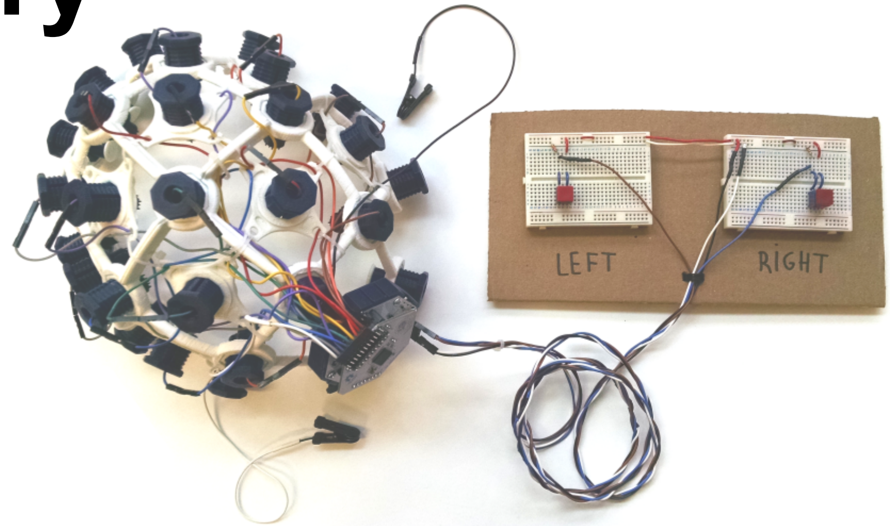
A study on motor imagery classification methods

Presented by Mehrnaz Motamed

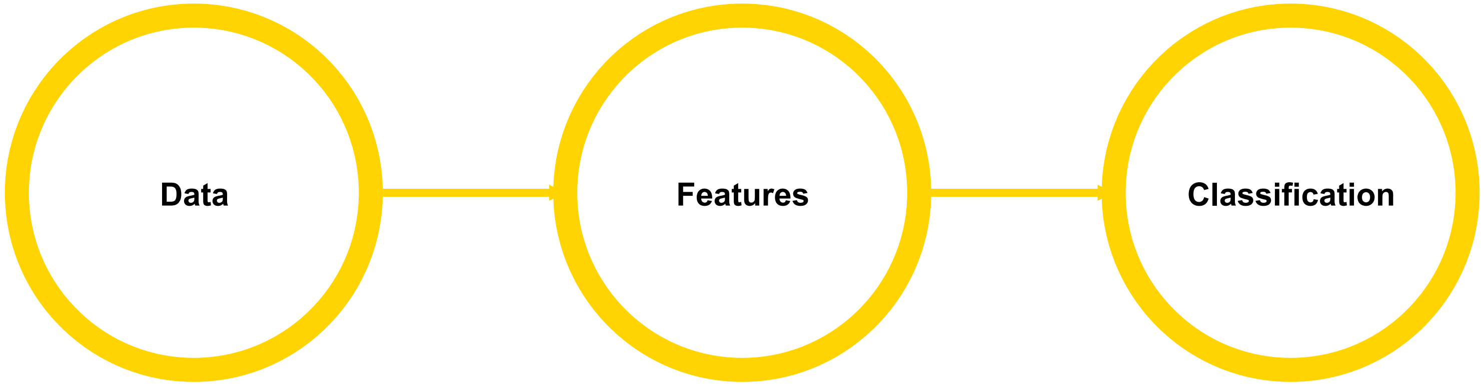
Motor Imagery

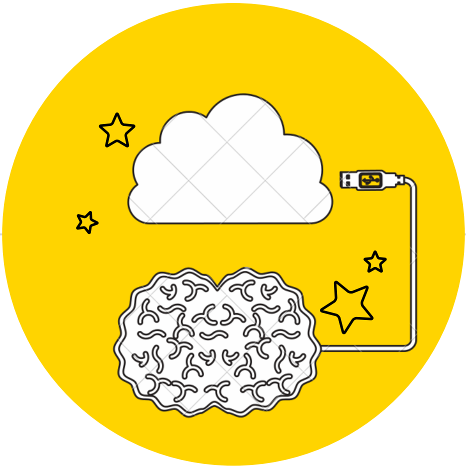


Motor imagery is a mental process by which an individual rehearses or simulates a given action.

Motor imagery reflects on alpha and mu rhythms.

