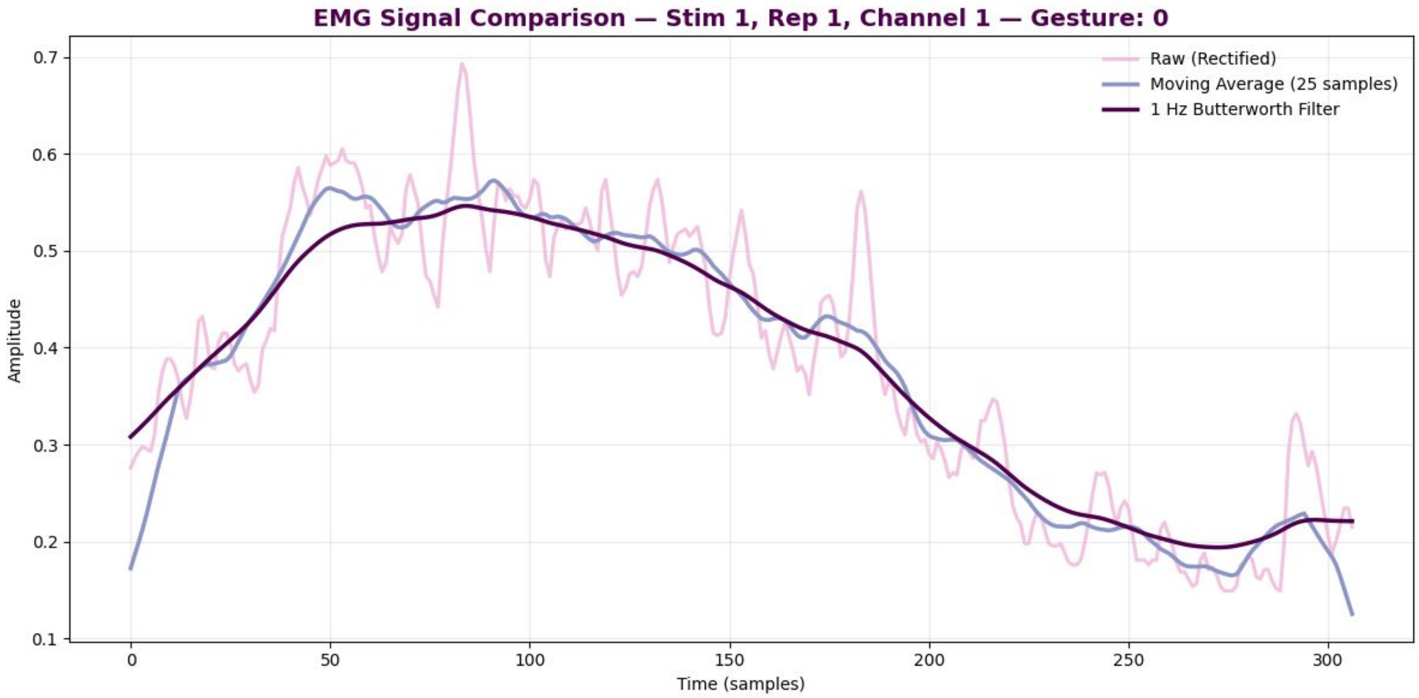
We do not observe any peaks. Data is clipped at 50Hz - line noise frequency.

Data appears to already be **filtered**.

