Newcastle University

Machine learning-based upper-limb prosthesis control

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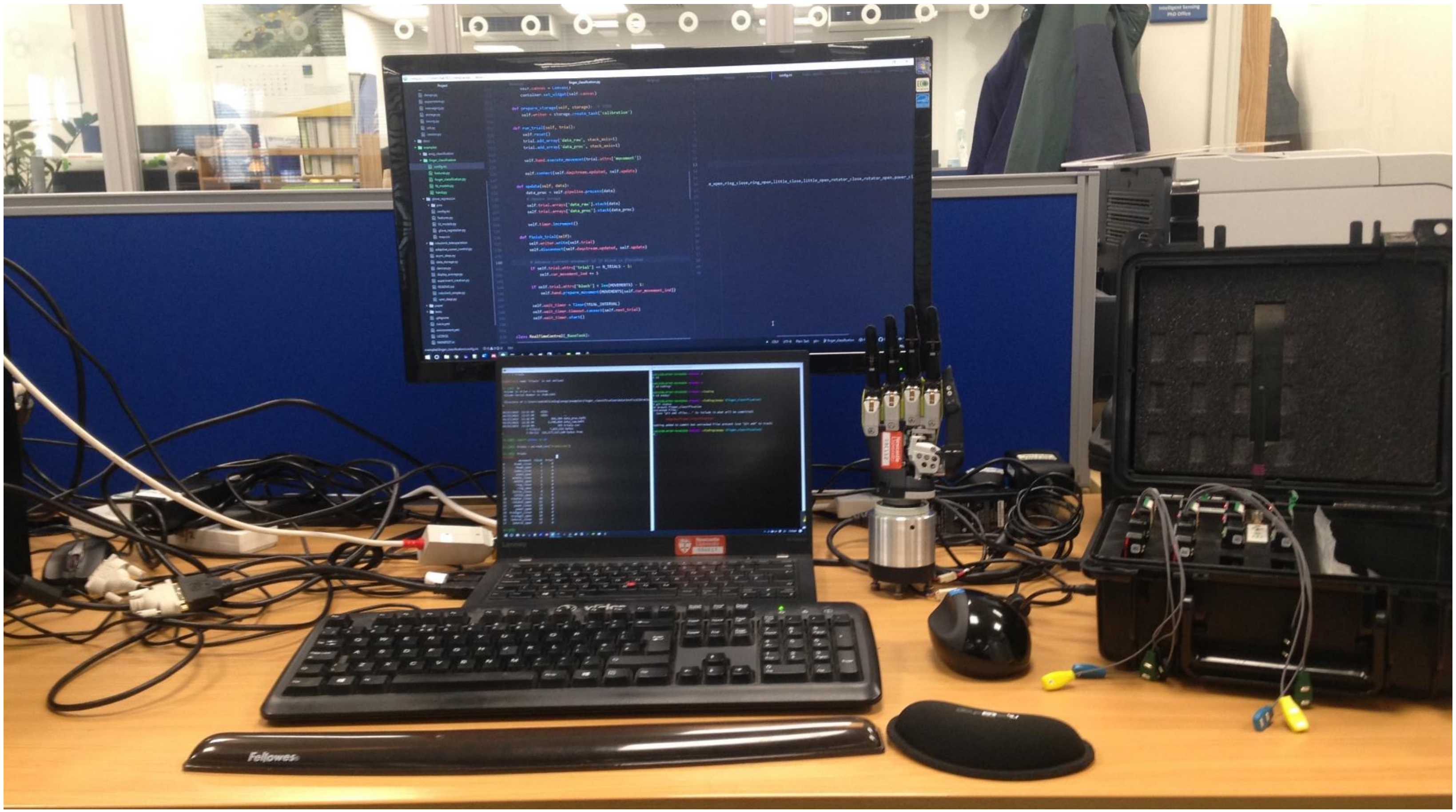
PyData Edinburgh
July 3, 2019

Intelligent Sensing

Where is the 'Py' ?



Where is the ‘Data’ ?

```
from sklearn.model_selection import PredefinedSplit
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.metrics import make_scorer
from sklearn.multioutput import MultiOutputClassifier
from sklearn.decomposition import PCA
from sklearn.dummy import DummyClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LogisticRegression, RidgeClassifier
from sklearn.discriminant_analysis import (LinearDiscriminantAnalysis,
                                           QuadraticDiscriminantAnalysis)
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier, ExtraTreesClassifier
from xgboost import XGBClassifier

from sklearn_ext.discriminant_analysis import RegularizedDiscriminantAnalysis
from sklearn_ext.metrics import (accuracy_score, hamming_score,
```

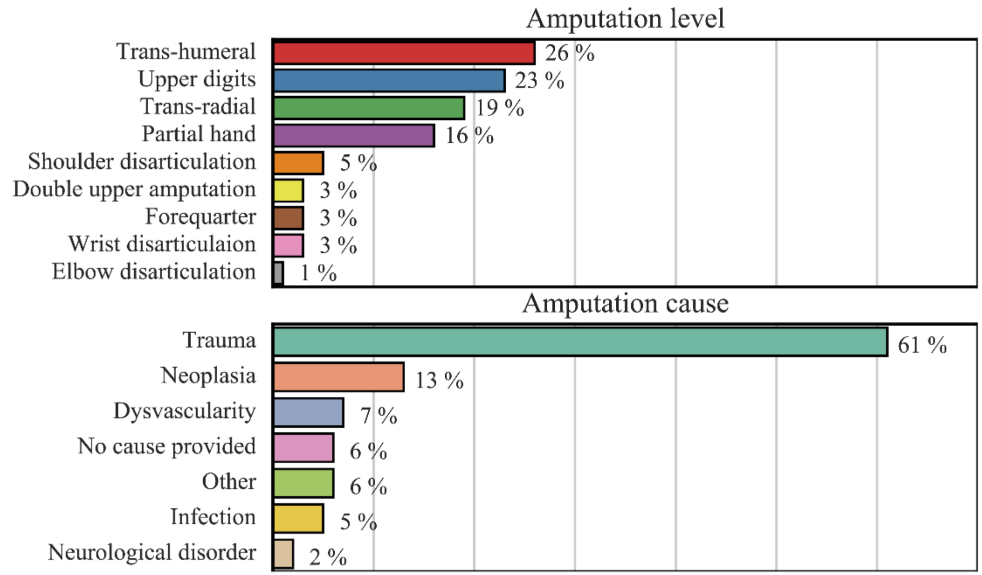
Intelligent sensing Lab

Our research is motivated by the potential of prosthetics to restore function to individuals with sensorimotor deficit, by transforming thought into action and sensation into perception.