Our process is easy





Data & Experiment

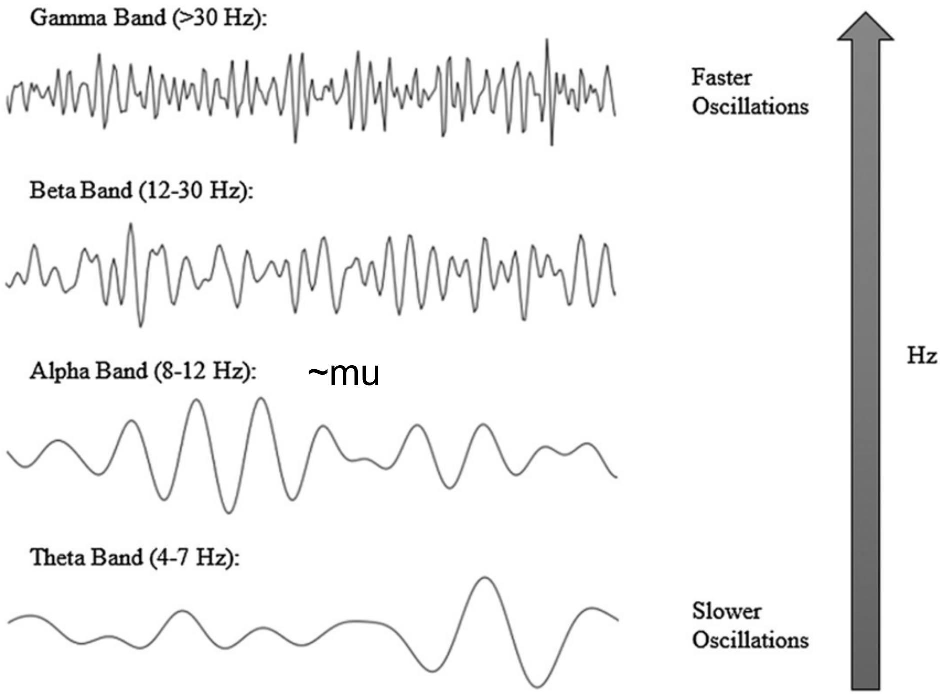
Data & Experiment

Calibration
First 2 runs
Visual cues (arrows)
4s cue
2s blank
2s cross (6s)

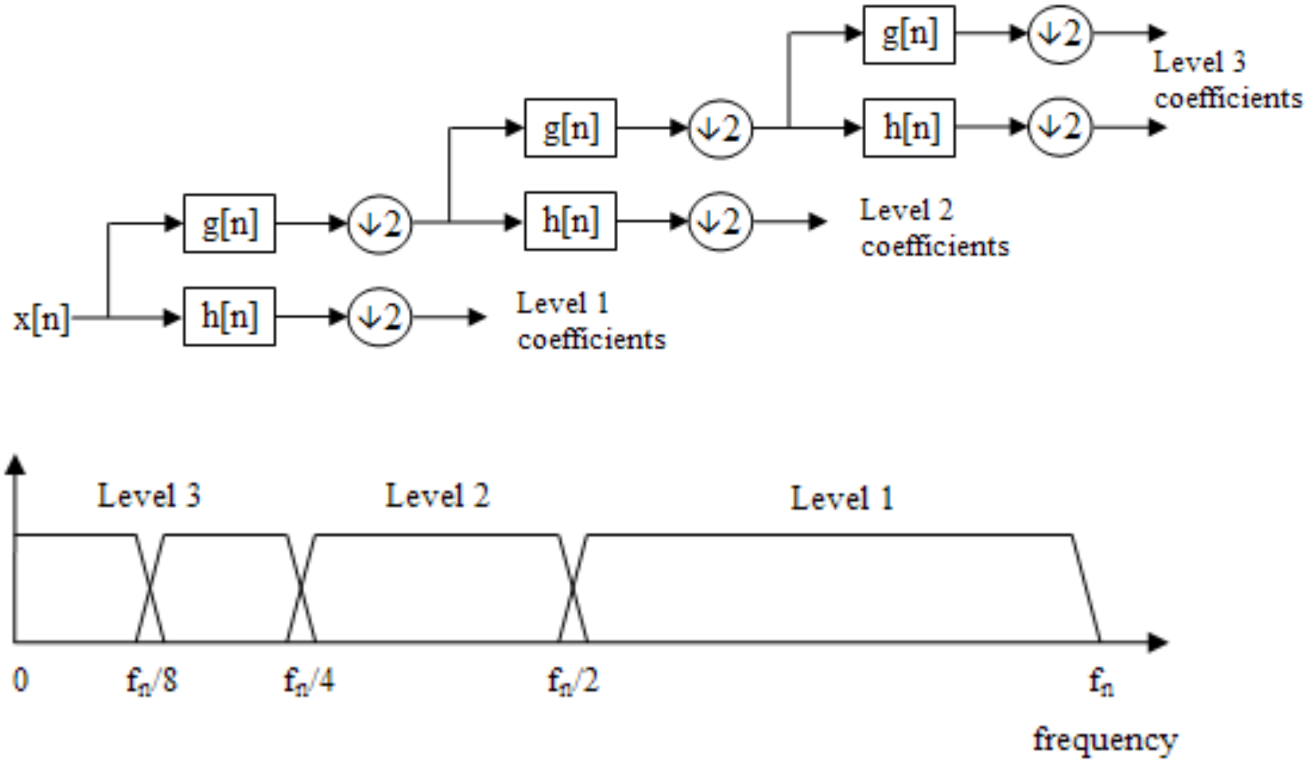
Evaluation:
4 runs evaluating
Soft acoustic stimuli:
Words left, right, foot
1.5-8s
Stop
1.5-8s
Not equal trials

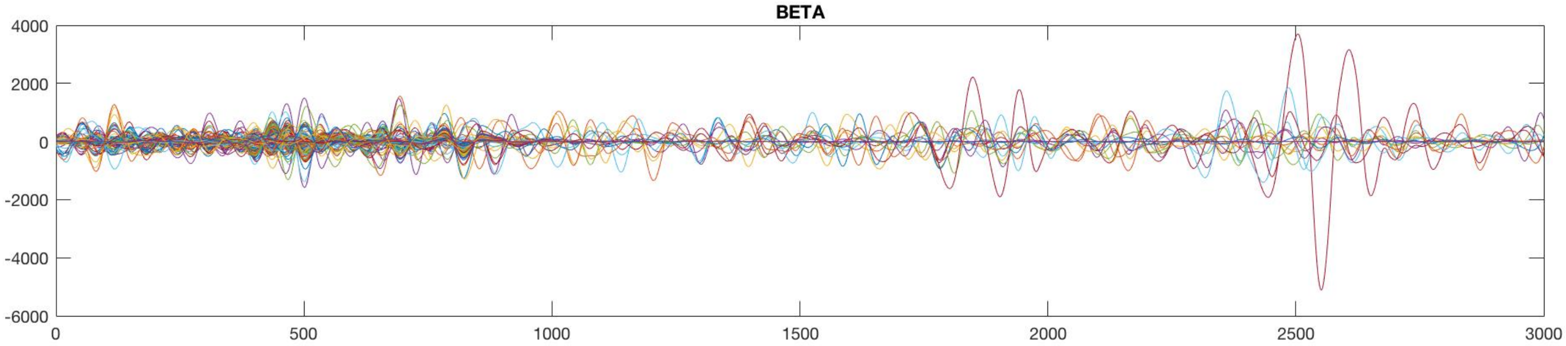
- Healthy subjects without feedback
- Two class selected out of three(left hand, right hand, foot) by each subject
- 59 eeg channels
- most densely distributed over sensorimotor areas
- Bandpassed 0.05-200 Hz
- 100Hz
- 200 trials