Visualising Data per Channel per Trial



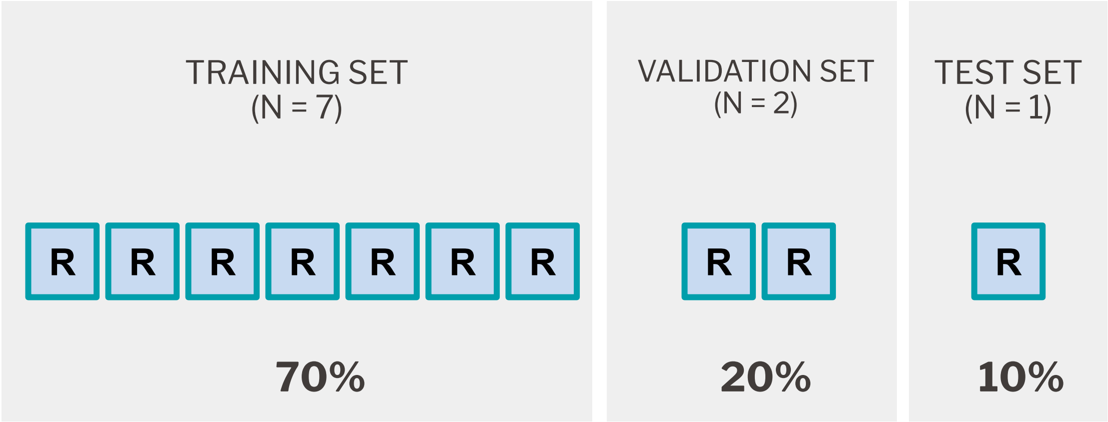
No trials dropped!



Tried different preprocessing methods based on literature and the labs.
Stuck with Raw, rectified data to avoid overly smoothing data.

Splitting the Data

For each of the 12 movements:



Splitting to ensure all 12 classes are **balanced** across the training, validation and testing dataset.

Feature Selection

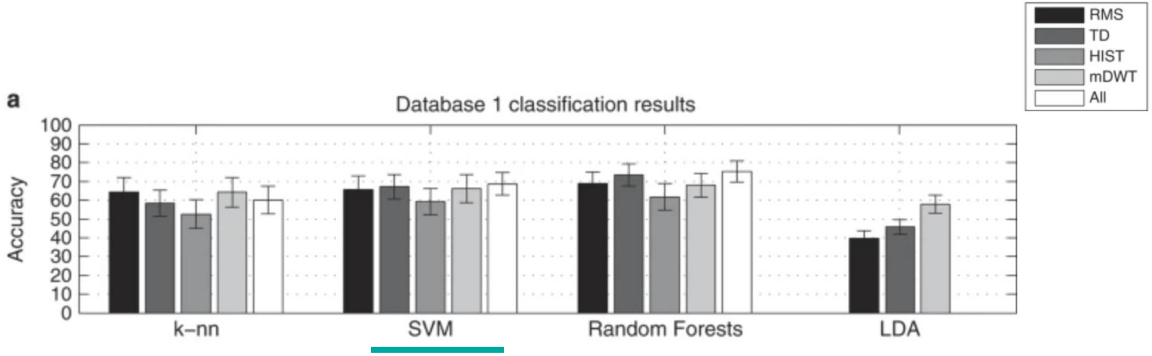
SOURCES ATZORI ET AL. (2014) + HUDGINS ET AL. (2002)

TIME DOMAIN

ROOT MEAN SQUARE (RMS)
MEAN ABSOLUTE VALUE (MAV)
WAVEFORM LENGTH (WL)
SLOPE SIGN CHANGE (SSC)
HISTOGRAM (HIST LOG ENTROPY)

