Decoding of Hand Gestures from Electrocorticography with LSTM Based Deep Neural Network

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Jathurshan Pradeepkumar [1], Mithunjha Anandakumar [1], Vinith Kugathasan[1],
Thilina D. Lalitharatne[2], Anjula C. De Silva[1], Simon L. Kappel[3]

1 Department of Electronic and Telecommunication Engineering, University of Moratuwa, Sri Lanka.

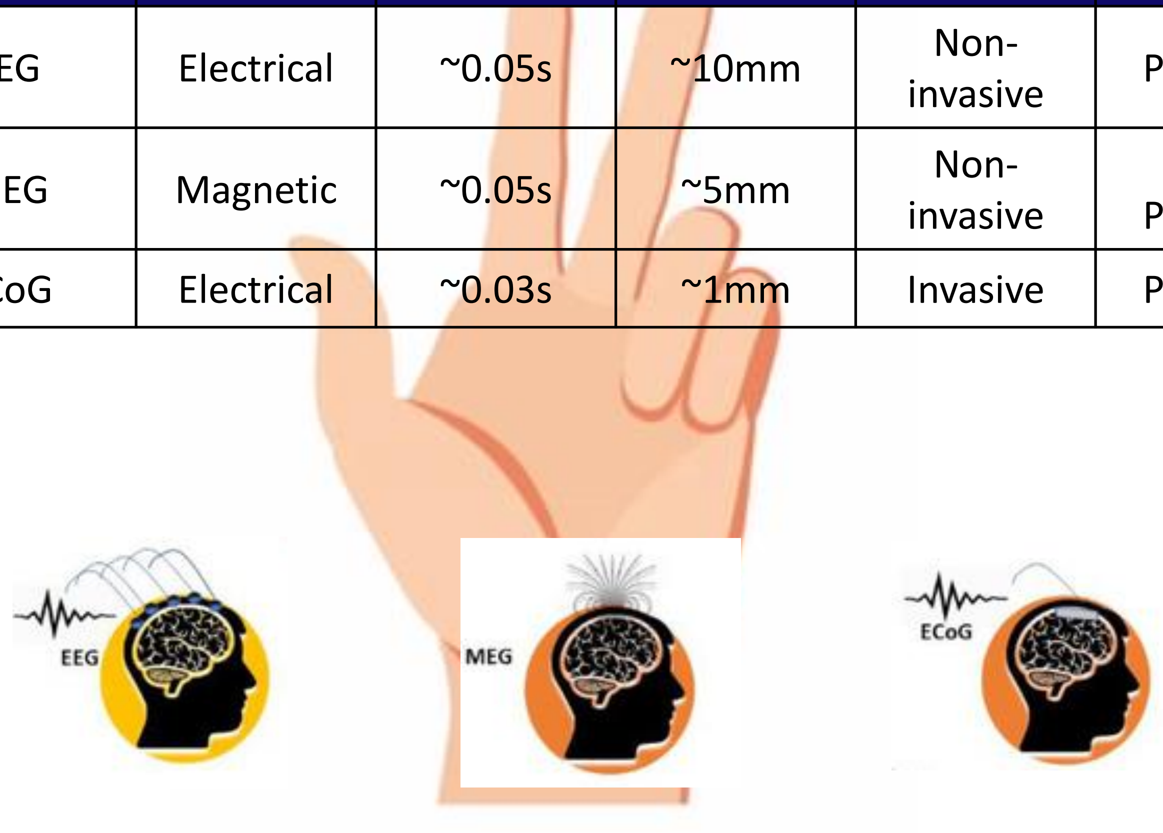
2 Dyson School of Design Engineering, Imperial College London, UK.

3 Department of Electrical and Computer Engineering, Aarhus University, Denmark.

Background

- ECOG – BCI
- Problem statement
  - Hand gesture decoder
  - Deep Learning

Modality	Signal Type	Temporal Resolution	Spatial Resolution	Method Type	Portability
EEG	Electrical	~0.05s	~10mm	Non-invasive	Portable
MEG	Magnetic	~0.05s	~5mm	Non-invasive	Non-Portable
ECoG	Electrical	~0.03s	~1mm	Invasive	Portable



T. Jiang et al., "Characterization and Decoding the Spatial Patterns of Hand Extension/Flexion using High Density ECoG, "IEEE Trans. Neural Syst. Rehabil. Eng., vol. 25, no. 4, pp. 370-379, 2017

Image Source : G. Pandarinathan, S. Mishra, A. M. Nedumaran, P. Padmanabhan, and B. Gulyás, "The potential of cognitive neuroimaging: A way forward to the mind-machine interface," *Journal of Imaging*, vol. 4, no. 5. 2018.