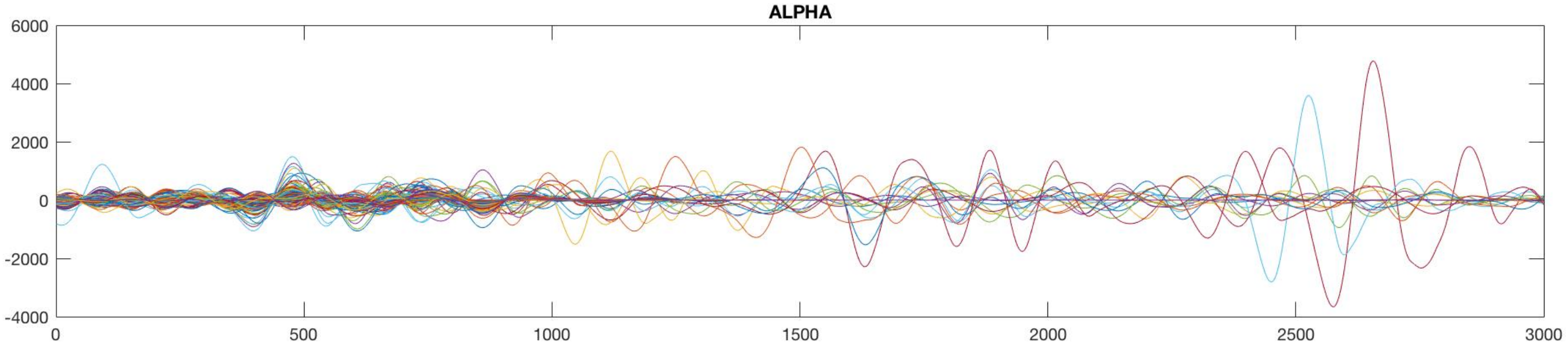
How can we extract mu and beta rhythms?