FREQUENCY DOMAIN

MARGINAL DISCRETE WAVELET TRANSFORM



COMPLEMENT WITH *NEW* FEATURES

SOURCE LECTURES + LABS

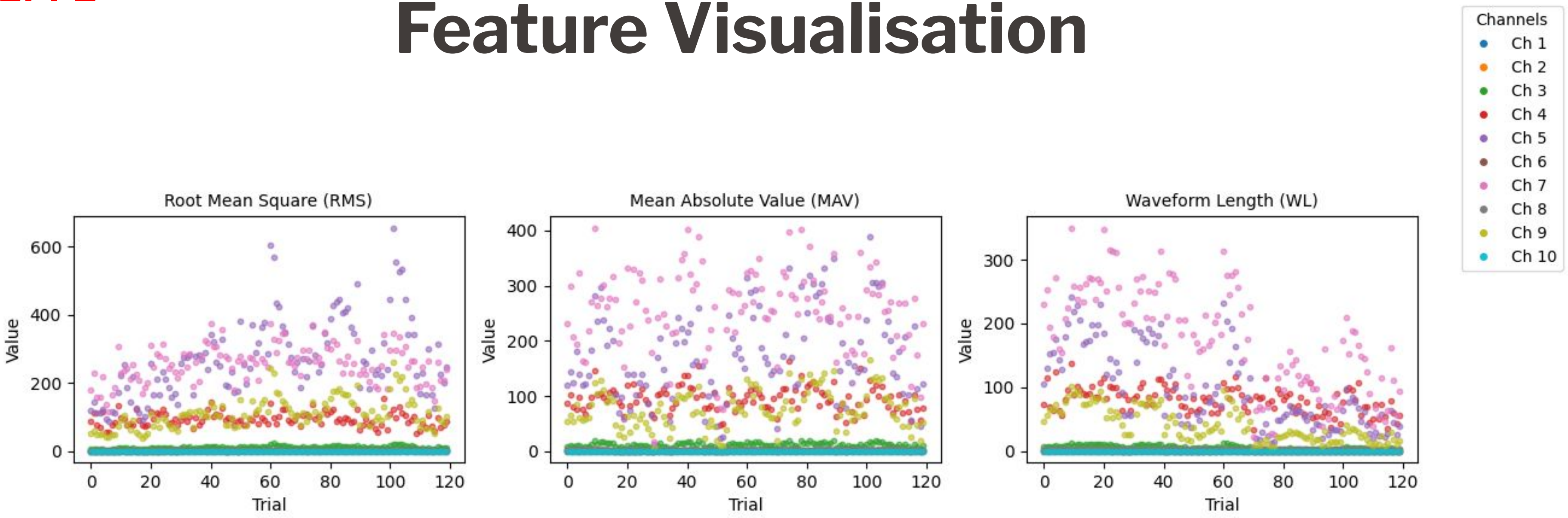
TIME DOMAIN

INTEGRATED EMG (IEMG)
VARIANCE (VAR)
WILLISON AMPLITUDE (WAMP)

FREQUENCY DOMAIN

POWER SPECTRAL DENSITY (PSD)

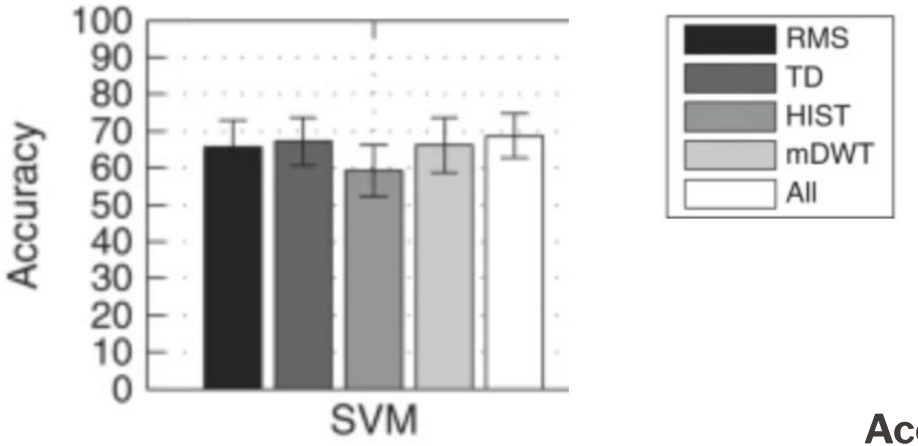
Feature Visualisation



Feature values differ between channels but remain relatively consistent within each channel for repeated executions of the same movement

Support Vector Machine Performance

Features	Best Model	Val accuracy	Test accuracy
All	RBF / C=1	0.96	0.84



Atzori et al. 2014
Best Accuracy: ~70%
Accuracy depends on feature set used

Dimensionality Reduction

Features	Best Model	Val accuracy	Test accuracy
All	RBF / C=1	0.96	0.84

Recursive Feature Elimination (RFE)

Principal Component Analysis (PCA)

Mutual Information

Dimensionality Reduction

Features	Best Model	Val accuracy	Test accuracy
All	RBF / C=1	0.96	0.84
RFE top 15	RBF / C=1	0.88	1
PCA 10 components	RBF / C=10	0.92	0.92
Mutual Info top 25	Linear / C=10	0.88	0.75