Demographics

- Scotland: ~ 460 upper-limb amputations every year

- USA: > 500,000 upper-limb amputees

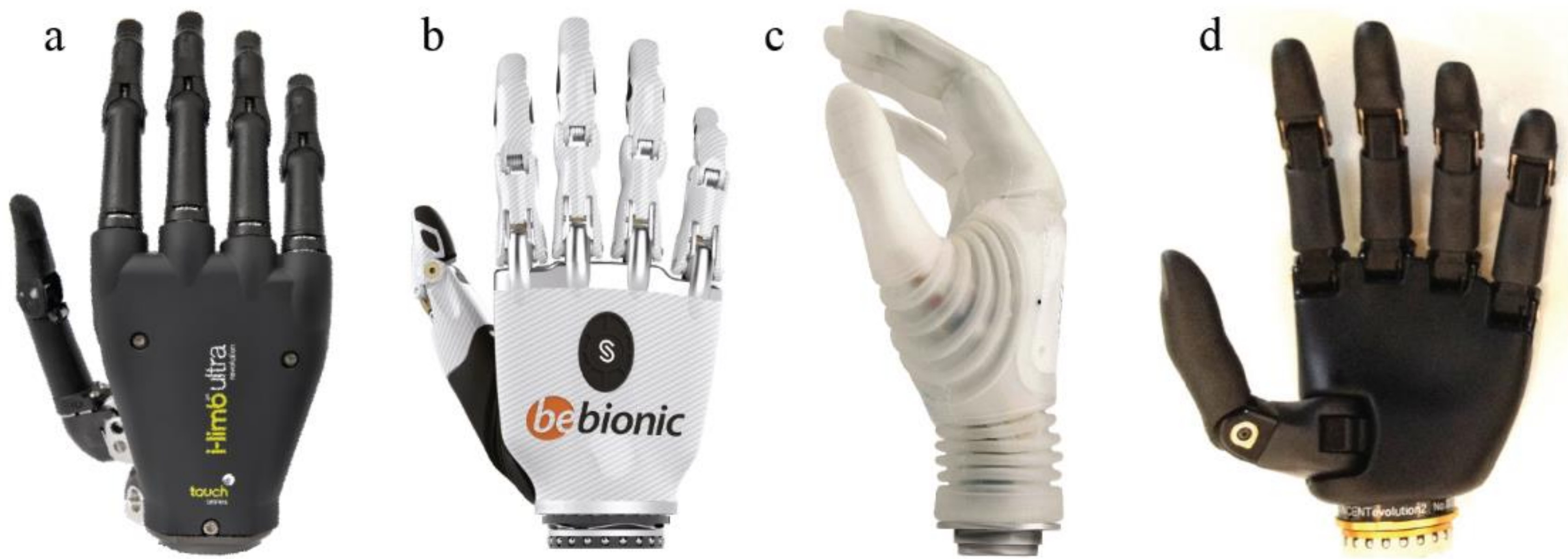


Upper-limb prostheses

https://en.wikipedia.org/wiki/Prosthesis

Upper-limb prostheses

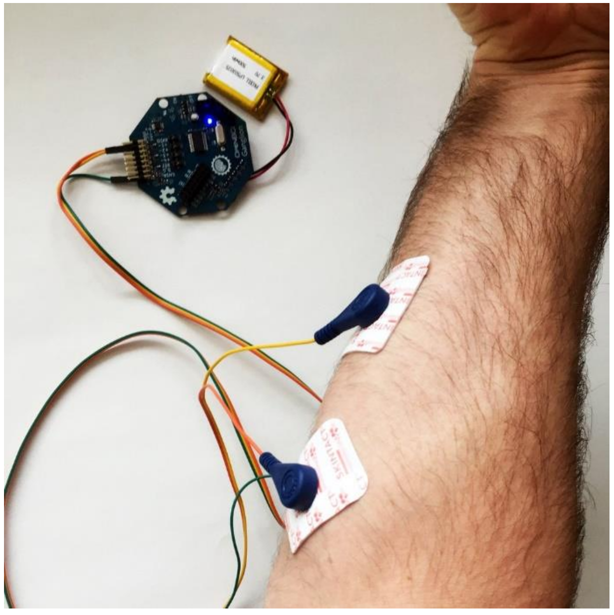
- Active (motorized) fingers
- Multiple degrees-of-freedom (DOFs)



(a) http://touchbionics.com/
(b) http://bebionic.com/
(c) https://www.ottobock.co.uk/
(d) https://vincentsystems.de/en/

Electromyography

- Electrical signal (surface or intramuscular)
- Muscle fiber neural activity
- Neural drive sent from the spinal cord to the muscles