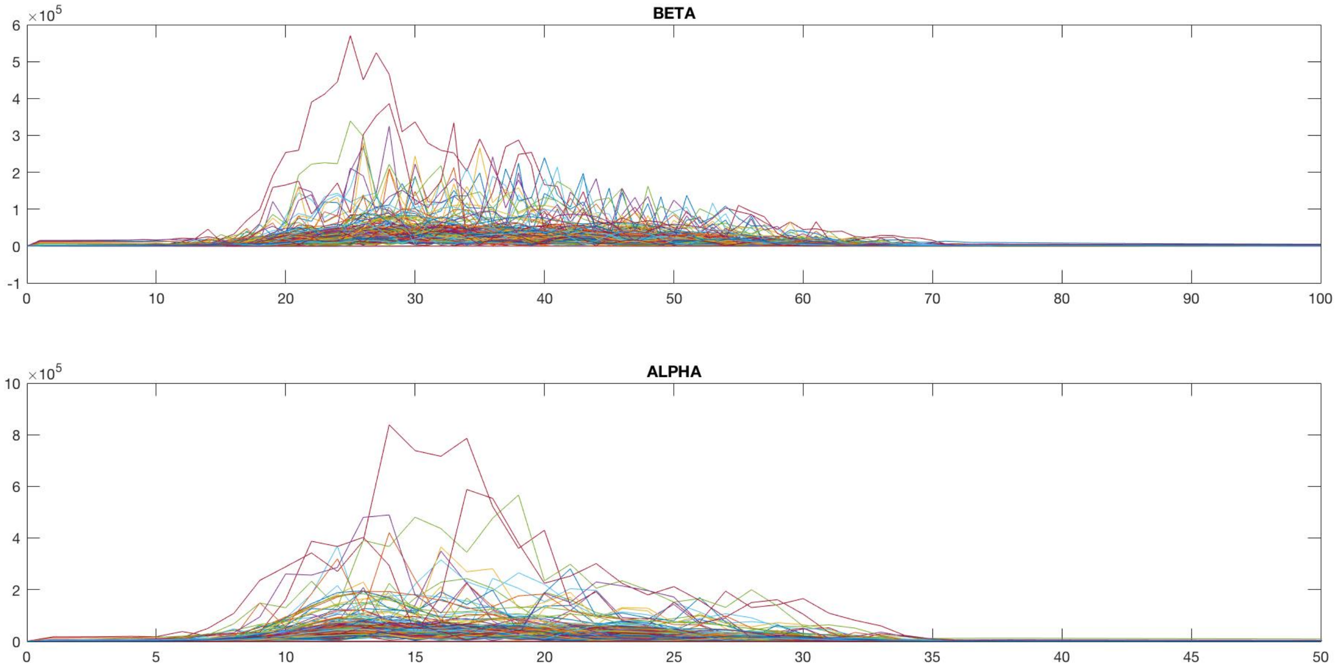


Wavelet Decomposition

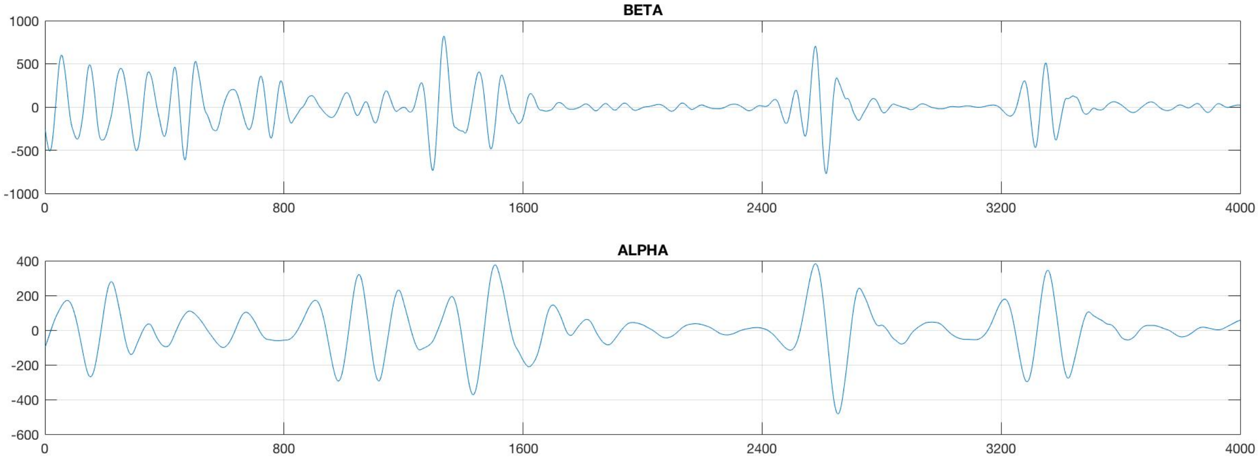

x[n]
g[n]
h[n]
↓2
Level 1
coefficients
Level 2
coefficients
Level 3
coefficients
Level 3
Level 2
Level 1
0
fn/8
fn/4
fn/2
fn
frequency


