# EMG Pattern Recognition in the Era of Big Data and Deep Learning

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2 categories of EMG pattern recognition :

* Feature engineering
  + Require human processing
* Feature learning
  + Require no explicit data transformation

Most commonly used EMG features :

* ZC = zero crossing
* SSC = slope sign change

No known optimum threshold on these 2 features (each person has its optimum)

Other EMG features :

* MAV = Mean absolute value
* WL = waveform length
* AR = Autoregressive coefficient
* CC = Cepstral coefficient
* WAMP = Wilson Amplitude
* SampEn = Sample Entrpy

<http://www.humanconnectomeproject.org/>

no benchmark for EMG data collection

* Difficult to mix or compare datasets
  + Lack of Big data
  + Biggest databe is NinaPRo
    - <http://ninaweb.hevs.ch/>

sEMG are represented as images.

* The classification is then an image classification problem which is known to be effectively done using deep learning
* majority vote over multiple frame is used to classify the signal

better to have a few well placed EMG électrodes than hundrets of them but no concencus on the optimal number

Other sources of information that can used to control prosthesis more accurately without invasive sensor

* EMG controlled prosthesis can use accelerometry as additional information to know its current position
* Emotion recognition

Feature Engineering

* Need to pre-process the signal in order to be classified by conventional machine learning algorithm (time domain to frequency domain, time-frequency domain…)
* Feature extraction : ZC, SSC, MAV…
  + Need to be able to find combination of all these features
    - Not practically feasilble to try all possibilities
    - Use dimensionality reduction but not using classical method which do not fit to big data
    - Use parallel computing (using GPU)
      * Topological simplification : a topological data analysis (TDA)
    - Use heuritics
      * Genetic algorithm (GA)
      * Particle swarm optimization (PSO)
      * Ant Colony optimization (ACO)
    - Standard feature projection
      * Principle component analysis (PCA)
* Support vector machine (SVM) show good results
* LDA, KNN, MLP, RF…

Feature learning

* Unsepervised learning
* Not based on handcrafted features
* Starts to show better results
* Needs large dataset
* Techniques :
  + deep stacking network (DSN)
  + tensor deep stacking network (T-DSN)
  + DistBelief (combination of model- and data-parallel schemes) : deals with model with billions of parameters
* 3 categories of deep learning models
  + Unsupervised pre-trained network (UPNs)
    - Stack auto encoder (SAE)
    - Deep belief network (DBN)
      * Used for EMG pattern recognition (better result than LDA SVN and MLP but need lots of time to reduce overfitting)
      * Split-merge DBM (SM-DBM)
        + Reduces overfitting
  + Convolutional neural network (CNN)
    - Sucessful in EMG pattern recognition (even for complex motions)
    - Can use spectrograms as input
    - Can use small window of EMG singal as inputs but gives lower level of accuracy
  + Recurrent neural network (RNN)
    - Takes time series information into account
    - RNN shows better accyracy than CNN and than CNN+RNN

Splitting dataset into 3 parts : training, validation and test

Future research should try to mix feature engineering and feature learning and try to minimize to computational cost of deep learning for clinical application

# Automatic ocular artifacts removal in EEG using deep learning

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OA = ocular artifacts

* Decrease the level of classification of EEG signals

EOG = electrooculogram

Easiest method: remove manually sequence of signal with OA

Oas are overlapped with the clean EEG signals in frequency domain

* So, should not delete parts with OA

4 categories of Oas removal method

* Artifact filters
  + Linear filtering method
  + Needs EOG signal reference
  + Needs uncomfortable electrode
* Blind Source separation (BSS)
  + ICA (independent component analysis)
  + Needs EOG signal reference
  + Needs uncomfortable electrode
* Wavelet transformation analysis
  + Thresholding technique
  + Does not need a EOG reference signal but the wavelet transformation can deteriorate the signal
* Neural network analysis
  + Replaces the thresholding function from wavelet decomposition
  + Needs EOG signal reference

The paper proposes a new DLN (Deep learning network) that

* does not need additional EOG recording as reference signal -> more comfortable as need less electrode
* Works with a few number of electodes
* Can remove OA online
* Strong generalization ability

The proposed DLN

* Uses SSAE
* Sigmoid activation function
* Trains on EEG without OA to avoid using EOG signal

Metrics

* PSD
  + Use PSD to avaluate the Oas removal effect
* Root mean square error
* EEG classification accuracy

Dataset

* BCI competition
* Some data was artificially generated
* Three classes of motor imagery (left hand, right hand, foot)

Result:

* The DNL shows better result for Oas removal than ICA, K-ICA and SOBI
* The DNL performs better than SAE between 13 and 20 HZ
* DNL is much more rapid than the other (time consumtion is a big issue in OA removal)
* DNL has good generalization even cross-subject