Recursive Feature Elimination (RFE)

Principal Component Analysis (PCA)

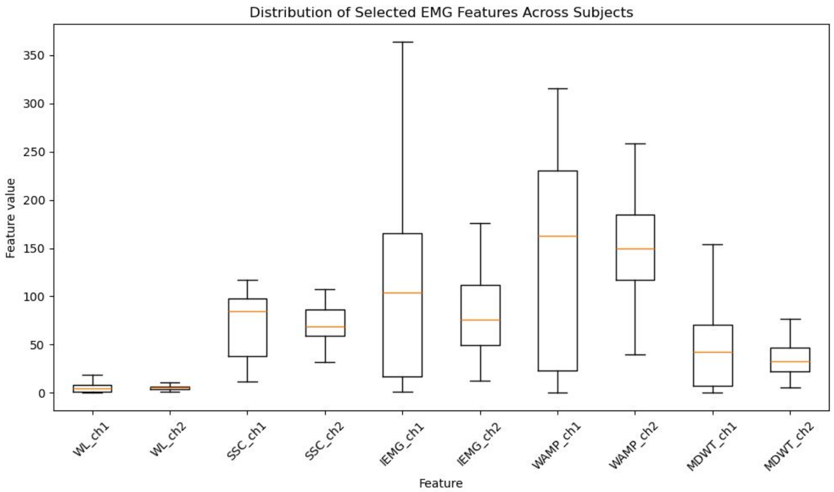
Mutual Information

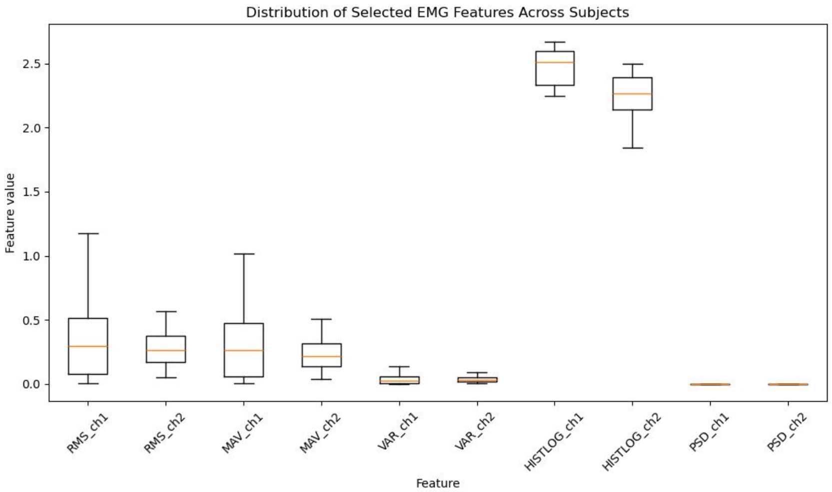
PART 2

GENERALISATION ACROSS SUBJECTS

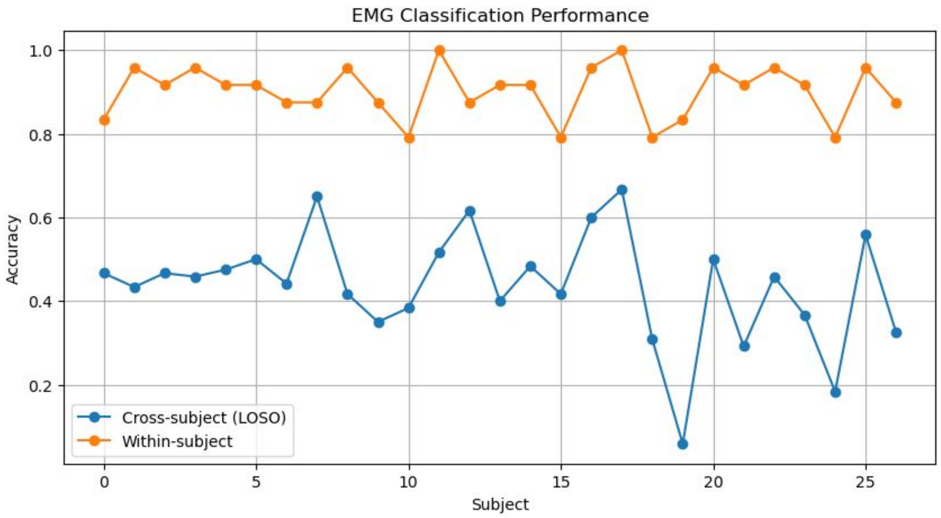