BETA
4000
2000
0
-2000
-4000
-6000
0
500
1000
1500
2000
2500
3000

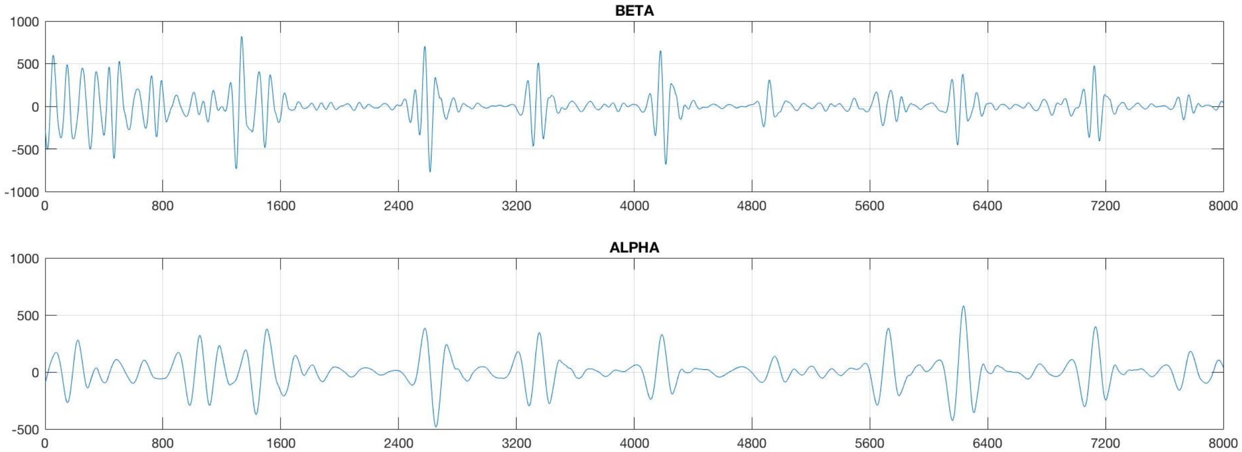

ALPHA
6000
4000
2000
0
-2000
-4000
0
500
1000
1500
2000
2500
3000

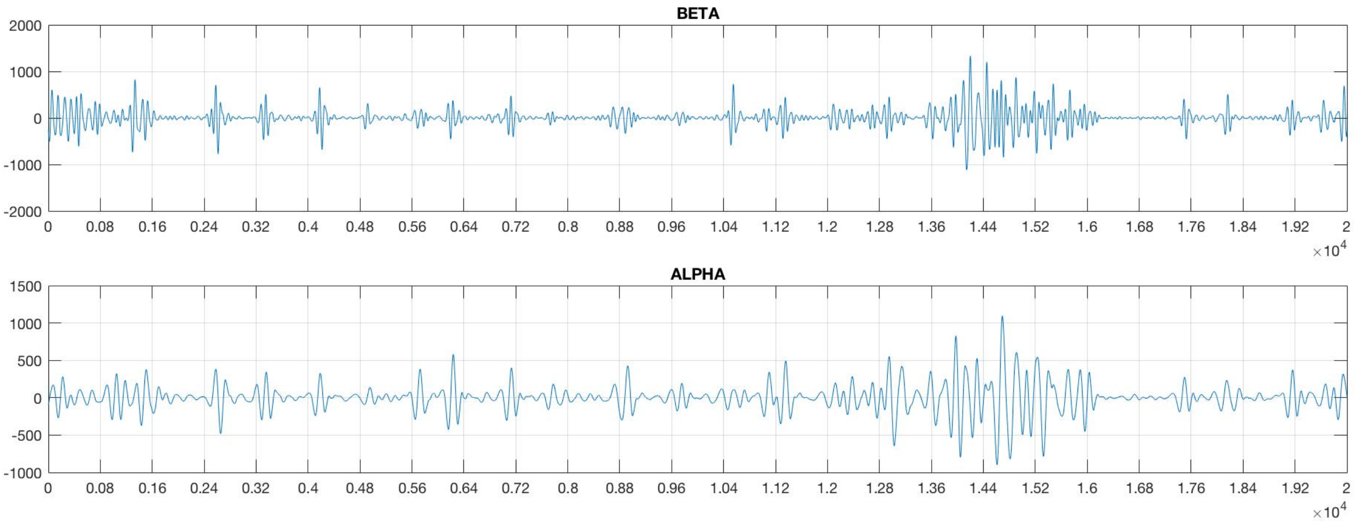

BETA
×10^5
6
5
4
3
2
1
0
-1
0
10
20
30
40
50
60
70
80
90
100
ALPHA
×10^5
10
8
6
4
2
0
0
5
10
15
20
25
30
35
40
45
50

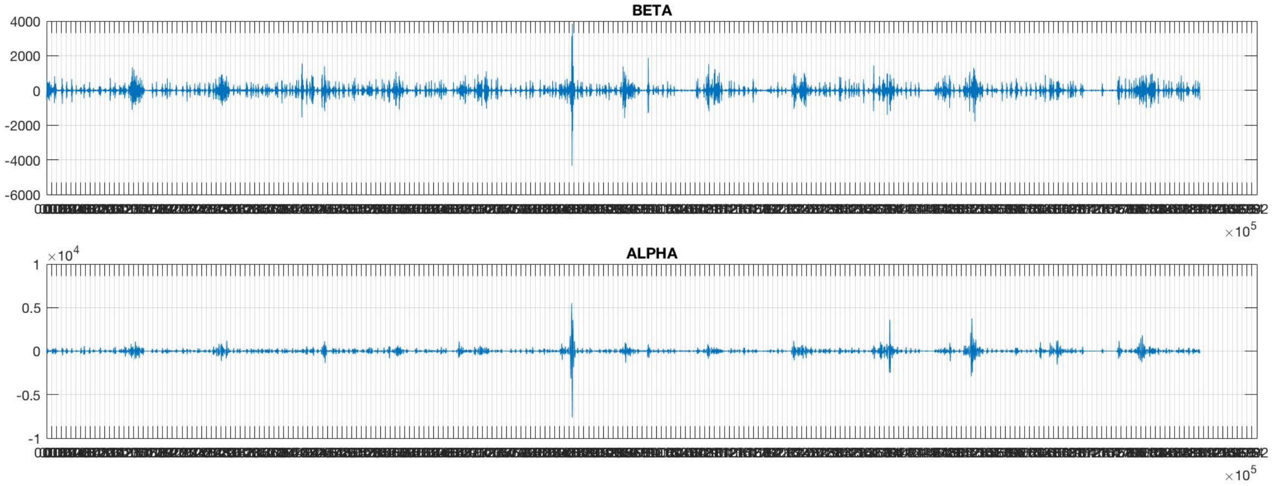
1 1 -1 1 1


BETA
1000
500
0
-500
-1000
0
800
1600
2400
3200
4000
ALPHA
400
200
0
-200
-400
-600
0
800
1600
2400
3200
4000

1 1 -1 1 1 1 1 -1 -1 1


BETA
1000
500
0
-500
-1000
0
800
1600
2400
3200
4000
4800
5600
6400
7200
8000
ALPHA
1000
500
0
-500
0
800
1600
2400
3200
4000
4800
5600
6400
7200
8000


BETA
2000
1000
0
-1000
-2000
0 0.08 0.16 0.24 0.32 0.4 0.48 0.56 0.64 0.72 0.8 0.88 0.96 1.04 1.12 1.2 1.28 1.36 1.44 1.52 1.6 1.68 1.76 1.84 1.92 2
×10^4
ALPHA
1500
1000
500
0
-500
-1000
0 0.08 0.16 0.24 0.32 0.4 0.48 0.56 0.64 0.72 0.8 0.88 0.96 1.04 1.12 1.2 1.28 1.36 1.44 1.52 1.6 1.68 1.76 1.84 1.92 2
×10^4


BETA
4000
2000
0
-2000
-4000
-6000
×10^5
ALPHA
×10^4
1
0.5
0
-0.5
-1
×10^5

Now we have mu and beta. Next:

features

Commonly used features

- FFT
- Wavelet coefficients
- Average time
- …

Spatial filter:

Σ_1 , Σ_2

channels $\times$concatenated timepoints → **CSP** → W , D

- Common spatial pattern (CSP) is a mathematical procedure used in signal processing for separating a multivariate signal into additive subcomponents which have maximum differences in variance between two windows.

$$W \Sigma_1 W^T = D \text{ and } W \Sigma_2 W^T = I - D$$

Classification

Common spatial pattern (CSP) is a mathematical procedure used in signal processing for separating a multivariate signal into additive subcomponents which have maximum differences in variance between two windows.
The CSP algorithm determines the component such that the ratio of variance (or second-order moment) is maximized between the two windows:

The CSP algorithm maximizes the variance of right hand trials, while simultaneously minimizing the variance for left hand trials.