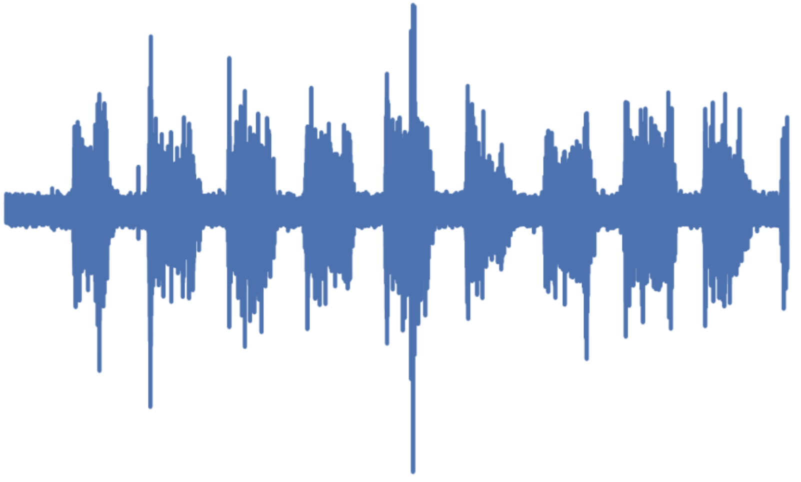


Photo credit: https://openbci.com/

EMG-based prosthetic control

THE USE OF MYO-ELECTRIC CURRENTS
IN THE OPERATION OF PROSTHESES

C. K. BATTYE, A. NIGHTINGALE, and J. WHILLIS, LONDON, ENGLAND

From Guy's Hospital Medical School

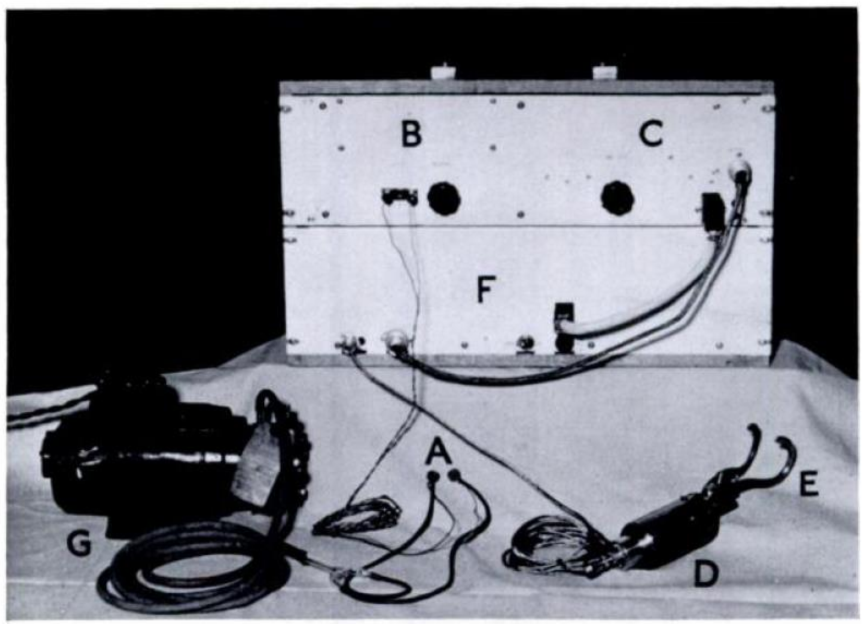
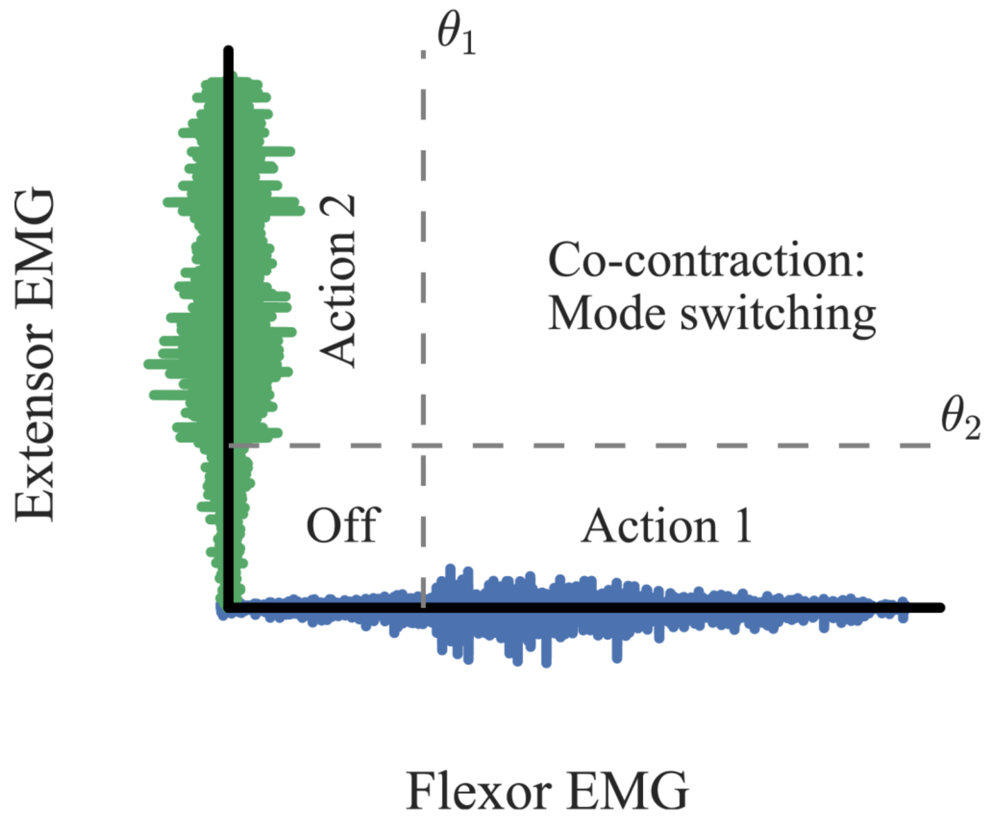


FIG. 1
The final apparatus.