Preprocessing + Feature Extraction

COMPLETE DATASET 27 Subjects - 10 Features



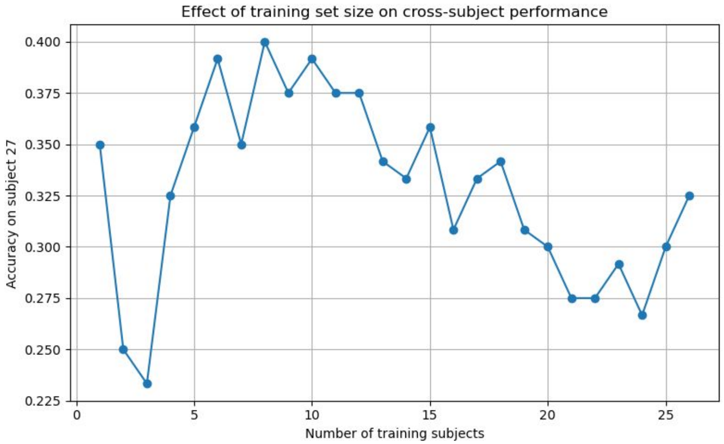


Cross-subject Classification

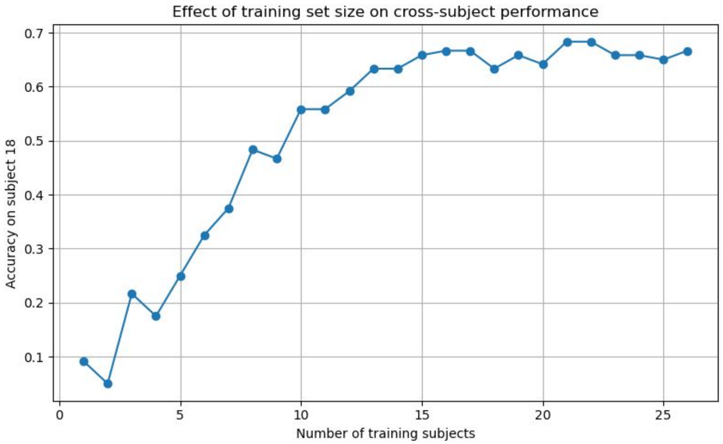


Mean cross-subject accuracy: 0.44 ± 0.13
Mean within-subject accuracy: 0.90 ± 0.06