W is a matrix of projections, where the i-th row has a relative variance of d_i for trials of class 1 and a relative variance of $1-d_i$ for trials of class 2
D is a diagonal matrix with entries $d_i \in [0, 1]$, with length n, the number of channels:

$W \Sigma_1 W^T = D$ and $W \Sigma_2 W^T = I - D$

Best discrimination is provided by filters with very high (emphasizing one class) or very low eigenvalues (emphasizing the other class)

We only include projections with the highest 2 and corresponding lowest 2 eigenvalues for our analysis.

LDA classifiers:

LDA

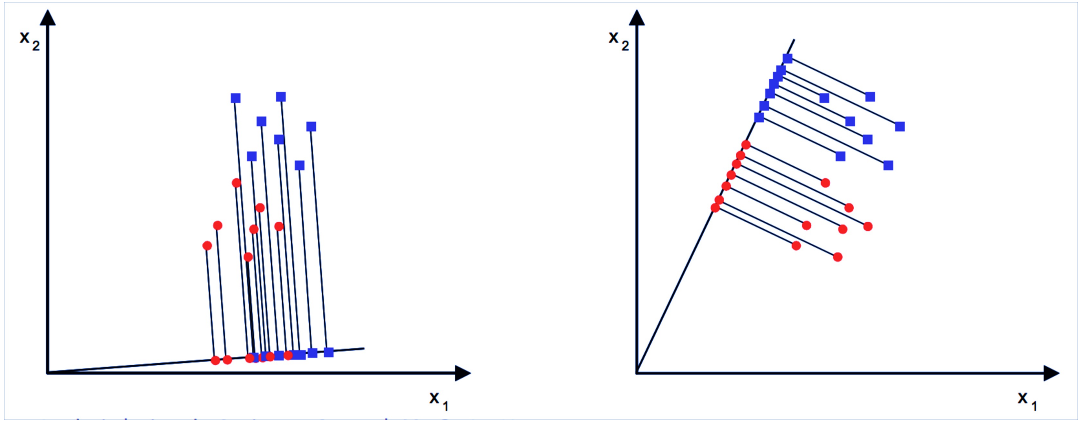
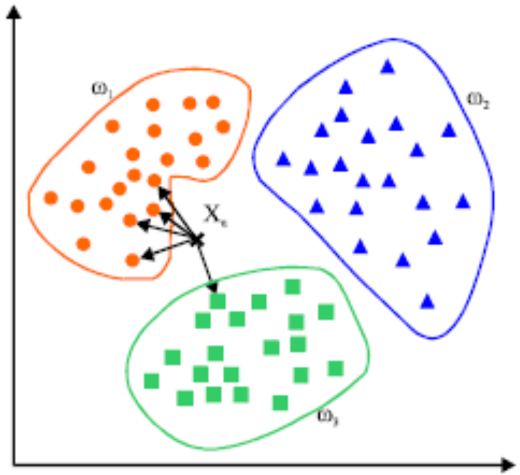


*Figure from Introduction to Common Spatial Pattern Filters for EEG Motor Imagery Classification
Tatsuya Yokota
Tokyo Institute of Technology
July 17, 2012

KNN classifiers

K nearest neighbors



KNN with cosine distance

Cosine KNN classifiers

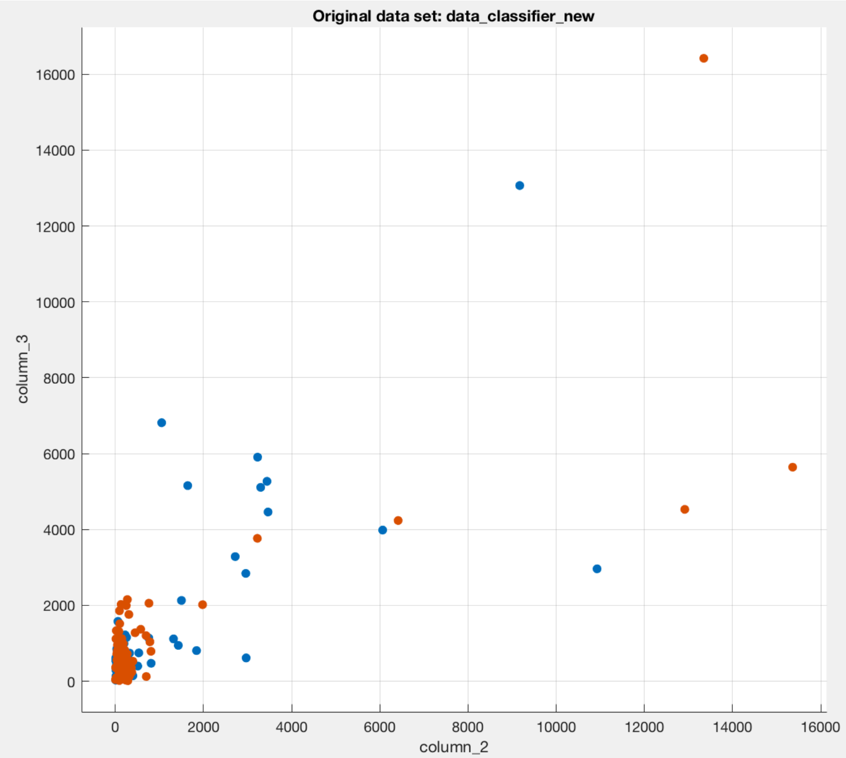
Cosine distance includes a dot product scaled by norms:

```
In[1]:= CosineDistance[{a, b, c}, {x, y, z}]
```

Out[1]=
$$1 - \frac{a\,x + b\,y + c\,z}{\sqrt{\mathrm{Abs}[a]^2 + \mathrm{Abs}[b]^2 + \mathrm{Abs}[c]^2}\;\sqrt{\mathrm{Abs}[x]^2 + \mathrm{Abs}[y]^2 + \mathrm{Abs}[z]^2}}$$