Previous Works

- High gamma frequencies (>65Hz) [1]

Preprocessing

- Support Vector Machine – SVM [1]
- Linear Discriminant Analysis – LDA [4]
- Time Invariant Linear Discriminant Analysis – TVLDA [3]
- Recurrent Neural Network – RNN [2]

Classification

- Feature Selection - Statistical based [3]
- Common Spatial Patterns – CSP [4]
- Principal Component Analysis – PCA[3]

Feature Reduction

* References on the slide 21

Previous Works

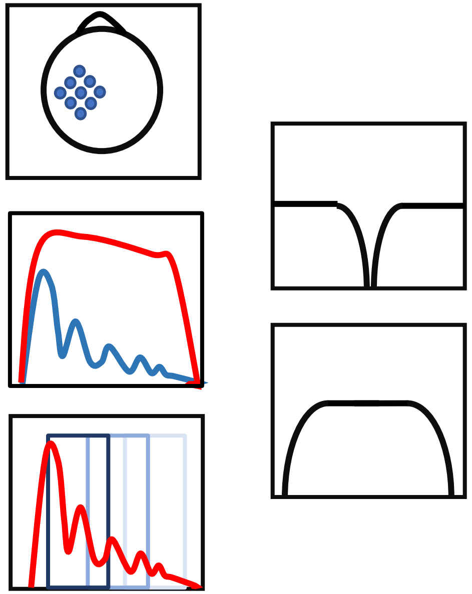
- Few studies have utilized temporal information [2,3]
- Equal importance to variations in different frequency bands
- Channel selection for each frequency band

We propose,

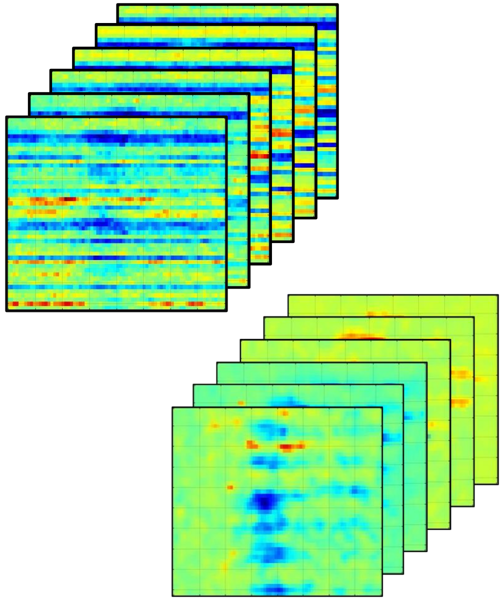
- Novel LSTM Based Deep Neural Network Architecture
- Channel Reduction by giving equal importance to each frequency band.
    - Statistical Based Channel Selection
    - PCA