Effect of Training Set Size



Accuracy for Subject #27



Accuracy for Subject #18

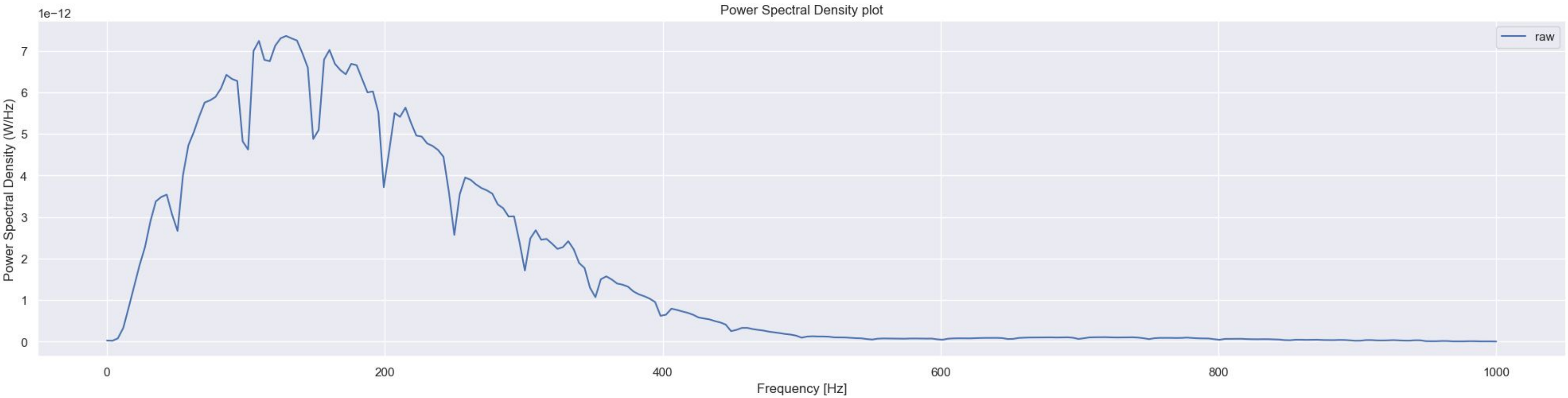
Effect of Training Set Size

performance gains became smaller beyond a moderate number of training subjects (e.g. 15)

PART 3

REGRESSION FOR JOINT ANGLES

Preprocessing and Splitting



Validation set: repetitions 2 and 7
Test set: repetition 5
Train set: other repetitions

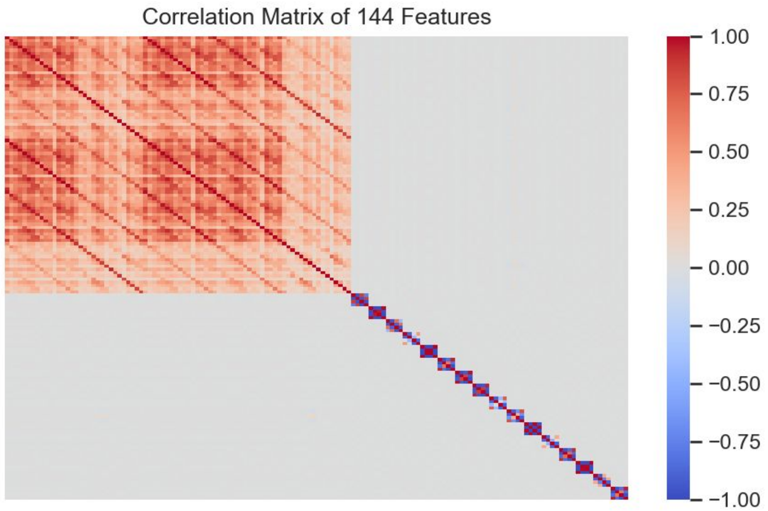
Taken from literature - Krasoulis et al., Effect of user adaptation on prosthetic finger control with an intuitive myoelectric decoder. Frontiers in Neuroscience, 2019

Sliding windows:

1. 128 ms per window (256 data points per window)
2. 50ms second incremental increase (100 data points increase)

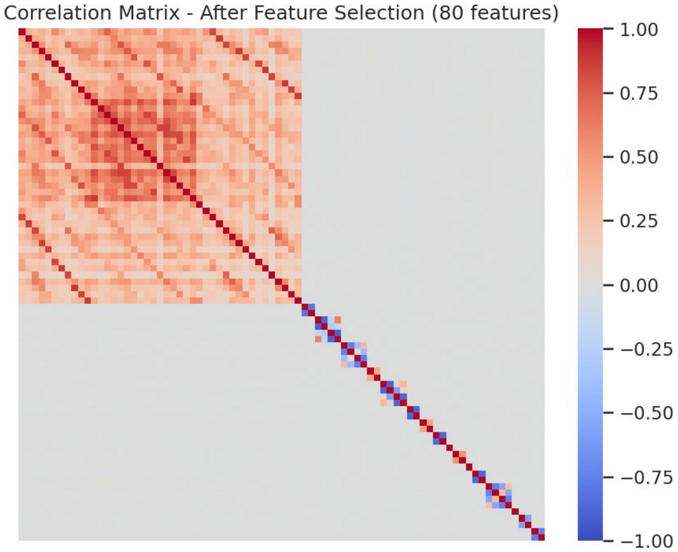
(60% overlap)

