# A bioelectric neural interface toward intuitive prosthetic control for amputees

*File name = A\_bioelectric\_neural\_interface\_towards\_intuitive\_p.pdf*

Using ENG (and EMG) to control a prosthetic hand in real time

Neuronix chip:

* Neural recorder: ENG
  + <https://en.wikipedia.org/wiki/Electroneurogram>
* Able to suppress motion and stimulation artifacts
* Chirurgical implantation

DOF: Degree of Freedom

* <https://pubmed.ncbi.nlm.nih.gov/28269405/>
* 15 DOF -> 2^15 possible gestures, but only some of them are useful

Training using 10 hand gestures. Each of them uses at least 2 DOF simultaneously

* Patient perform a movement with its able hand while imagining doing the same with its missing hand
* Data glove captures able hand motion (VMG 30, Virtual Motion Labs TX: <https://www.virtualmotionlabs.com/>)
  + Used as « ground-truth label for training and benchmarking in deep learning model »
    - https://en.wikipedia.org/wiki/Ground\_truth
* Implant captures missing hand neural signal

Deep learning:

* RNN : custom model
* Objective: show that the Scorpius chip get enough information to decode multiple DOF and find the best machine learning approach to do so
* Reduction of the dimensionality of the input to reduce the needed resources to be able to use the decoder online (in real time?)
* Convolutional layers + ReLU + dropout for some layers
* 15 AI model are trained to each decode the trajectory of a single DOF
* Comparation with SVM, RF, MLP, CNN
* Performance metric: MSE and VAF
  + Performance = quantitative regression prediction of the decoding algorithm

Result:

* ENG show 2 types of data. They use electrodes which gives both kinds
  + CAP = compound of action
  + Spike = single axon potentials
* They were able to get different result from 2 different gestures (rest and grip)
* Spectrogram analysis of 3 different gesture shows different signatures.
* The proposed deep learning model (RNN) always gives better results than the others (even better than CNN) using both metrics on every DOF
* The signal acquired is independent from the arm position
* The model can predict the movement of all 5 fingers using ENG but not using EMG. EMG does not contain enough information

# A Review on Commercially Available Anthropomorphic Myoelectric Prosthetic Hand, Pattern-Recognition-Based Microcontrollers and sEMG Sensors used for Prosthetic Control

*File name = calado2019.pdf*

Comparitson of different Transradial myoelectric prosthesis which are based on

* Use non-invasive sEMG (surface EMG) sensor for signal classification using a data windowing.
* Each window belongs to a specific class corresponding to a gesture.

Number of sensors can be between 4 and 16 (depending of the number of gesture to classify)

Protheses brands

* Bebionic, i-limb, hero arm, ultra revolution, LUKE arm, Michelangelo hand, taska hand, Vincent evolution 3

Comparison points:

* DOF, number of actuators, available sizes, weight, maximum grasps and carry load, number of grip patterns, price

# Development of Myoelectric Robotic/Prosthetic hands with Cybernetic control at biological systems engineering laboratory, Hiroshima University

*File name = Fujipress\_JTM-31-1-3.pdf*

Prosthetic arm+hand controlled using EMG on remaining muscles

Independent control of each finger

Try to obtain natural motion of the hand

Description of an experiment where a person controls an artificial arm using EMG sensor placed on its arm. (no missing arm here)

Set of elementary finger gesture and combine finger gesture to train de model.

The discrimination rate was of 99% for elementary motion and 87 for combined motion

# Hand gesture recognition based on motor unit spike trains decoded from high-density electromyography

*File name = Hand gesture recognition based on motor unit spike trains decoded from high-density electromyography.pdf*

HMI = human interface machine

Simplest way to control an artificial hand using EMG = use each EMG channel to directly control a single DOF

* Simple but not sufficient for long time training
* Need pattern recognition of EMG signals

Frequency domain better than time domain

192 EMG electrodes are used

* During preprocessing, 10% of them were manually discarded when they presented too much noise caused by poop contact between the skin and the electrode

MUAP, MUAP extraction

* <https://www.sciencedirect.com/topics/nursing-and-health-professions/motor-unit-potential#:~:text=Motor%20unit%20action%20potentials%20(MUAPs,the%20needle%20electrode54%20(Fig>.