Results

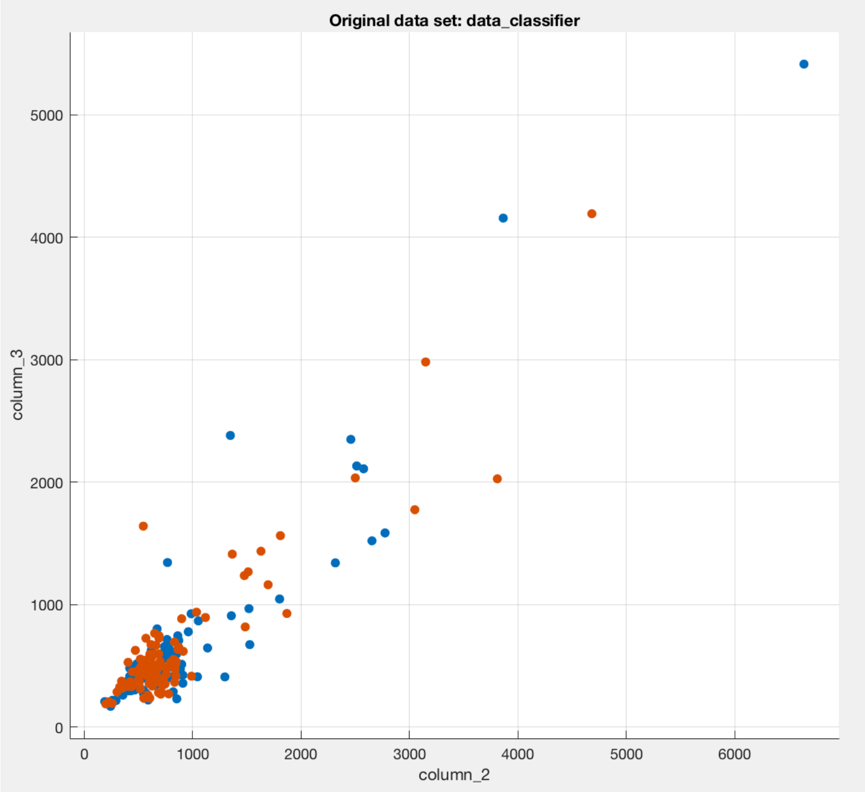
Classification using fft of mu and beta



5 fold cross validation
cosine KNN accuracy: 64.5%
fine KNN: 57%
Linear SVM: 59%
Logistic Regression : 54%
LDA: 54.5%

Mean and absolute mean time and frequency

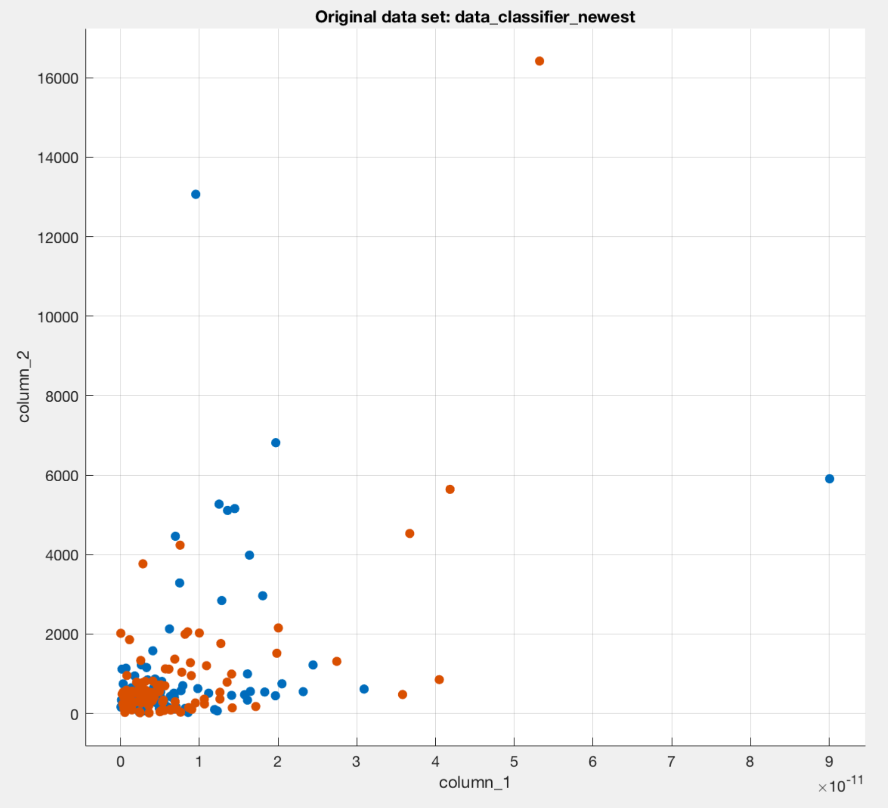
5 fold cross validation
Ensemble bag trees accuracy: 68%
Cosine KNN: 64.6%
Linear SVM: 59.5%
Logistic Regression : 56%
LDA: 54%