Feature Extraction and Correlation



Features
Mean, Standard Deviation, Maximum Amplitude, Wilson Amplitude, Waveform Length, Log-Variance, Slope Sign Change, 4th-Order Autoregressive Coefficients

16 channels x 11 features = 176 features.
144 after removing the constant features.
We selected only 80 final features after removing one of the feature from feature-pairs which were the most correlated.



Hyperparameters optimization

Kernel / C	0.01	0.1	1	10	100
linear	694.53	586.32	579.65	578.98	584.07
rbf	1042.09	932.74	550.88	352.97	303.82

FIGURE 3.4
SVR performance (MSE) comparison

We test different models to find the optimal hyperparameters

Metric Choice and final results

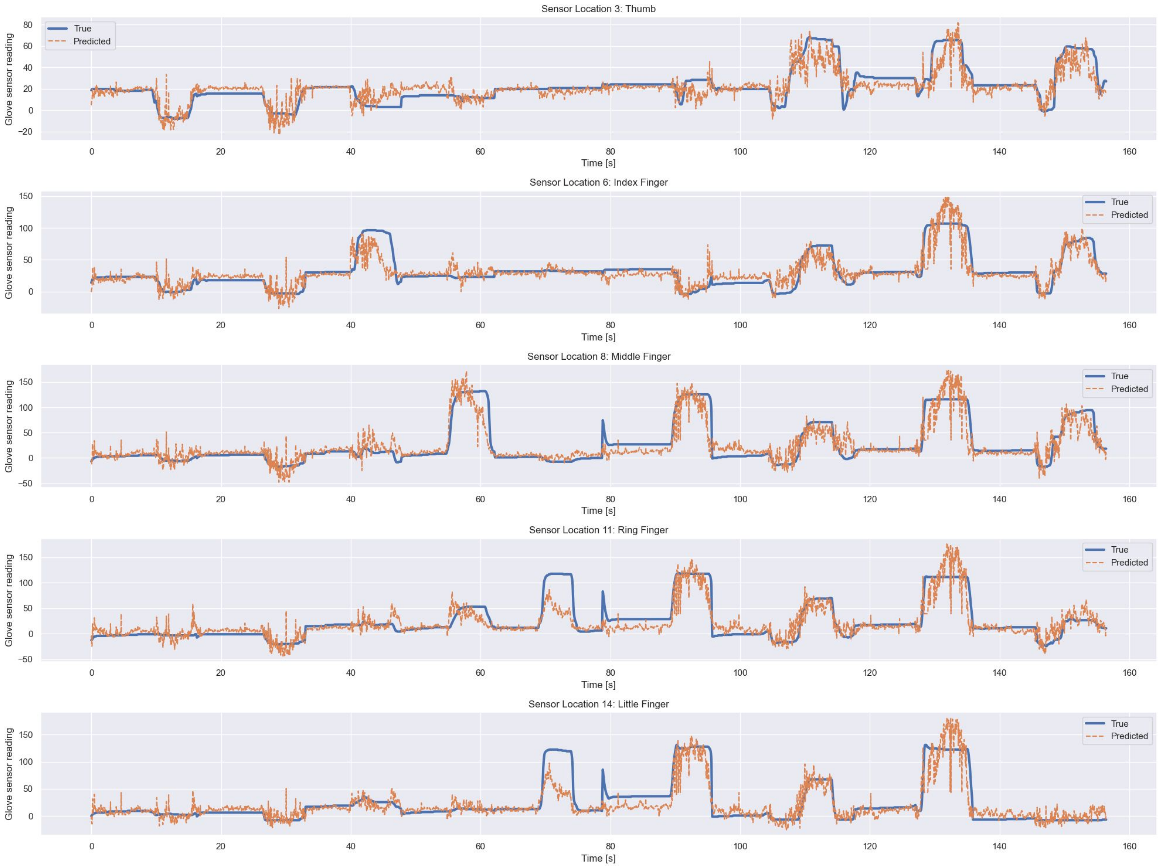
Metric used: R^2

MSE penalizes large errors and is optimal for Gaussian noise assumptions, but R^2 is more appropriate here as it normalizes by label variance. We use $R^2 = 1 - MSE/Var(y)$ to assess test performance.