* References on the slide 21

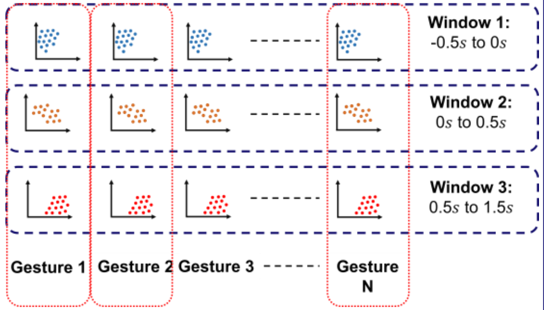
Overview



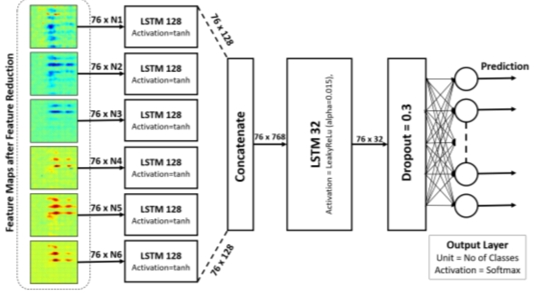
Preprocessing



PSD Based Feature Extraction



Statistical and PCA based Feature Reduction



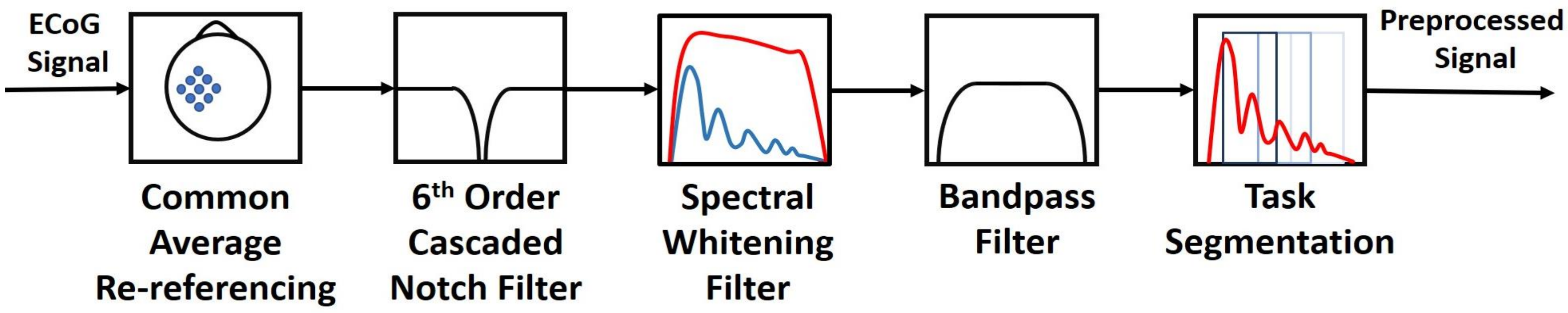
LSTM based Classification

Dataset & Preprocessing

- 'FingerFlex' Dataset *
- 7 participants
- 150 trials/participant
- 1 kHz Sampling Rate

Table : Datasets

Code	Age	Gender	Handedness	Hemisphere	No. Of Electrodes
bp	18	F	Right	Left	46
cc	21	M	Right	Right	63
zt	27	F	Right	Left	61
jp	35	F	Right	Left	58
ht	26	M	Right	Left	64
wc	32	M	Right	Left	64
jc	18	F	Right	Left	47



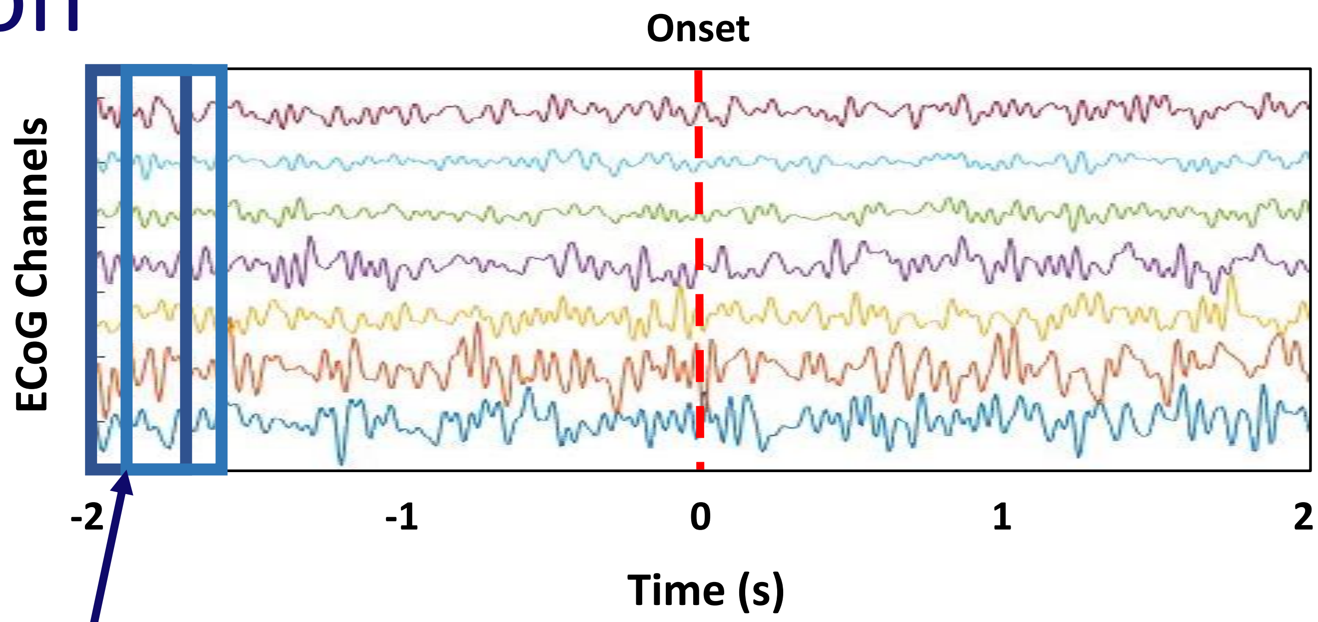
* K. Miller et al., "Human Motor Cortical Activity Is Selectively Phase-Entrained on Underlying Rhythms," PLoS Computational Biology, vol. 8, no.9, 2012.