Battye et al., The Journal of bone and joint surgery, 1955

EMG-based prosthetic control

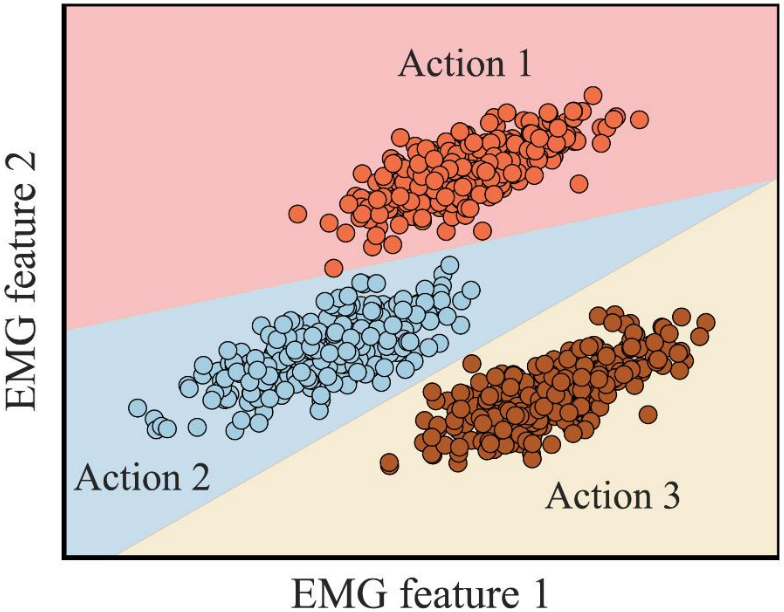


Mode-switching prosthetic control

- Unnatural for the user
- Increases cognitive load
- Prosthesis under-actuation
- Leads to high prosthesis rejection rate
- … but robust

Machine learning for prosthesis control

- More intuitive, natural control
- Simultaneously access multiple grips

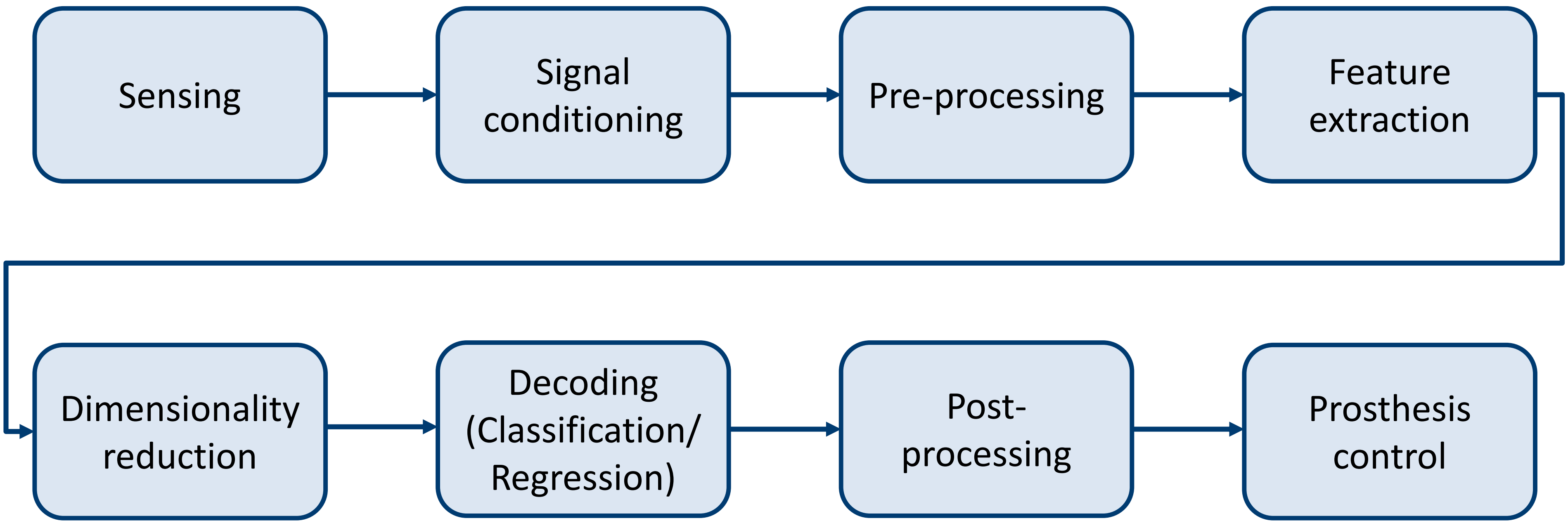


Machine learning for prosthesis control

Implementation

- Collect training data
- Associate muscle patterns to prosthetic hand activations (e.g. grips)
- Deploy for real-time control

Pipeline


Sensing
Signal conditioning
Pre-processing
Feature extraction
Dimensionality reduction
Decoding (Classification/ Regression)
Post-processing
Prosthesis control

Newcastle University

Machine learning for prosthesis control

Intelligent Sensing

Technical considerations

- Processing must take place in real-time, on embedded platforms (computational / memory constraints)
- Short response delay
- Non-stationarities / covariate shift

Challenges: non-stationarities

- Muscle fatigue
- Electrode shifts / displacements
- Arm posture (*limb position effect*)

frontiers in Neurorobotics

REVIEW
published: 21 September 2018
doi: 10.3389/fnbot.2018.00058

Check for updates

Causes of Performance Degradation in Non-invasive Electromyographic Pattern Recognition in Upper Limb Prostheses

Iris Kyranou[1,2,3], Sethu Vijayakumar[1,2] and Mustafa Suphi Erden[1,3]*

Challenges: real-time control vs. offline

- Disparity between offline and real-time control results
- Different metrics (e.g. accuracy vs. completion rate / time)

