

# BR41N.IO

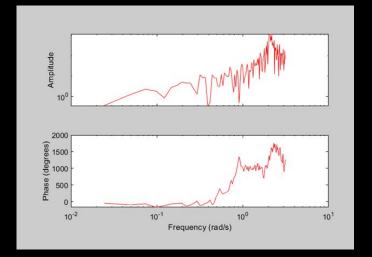
THE BRAIN-COMPUTER INTERFACE DESIGNERS HACKATHON

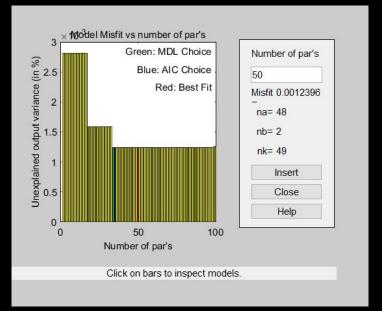
## **ECoG Hand Pose Data Analysis**

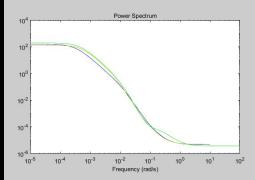
Amardeep, Bruno, Deepa, Lucas, Salina

- Preprocessing
  - Detrending
  - Notch Filter 50Hz and Harmonics
  - High-Gama filtering (70-140 Hz Bandpass)
  - Separation on Class Epochs (from -0.2s~2s)
  - Downsampling (200Hz)
  - Hilbert Enveloping
- Various Classifications Methodologies!

- ARMAX,ARMIA, FIR, Box Jenkins and SSM
- Time series modelling and forecasting experiments using system identification toolbox.
- Polynomial model tests and validation using error analysis and noise reduction.

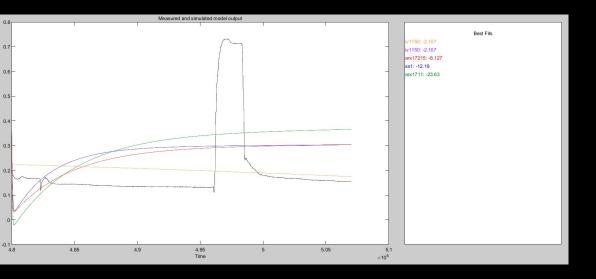






## TIME SERIES MODELLING- MATLAB

- Data for hand pose is cleaned and modelled against state space models and polynomial models.
- ARMAX, ARX, FIR and Box Jenkins algorithms were applied on the dataset after removing means and trends.
- System identification toolbox allows for addition of order selection and parameter experiments.



Status: Estimated using N4SID with prediction focus

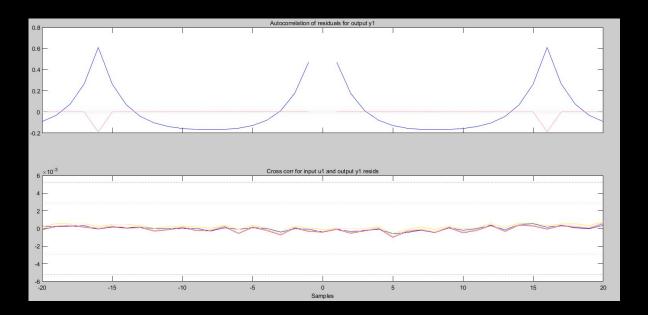
Fit to estimation data: **100%**, FPE: 2.24356e-21

Termination condition: Maximum number of iterations reached.