Final results:

1. $R^2 = 0.68$ on validation set
2. $R^2 = 0.70$ on test set

Results visualization



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Finger comparison

FIGURE 3.6

R^2 values for each finger sensor location.

Sensor / Finger	Thumb	Index	Middle	Ring	Little
R^2	0.700	0.673	0.743	0.675	0.698

Middle finger: dedicated tendon compartment.

Ring finger: biomechanically coupled to adjacent finger.

Thumb: relies on intrinsic hand muscles not captured by forearm sEMG, and extrinsic muscles overlap with wrist muscles, causing crosstalk.

Team Contributions

Contribution	Team Member
Part I	Pamela van den Enden Uribe, Khushi Singh, Arnault Dominic Philippe Stähli
Part II	Heliya Shakeri
Part III	Arnault Dominic Philippe Stähli, Angana Mondal

References

Atzori, M., Gijsberts, A., Castellini, C., Caputo, B., Hager, A.-G. M., Elsig, S., Giatsidis, G., Bassetto, F., & Müller, H. (2014). Electromyography data for non-invasive naturally-controlled robotic hand prostheses. *Scientific Data, 1*, 140053. https://doi.org/10.1038/sdata.2014.53

Hudgins, B., Parker, P., & Scott, R. N. (1993). A new strategy for multifunction myoelectric control. *IEEE Transactions on Biomedical Engineering, 40*(1), 82–94.

THANK YOU!

References

Atzori, M., Gijsberts, A., Castellini, C., Caputo, B., Hager, A.-G. M., Elsig, S., Giatsidis, G., Bassetto, F., & Müller, H. (2014). Electromyography data for non-invasive naturally-controlled robotic hand prostheses. *Scientific Data, 1*, 140053. https://doi.org/10.1038/sdata.2014.53

Hudgins, B., Parker, P., & Scott, R. N. (1993). A new strategy for multifunction myoelectric control. *IEEE Transactions on Biomedical Engineering, 40*(1), 82–94.

EPFL

Feature Selection

TIME DOMAIN FEATURES

ROOT MEAN SQUARE (RMS)

MEAN ABSOLUTE VALUE (MAV)

WAVEFORM LENGTH (WL)

SLOPE SIGN CHANGE (SSC)

INTEGRATED EMG (IEMG)

VARIANCE (VAR)

WILLISON AMPLITUDE (WAMP)

HISTOGRAM

FREQUENCY DOMAIN FEATURES

POWER SPECTRAL DENSITY (PSD)

MARGINAL DISCRETE WAVELET TRANSFORM

Sources:
Atzori et al. (2014)
NX421 lectures/labs

EPFL

Feature Selection

TIME DOMAIN FEATURES

ROOT MEAN SQUARE (RMS)
Overall power of the signal

MEAN ABSOLUTE VALUE (MAV)
Average amplitude of rectified signal

WAVEFORM LENGTH (WL)
Cumulative variation or complexity of signal.

SLOPE SIGN CHANGE (SSC)
Number of slope changes in signal.

INTEGRATED EMG (IEMG)
Summation |EMG| signal over time.

VARIANCE (VAR)
Power or spread of EMG signal.

WILLISON AMPLITUDE (WAMP)
times the amplitude exceeds set threshold.

HISTOGRAM
Log of amplitude histogram to quantify signal complexity

FREQUENCY DOMAIN FEATURES

POWER SPECTRAL DENSITY (PSD)
Mean power distribution

MARGINAL DISCRETE WAVELET TRANSFORM
Sum of absolute wavelet coefficients across all levels per channel (3 levels)

Sources:
Atzori et al. (2014)
NX421 lectures/labs