Offline Accuracy: A Potentially Misleading Metric in Myoelectric Pattern Recognition for Prosthetic Control

Max Ortiz-Catalan, *IEEE Member*, Faezeh Rouhani, Rickard Brånemark, and Bo Håkansson

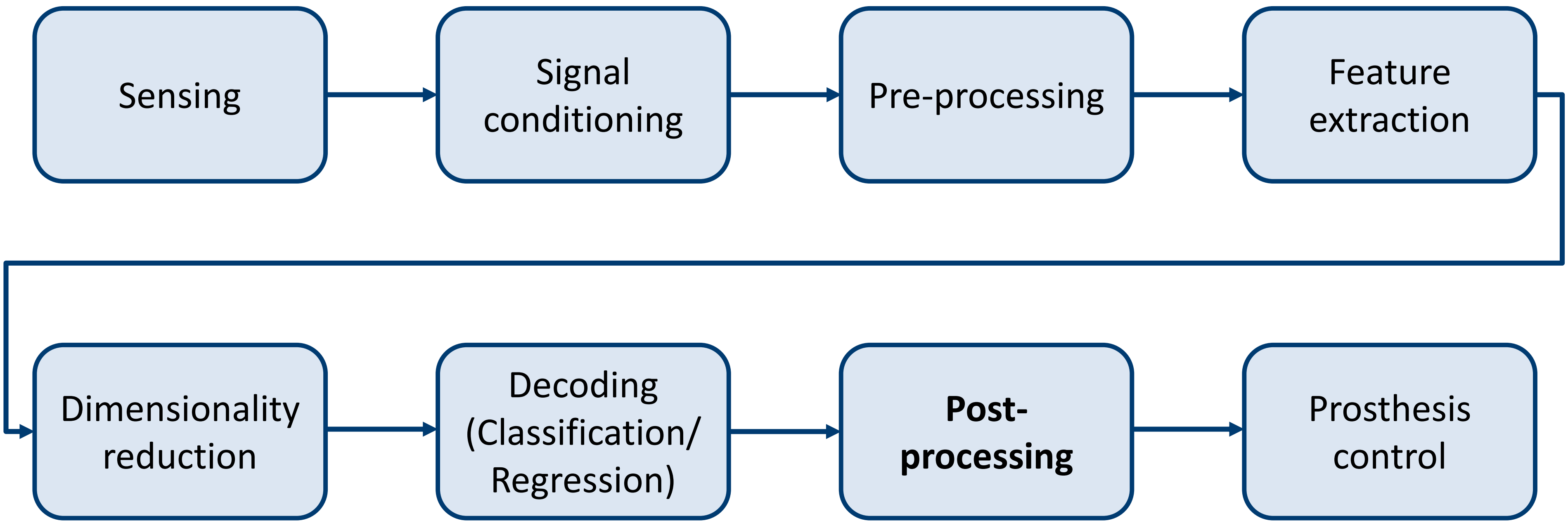
Translating Research on Myoelectric Control into Clinics—Are the Performance Assessment Methods Adequate?

Ivan Vujaklija[1,2], Aidan D. Roche[3], Timothy Hasenoehrl[4], Agnes Sturma[3,5], Sebastian Amsuess[6], Dario Farina[2] and Oskar C. Aszmann[3,7]*

Metrics: why accuracy may not be enough

- Class imbalance
- False positives vs. false negatives: which should be penalised more?
- Is class prediction the only thing we are interested in?