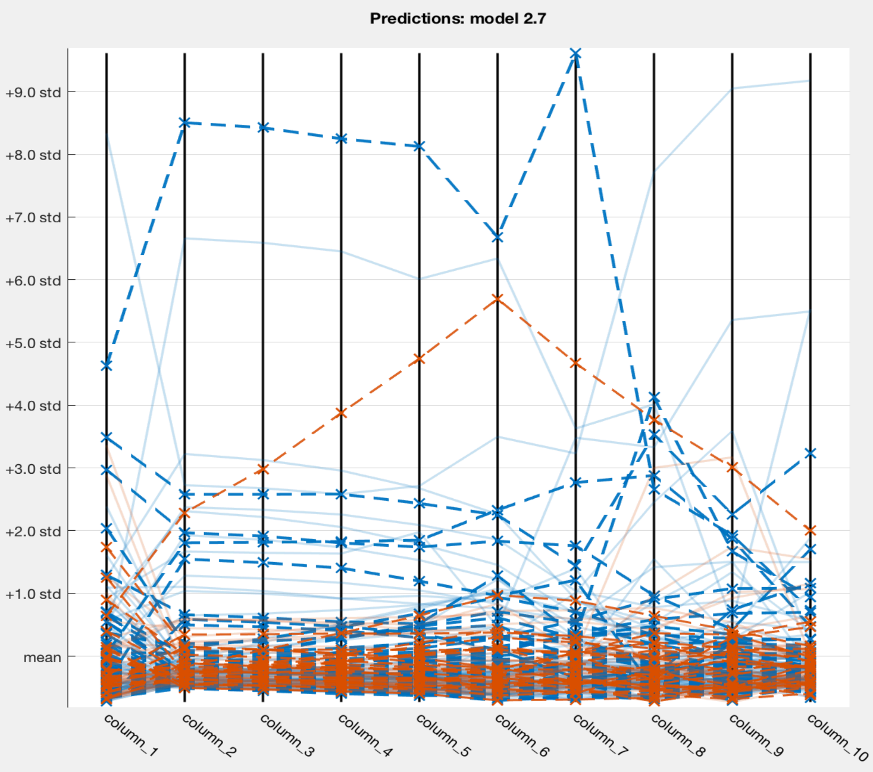


Frequency domain analysis

Ensemble bag trees accuracy: 68%
 cosine/cubic KNN: 66%
Large number of features: many
Methods could not be implemented

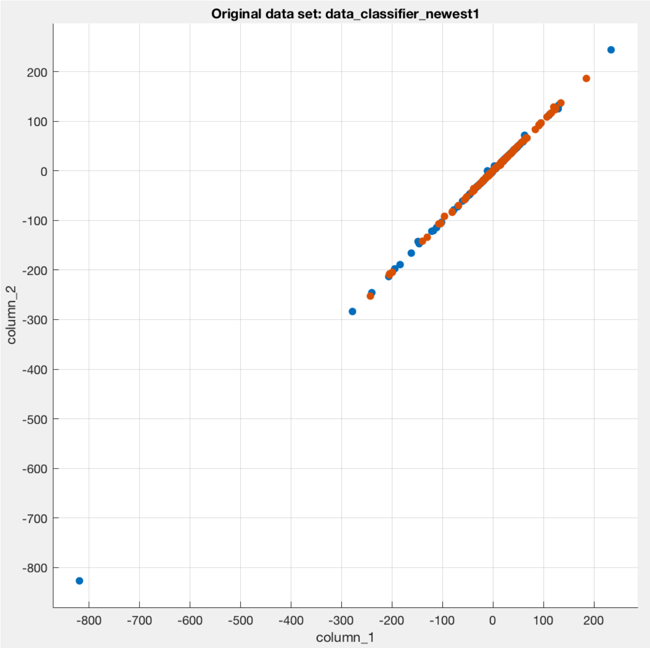
Cosine: distance metric




Predictions: model 2.7
+9.0 std
+8.0 std
+7.0 std
+6.0 std
+5.0 std
+4.0 std
+3.0 std
+2.0 std
+1.0 std
mean
column_1
column_2
column_3
column_4
column_5
column_6
column_7
column_8
column_9
column_10

Using Time

Cosine KNN, medium tree: 65.5%
Fine KNN: 64%



Discussion and conclusions

Better Accuracy:

- Feature selection
- More complex models
- More filters

#.	contributor	mse
1.	Zhang Haihong	0.382
2.	Dieter Devlaminck	0.383
3.	Kai Keng Ang	0.397
4.	Jun Lv	0.442
5.	Liu Guangquan	0.455
6.	Abdul Satti	0.459
7.	Fabian Bachl	0.466
8.	Jinyi Long	0.475
9.	Yunjun Nam	0.477
10.	Emily Mankin	0.499
11.	Cedric Gouy-Pailler	0.557
12.	Jing Jin	0.559
13.	Michael Buschbeck	0.679
14.	(*) Teodoro Solis-Escalante	0.692
15.	Chen Guangming	0.842
16.	Yu Huang	0.859
17.	Astrid Zeman	0.915
18.	Padma Palash	0.928
19.	Eric Gottschalk	0.930
20.	Sung Wook	0.972
21.	Manuel Moebius	1.007
22.	Rui Li	1.150
23.	Li Ke	1.156
24.	Yang Banghua	1.312

Conclusion

- Some channels seem to have more influence, yet we have to figure it out in practice (e.g. D4,D5)
- Cosine KNN seems to work best, while LDA does not perform as well in general. This is because of the nature of our features.
- We also calculated Correlation function, yet machine learning techniques seem to find better responses
- Time domain features seem to maintain as good results as frequency domain features. This is because they inherently have the same information within themselves.

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- ANALYSIS OF EEG FOR MOTOR IMAGERY BASED CLASSIFICATION OF HAND ACTIVITIES, A.Sivakami1 and S.Shenbaga Devi, 2015
- A Review on Motor Imagery Signal Classification for BCI, Rupal Chaudhari, Hiren J. Galiyawala, CGPIT, Uka Tarsadia University Surat, India, 2017.

Thanks!

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