J. Gruenwald, A. Znobishchev, C. Kapeller, K. Kamada, J. Scharinger, and C. Guger, "Time-variant linear discriminant analysis improves hand gesture and finger movement decoding for invasive brain computer interfaces," Front. Neurosci., vol. 13, no. Sep, 2019.

Feature Extraction

$$x_m$$

ECoG segment for gesture trial m



$$x_m^{(t)}$$

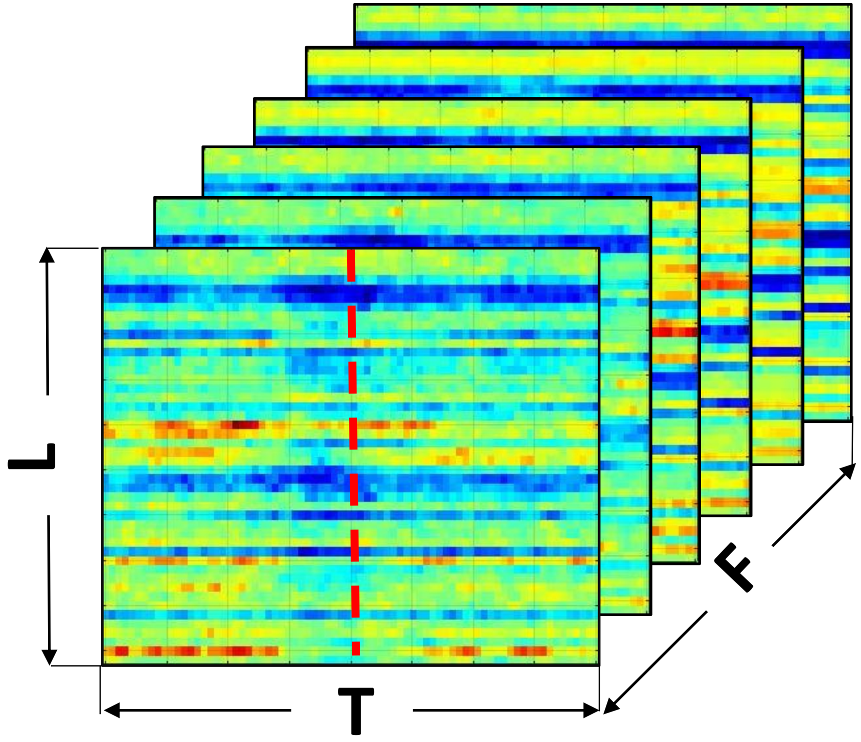
Window Size : 250 ms
Overlap : 50 ms

$$PSD\ for\ each\ segment: S_{l,m}^{(t)}(k) = \frac{1}{N}\left|\sum_{n=0}^{N-1} h(n) x_{l,m}^{(t)}(n) e^{-\left(\frac{j2\pi kn}{N}\right)}\right|^2$$

l : ECoG Channel
m : Gesture Trial
N : Total number of samples
t : A segment of $x_{(l,m)}$
k : frequency bin
$h(n)$: Hamming window

Feature Extraction

$$PSD\ for\ each\ segment: S_{l,m}^{(t)}(k)$$



Frequency Bands :