Metrics: why accuracy may not be enough

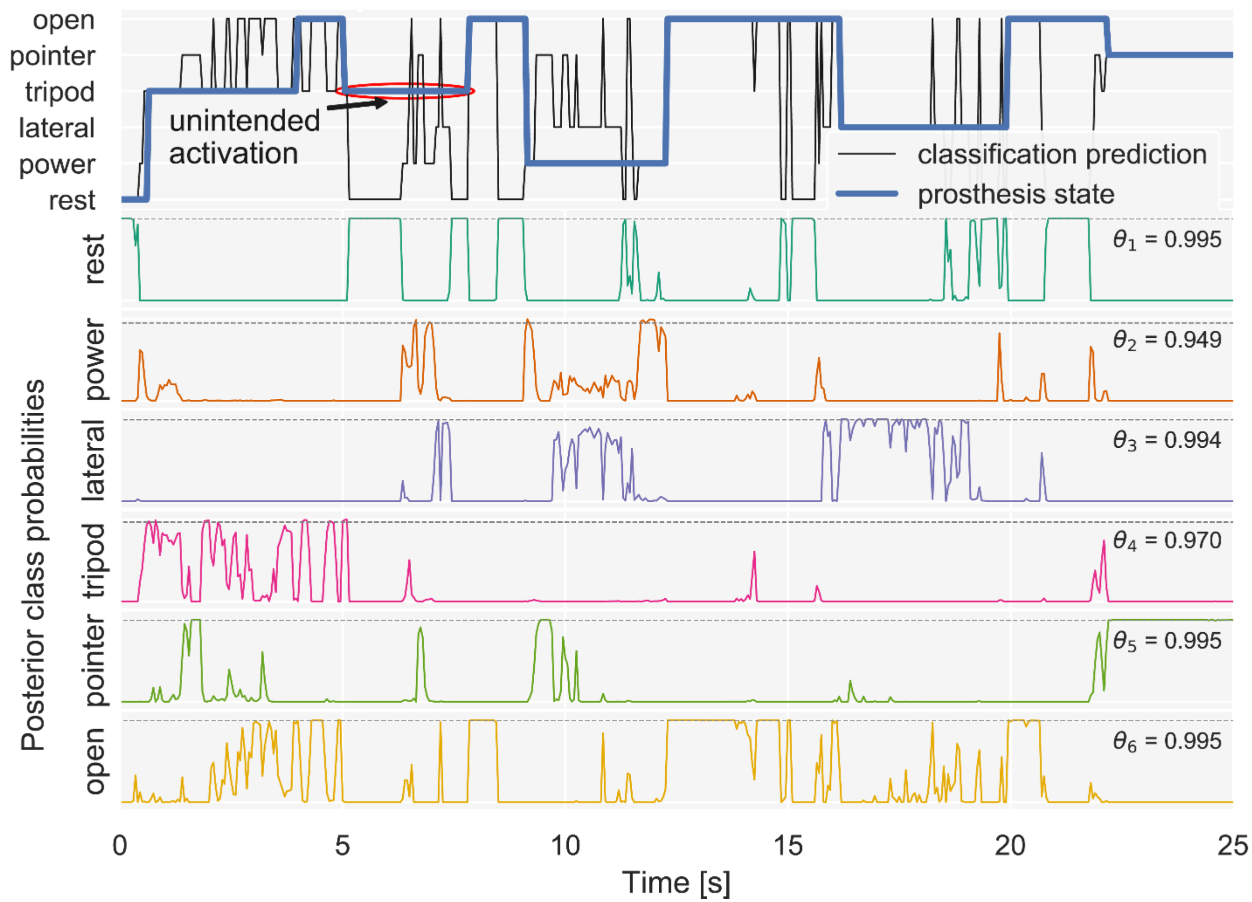


Post-processing

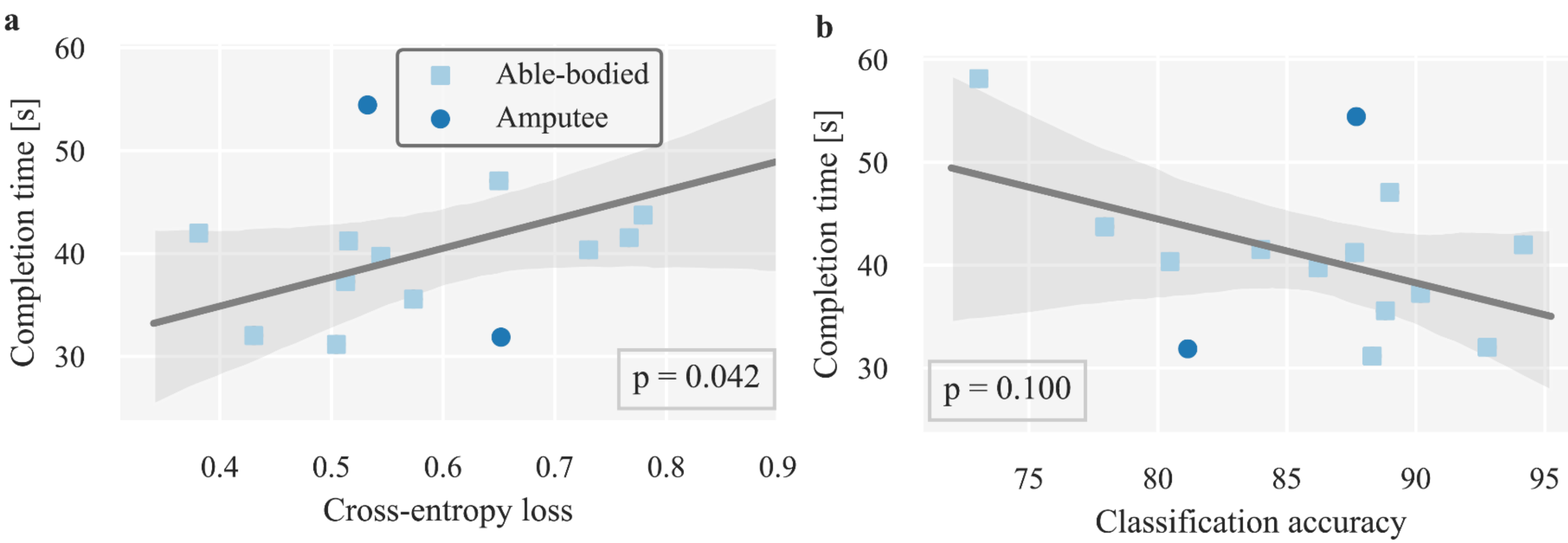
$$\text{prosthesis command} = \begin{cases} \text{prediction}, p \geq \theta \\ \text{None}, \text{otherwise} \end{cases}$$

- Posterior probabilities are important
- What metric to use for hyper-parameter optimization
- Accuracy, Log-loss, Precision, Recall, F1, AUC, …
- How to select confidence thresholds θ