MUSTs <-> spike trains

* <http://www.neuwritewest.org/blog/2015/1/3/ask-a-neuroscientist-whats-a-spike-train#:~:text=In%20a%20nutshell%2C%20spike%20trains,each%20other%20all%20the%20time>.

Natural gradient descent algorithm

* <https://towardsdatascience.com/natural-gradient-ce454b3dcdfa>

Classification of musts using support vector machine

MUC based approach for hand gesture recognition

* Shown better than the use of multiple channel EMG amplitude (RMS based approach)

Classification accuracy greater than 95% for 11 motions

# Motor-commands decoding using peripheral nerve signals: a review

*File name = Hong\_2018\_J\_Neural\_Eng\_15\_031004.pdf*

Description of the stat of the art for prosthesis control using EMG and ENG

Human hand has 27 DOF

Focus on PNS = peripheral nerves

* Outside the CNS = central nervous system = brain + spinal cord

Voluntary nerve control is the main source of meaningful signal for movement control

* Less focus on autonomous nerve control

Recording nerve interface can be placed inside or around nerves to record voltage signal representing the neural activity

Farina and Aszmann requirement for better prosthetic performances

* Better peripheral nerve data-recording interfaces and decoding of user intention
* Development of algorithms that do not require the individual to concentrate on trying to move the prosthetic
* Provision of crucial sensory inputs to the brain (sensation feeling through the prosthetic), Providing feedback

Types of ENG

* Extra neural
  + Lots of different sensor shape (helical, spiral, FINE = float interface nerve electrode) that try to increase the contact surface with the nerve but do not breach the protective sheath of the nerve
* Intra neural: better performances but more invasive and risk of nerve damage
  + Example: longitudinal intra-fascicular electrode (LIFE)
    - - allows classification accuracy above 80% when tested on rats’ sciatic nerves
  + Example: Transverse intra-fascicular multi-channel electrode (TIME)
  + Example: Micro electrode array (MEA)

Regenerative interface

* Type of intra neural sensor
* After being placed, the axons can grow through its holes and make functional connections with electrical sites
* The most invasive but also the one with highest selectivity
* Need time after implantation for the axons to grow back (months)
  + Axon: <https://en.wikipedia.org/wiki/Axon>

EMG: also exist intra and extra sensor

* Surface EMG
  + Non invasive
  + Easy to use but not natural to control a prosthesis (only information from remaining muscle can be taken)
  + Only to perform a set of precomputed motion
  + Does not allow good classification
* Invasive EMG

LIFE: able to give sensation of touch

2 Types of signal ca be obtained from peripheral nerves

* Population activity
* Spike activity

Use filter to remove noise from signal

* common average reference for removal of EMG artifacts
* thresholding for removal of transient low-amplification noise
* band-pass filters for oscillatory noise
* adaptive filters for time varying noise
* de-trending of signal for removal of baseline voltage shifts

deeper processing techniques

* Bayesian spatial filters for source signal extraction algorithm
* Wavelet denoising

Spike detection algorithm

* Using thresholding

Spike sorting algorithm: they present multiple ones

* Algo 1
  + Group the spike based on their shapes
  + Apply noise removal
  + Align spikes with respect to their amplitude peak
  + Template of Spikes shapes are generated
  + Regroup the spikes with similar features/shape/size in new groups
* Algo 2
  + Based on PCA
* Algo 3
  + Convolutive independent component analysis
  + Uses Bayesian model estimation

Feature extraction for population-activity signal

Classification technique

* SVM
* Kalman filter-based decoding (Kalman filtering = KF)
* Clustering
* K-means clustering
* Fuzzy C-means clustering
* Density-based clustering
* Bayesian clustering
* O-sort clustering

Techniques of performance evaluation