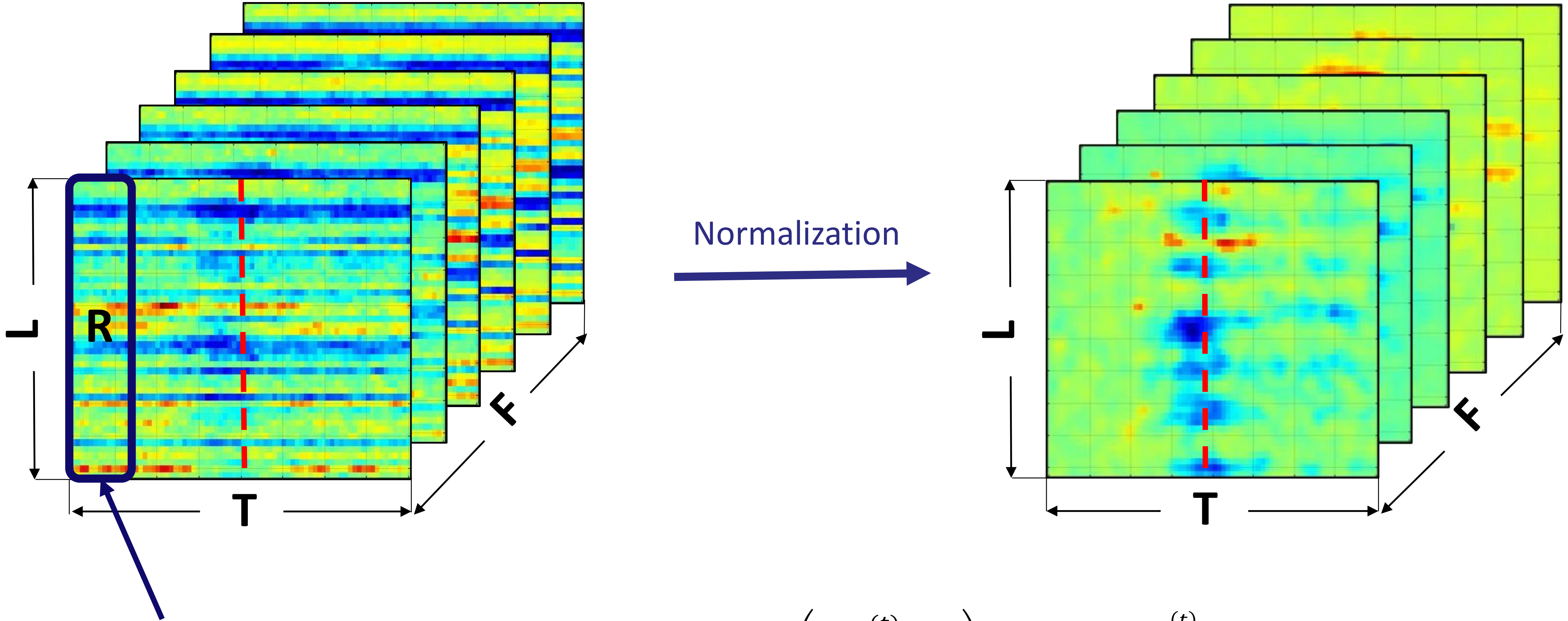
- Theta : 4-8 Hz
- Alpha : 8-12 Hz
- Beta : 12-40 Hz
- Low Gamma : 40-70 Hz
- High Gamma : 70-135 Hz
- High Frequency : 135-200 Hz

Average PSD for Frequency Band f:

$$A_{l,m,f}^{(t)} = \frac{1}{N_f}\left|\sum_{i=1}^{N_f} S_{l,m}^{(t)}(k_{f,i})\right|$$

N_f: Total number of frequency bins
$k_{f,i}$: i^{th} frequency bin for frequency band
f : Frequency band
$S_{l,m}^{(t)}$: PSD of each segment

Feature Extraction



Relaxation Period

-2s to -1.5s

$$A^{(t)}_{norm,l,m,f} = 10log_{10}\left(\frac{A^{(t)}_{l,m,f}}{\bar{A}_{relax,l,m,f}}\right)$$

$A^{(t)}_{norm,l,m,f}$: Normalized PSD

$A^{(t)}_{l,m,f}$: Average PSD for frequency band f

$\bar{A}_{relax,l,m,f}$: Average relaxation PSD

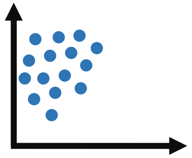
Y. Li et al., “Gesture Decoding Using ECoG Signals from Human Sensorimotor Cortex: A Pilot Study,” Behav. Neurol., vol. 2017, pp.1-12, 2017.