Number of iterations: 20, Number of function evaluations: 96

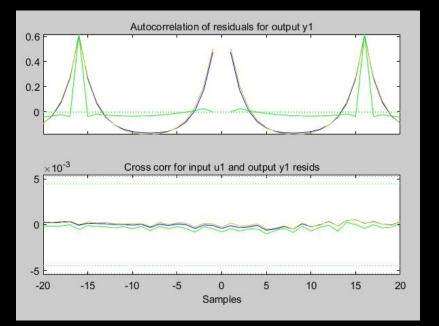
Status: Estimated using PEM with prediction focus

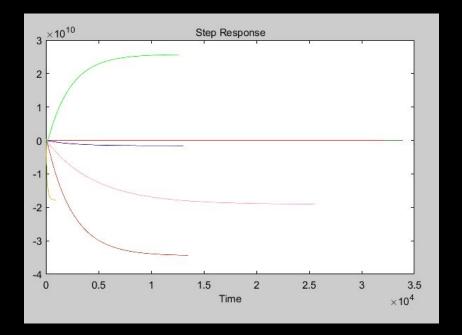
Fit to estimation data: **99.19%**, FPE: 2.96609e-06



**Status:** Estimated using N4SID with prediction focus

Fit to estimation data: **98.83%**, FPE: 6.56351e-06





```
Discrete-time ARX model: A(z)y(t) = B(z)u(t) + e(t)

A(z) = 1 - z^-1 - 2.68e-08 z^-2 - 2.037e-08 z^-3 + 4.979e-08 z^-4 - 3.265e-08 z^-5

- 1.266e-08 z^-6 + 2.085e-08 z^-7 - 2.936e-08 z^-8 + 4.379e-08 z^-9 - 3.041e-08 z^-

-10 + 9.161e-09 z^-11 - 6.709e-09 z^-12 + 5.334e-09 z^-13 - 7.097e-09 z^-14

+ 1.079e-09 z^-15 - 0.6541 z^-16 + 0.6541 z^-17
```

```
Continuous-time identified state-space model:

dx/dt = A x(t) + B u(t) + K e(t)

y(t) = C x(t) + D u(t) + e(t)

A =

x1  x2

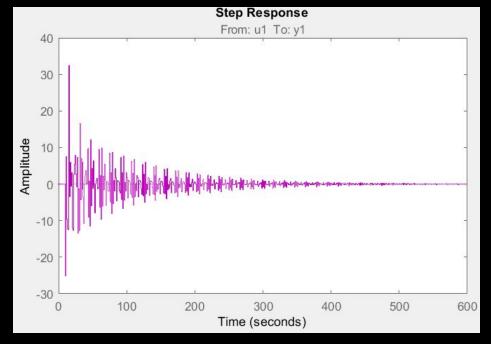
x1 -1.526e-05 -0.002405
```

```
Discrete-time ARIMAX model: A(z)y(t) = B(z)u(t) + [C(z)/(1-z^{-1})]e(t)

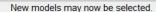
A(z) = 1 + 2.079 z^{-1} + 2.415 z^{-2} + 2.679 z^{-3} + 2.371 z^{-4} + 2.066 z^{-5} + 2.395 z^{-6} + 2.19 z^{-7} + 1.526 z^{-8} + 0.7685 z^{-9} + 0.08559 z^{-10}

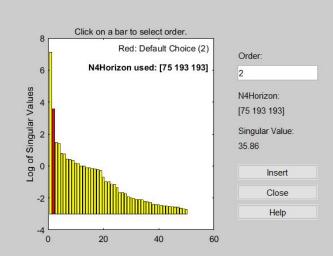
B(z) = -25.16 z^{-10} - 19.58 z^{-11} - 9.849 z^{-12} - 26.77 z^{-13} - 19.3 z^{-14} + 17.53 z^{-15} + 16.46 z^{-16} + 24.31 z^{-17} + 32.99 z^{-18} + 9.372 z^{-19}

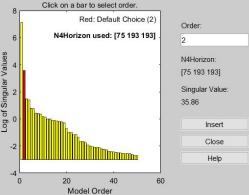
C(z) = 1 + 2.169 z^{-1} + 2.587 z^{-2} + 2.927 z^{-3} + 2.595 z^{-4} + 2.165 z^{-5} + 2.602 z^{-6} + 2.575 z^{-7} + 1.989 z^{-8} + 1.323 z^{-9} + 0.4207 z^{-10}
```