Confidence-based rejection



Optimisation metric

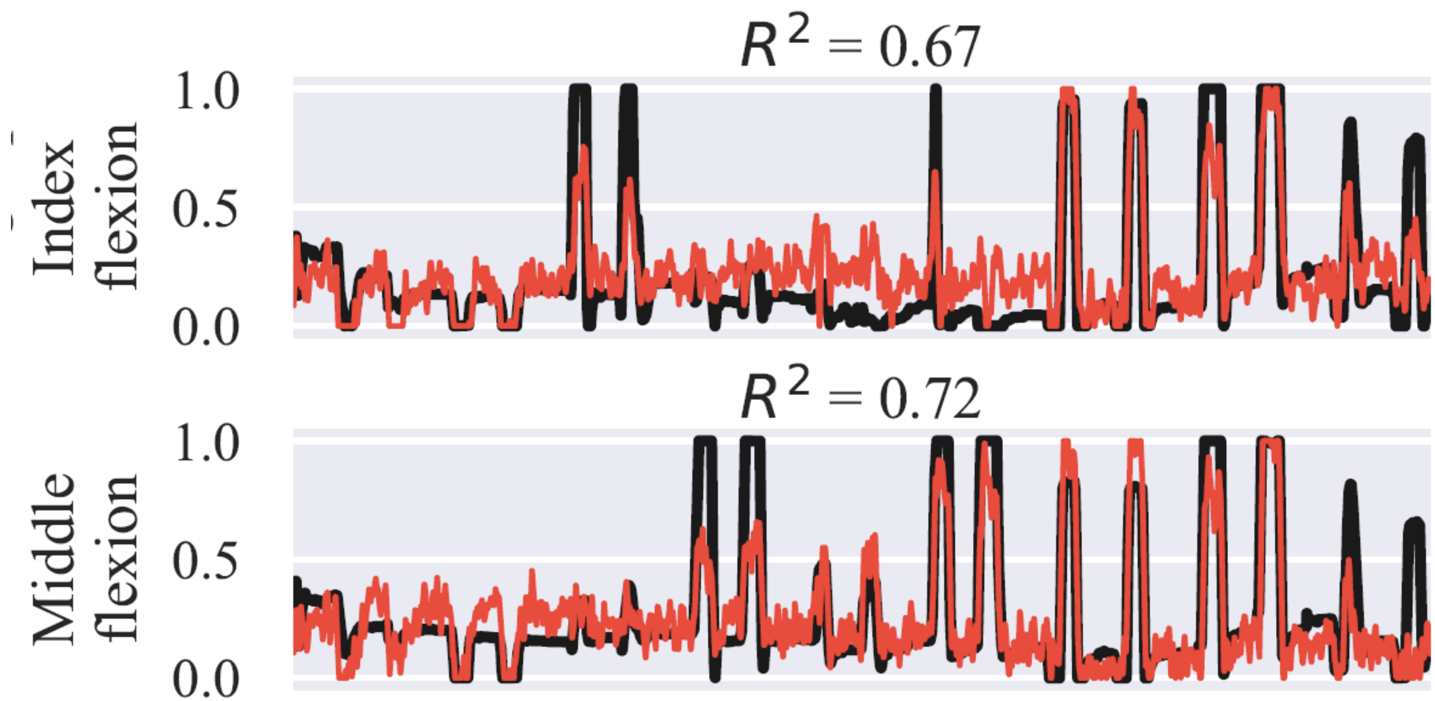


Challenges: Discrete vs. Continuous control

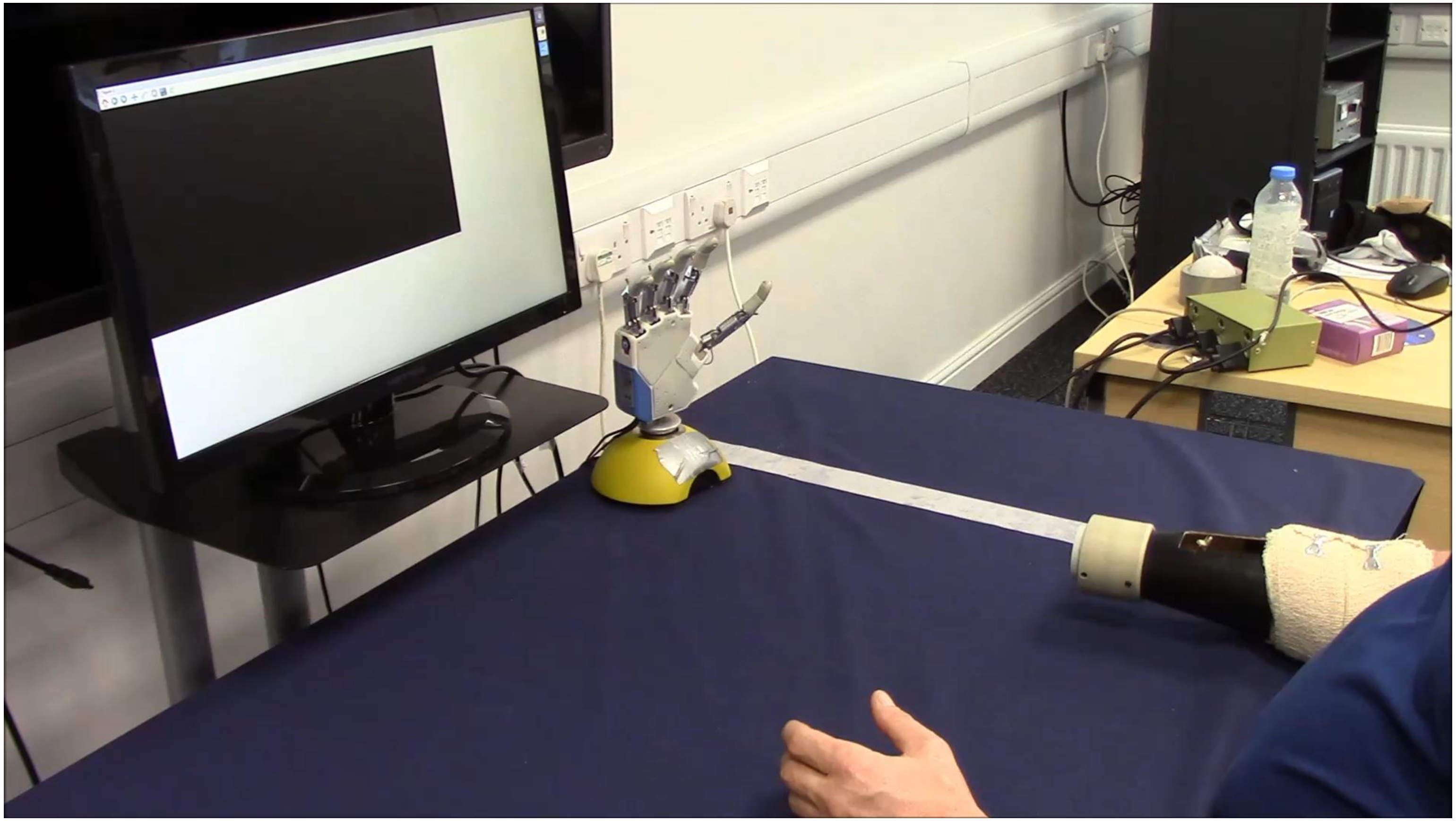
Photo credit: Iris Kyranou

Challenges: Discrete vs. Continuous control

- Independent finger control (position, velocity, force)
- Regression vs. classification