#### Model Misfit vs number of par's 0.01 Blue: MDL Choice Number of par's Blue: AIC Choice 38 € 0.008 Red: Best Fit Misfit 0.0046545 900.00 na= 35 nb= 3 nk= 1 Insert ₹ 0.002 Close Help 20 60 80 Number of par's







## Status: Estimated using N4SID with prediction focus

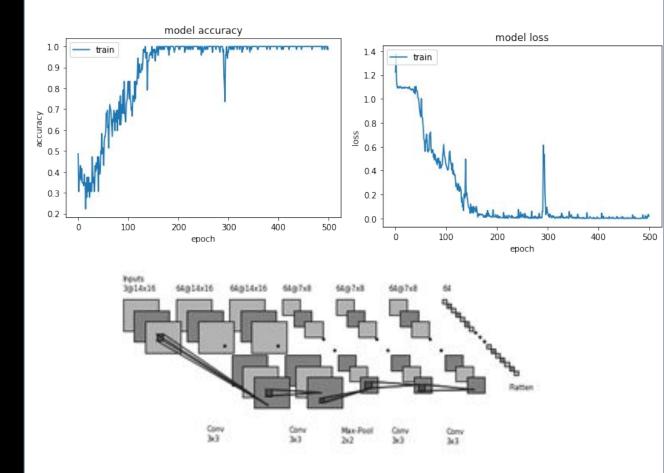
Fit to estimation data: 98.91%, FPE: 5.0093e-06

								Norm of	First-order
Impr	ovement (%) It	eration	Cost ste	p opt	imality	Expected	Achieved	Bisections	
0	4.69629e-06	- 3	.62e+07 2	20.8					
1	4.17459e-06	3.14	1.42e+07	20.8	11.1	2			
2	4.14543e-06	0.591	1.2e+07	11.7	0.699	3			
3	4.11706e-06	0.417	1.04e+07	11.4	0.684	3			
4	3.96814e-06	0.632	7.53e+06	11	3.62	2			
5	3.79486e-06	0.757	1.08e+07	7.81	4.37	1			
6	3.73595e-06	0.533	1.87e+07	3.1	1.55	0			
7	3.71418e-06	0.347	2.78e+07	1.35	0.583	0			
8	3.70704e-06	0.331	8.38e+06	0.948	0.192	0			
9	3.69764e-06	0.17	1.58e+07	0.785	0.254	1			
10	3.68309e-06	0.235	9.66e+06	0.511	0.393	0			
11	3.68238e-06	0.105	7.38e+06	0.194	0.0193	2			
12	3.67828e-06	0.0767	1.7e+06	0.138	0.111	0			
13	3.67764e-06	0.0999	1.59e+06	0.0323	0.0176	5 0			
14	3.67747e-06	0.0558	1.16e+06	0.0195	0.0046	5 1			
15	3.67732e-06	0.00148	1.83e+05	0.0086	0.0041	12 0			

Termination condition: Near (local) minimum, (norm(g) < tol). Number of iterations: 15, Number of function evaluations: 46

**Status:** Estimated using SSEST with prediction focus Fit to estimation data: **99.07%**, FPE: 3.67745e- 7

- 2D-Convolutional Neural Network
  - Using the EEG Signal as a (pseudo)image matrix (61,110,3)
  - Inspired on VGGNet model With only 3x3 convolutions and 2x2 Maxpolings
  - 10-Fold CV shows and average accuracy of 79%



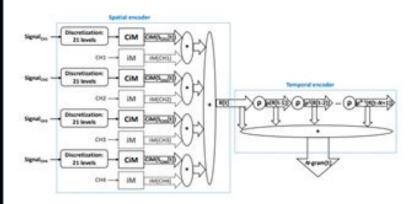
Training accuracy and loss of and early test model and architecture of the model

R. Laezza, "Deep neural networks for myoelectric pattern recognition - An implementation for multifunctional control," 2018.