Simultaneous control of multiple DOFs

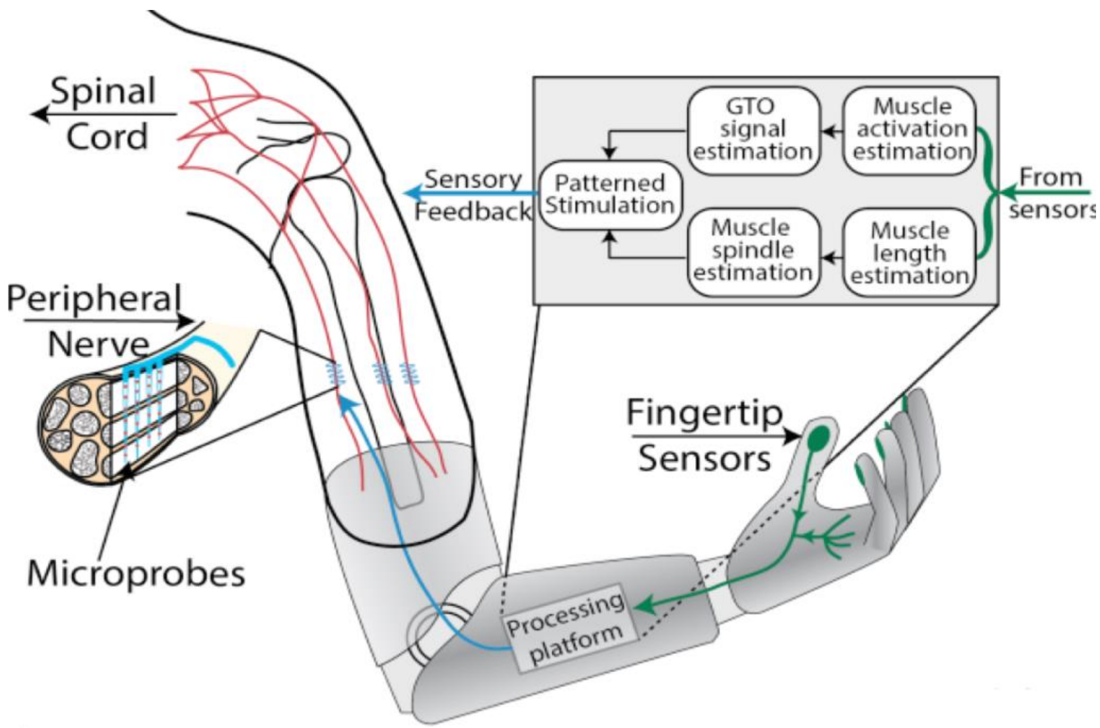


Challenges: sensory feedback

- Humans rely on sensory feedback
- Visual feedback is also important
- Increase sense of ownership and embodiment
- Reduce phantom limb pain

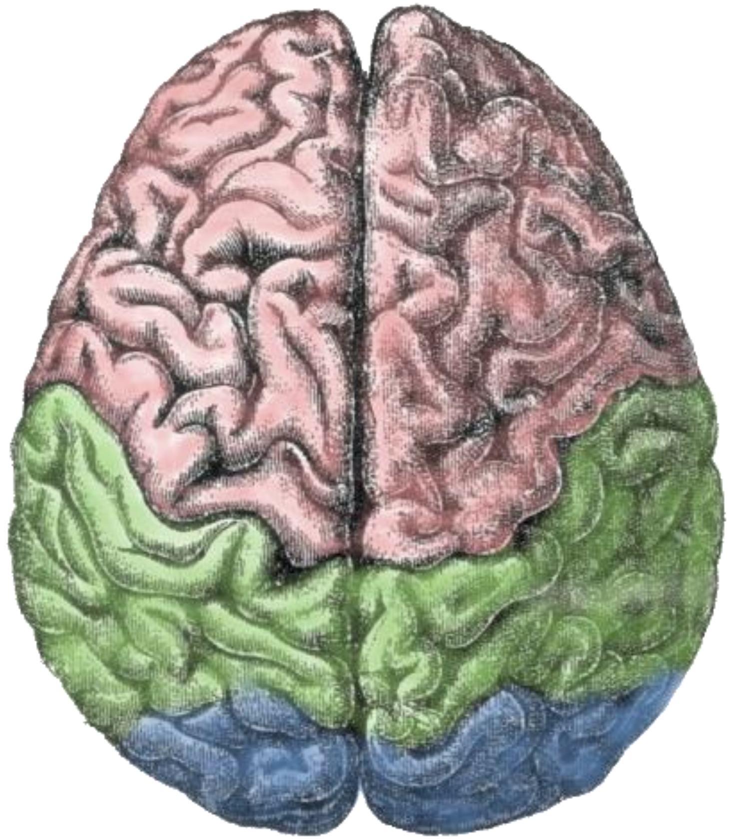
Challenges: sensory feedback

- Electrotactile vs. vibrotactile surface stimulation
- Alternative: direct nerve stimulation



http://www.senseback.com/about-senseback/

“Machine” is not the only type of learning taking place



https://en.wikipedia.org/wiki/Human_brain

Recap

- Machine learning can be used to improve dexterity of upper-limb prosthesis control
- Some EMG datasets publicly available (e.g NINAPRO)
- Classification accuracy is not everything! Make sure to pick and optimise the most appropriate metric
- Beware of non-stationarities and covariate shift

Thank You

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www.intellsensing.com