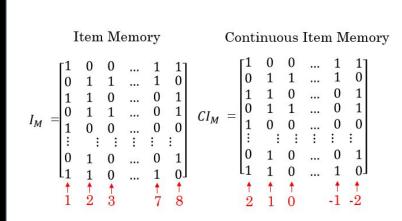
- Hyperdimensional Computing
  - Initially proposed by Kanerva, for NPL processing. Some studies on biosignals
  - Brain inspired using high dimension (<10.000) (pseudo)random i.i.d binary vectors.
  - 10-Fold CV shows and average accuracy of 65%

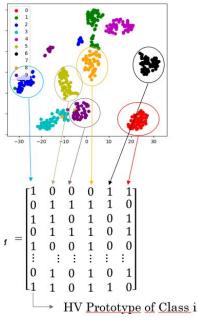
A. Rahimi et al. "Hyperdimensional biosignal processing: A case study for EMG-based hand gesture recognition," in 2016

P. Kanerva, "Hyperdimensional computing: An introduction to computing in distributed representation with high-dimensional random vectors,"



Pipeline of the spatial and temporal encoding process (adapted from reference)

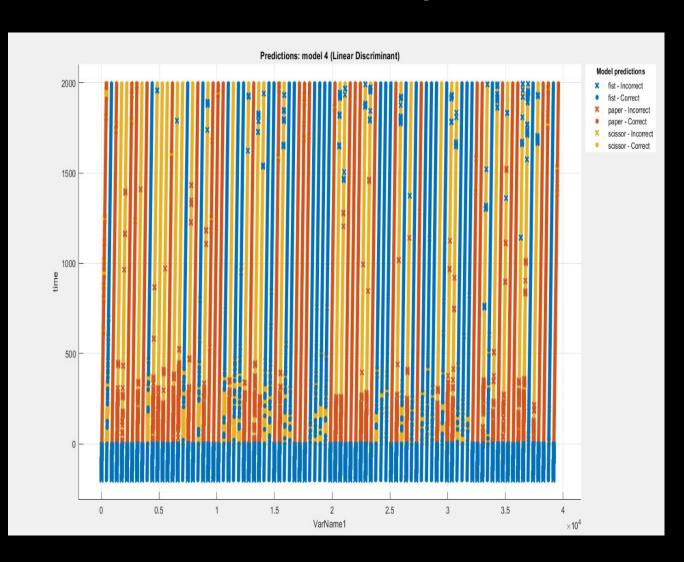




Representations of the Memories used in the classification algorithm

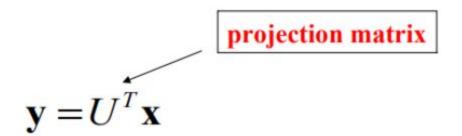
## Principal Component and Linear Discriminant Analysis

- First Band pass filter is applied
- then 10 cross validation partitioning the data set into folds and estimating accuracy on each fold.
- Principal Component Analysis (PCA) is first applied to the data set .
- The goal of PCA is to reduce the dimensionality of the data while retaining as much as possible of the variation present in the dataset.
- PCA weights are computing based only on training data .
- LDA is then applied to find the most discriminative directions.
- 10-Fold CV shows and average accuracy of 86.1%



## LDA

Methodology



 LDA computes a transformation that maximizes the between-class scatter while minimizing the within-class scatter:

$$\max \frac{|U^T S_b U|}{|U^T S_w U|} = \max \frac{|\tilde{S}_b|}{|\tilde{S}_w|} \qquad \boxed{\text{products of eigenvalues !}}$$

 $\tilde{S}_{b}, \tilde{S}_{w}$  : scatter matrices of the projected data  ${f y}$ 

## What We Would Do

- Better Preprocessing!
  - More Frequencies
  - Channel selection
- More emphasis on length of the classification window
- Rigorous comparison between models

Thank You!