Feature Reduction

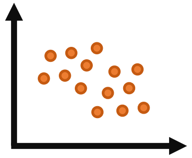
1. Statistical Based Channel Selection

2. Principal Component Analysis

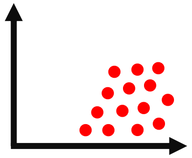
Statistical Based Channel Selection



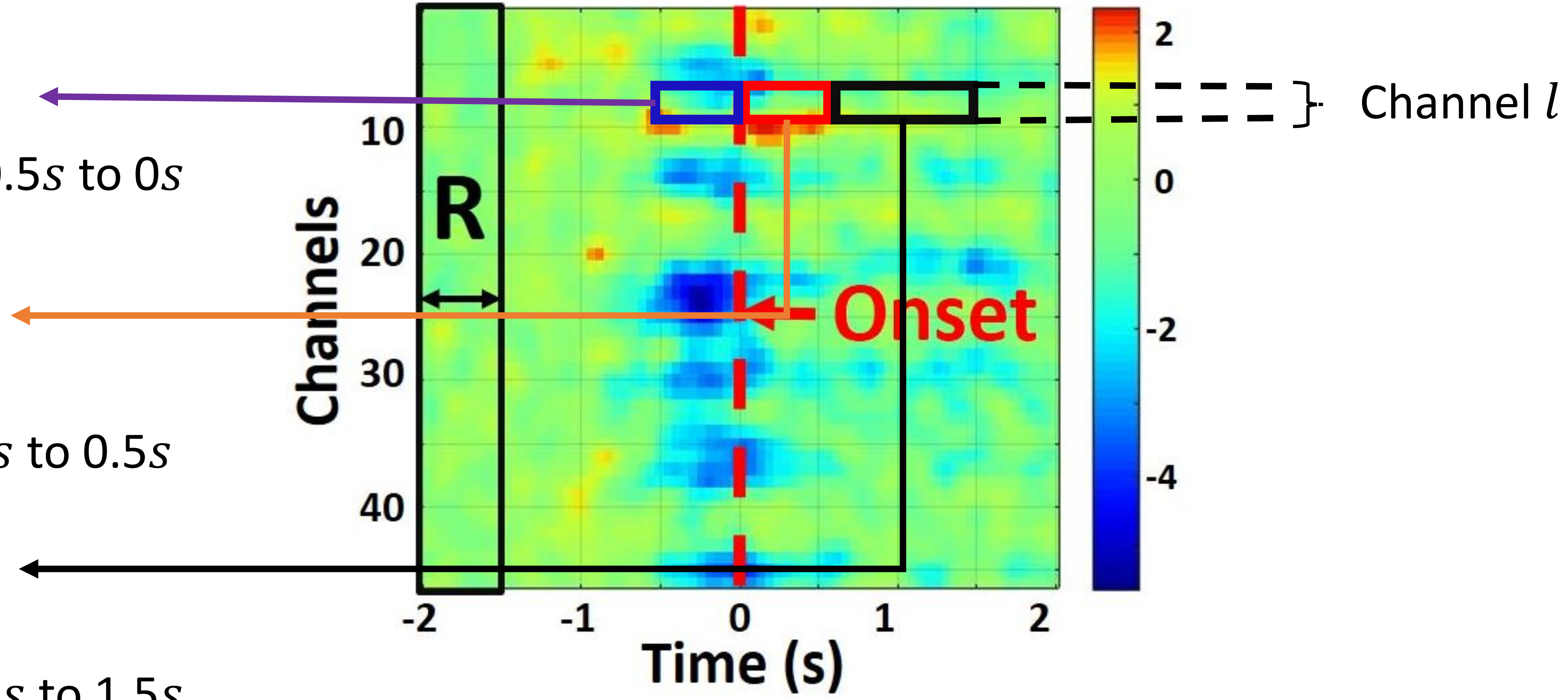
Before onset: $-0.5s$ to $0s$



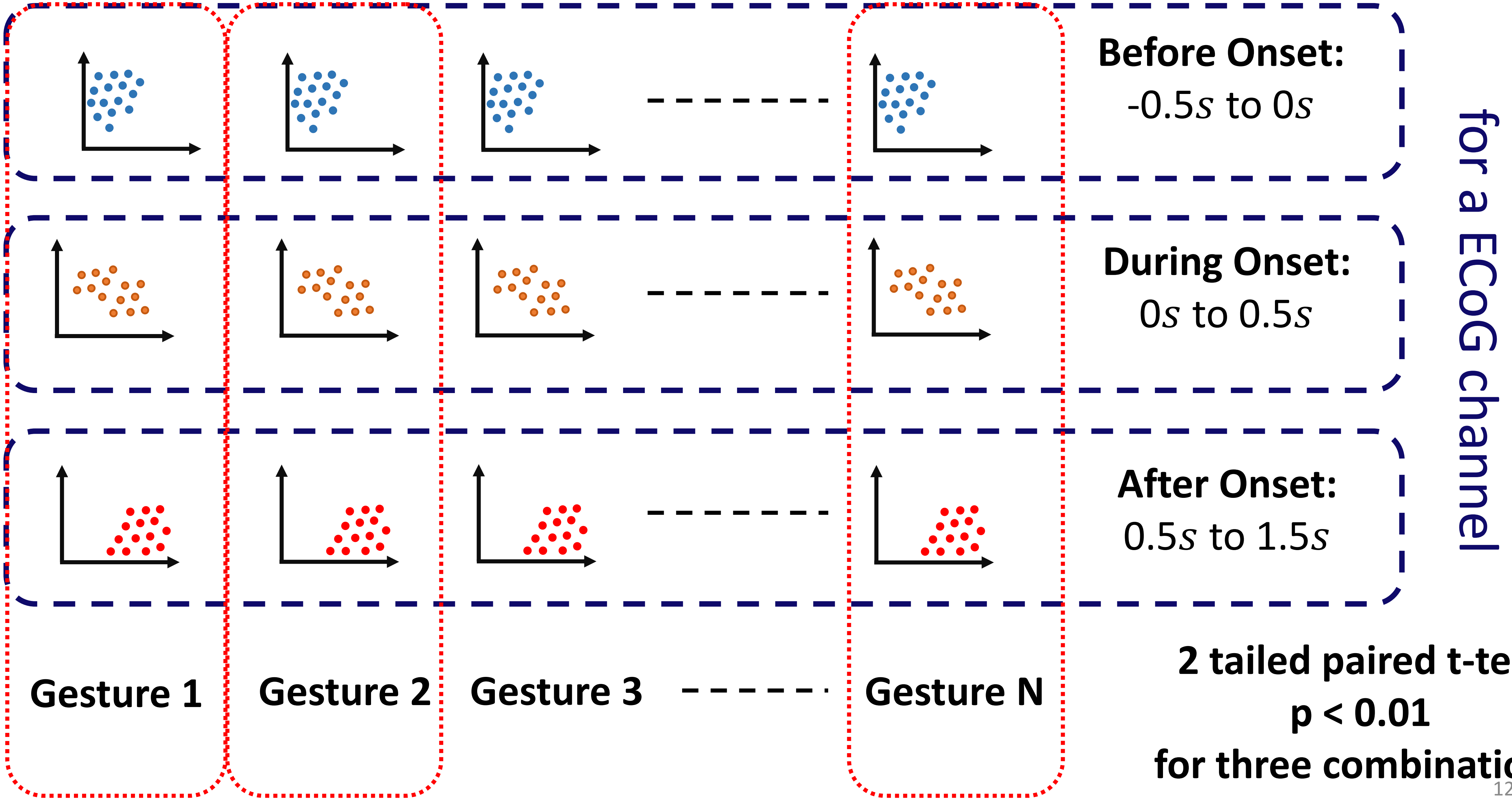
During onset : $0s$ to $0.5s$



After onset: $0.5s$ to $1.5s$



Statistical Based Channel Selection



2 tailed paired t-test
$p < 0.01$
for three combinations

Principal Component Analysis

PCA along this axis

Channels	Gesture Trial 1					Gesture Trial 2					Gesture Trial M				
	Segment 1	Segment 2	Segment 3	......	Segment T	Segment 1	Segment 2	Segment 3	......	Segment T	Segment 1	Segment 2	Segment 3	......	Segment T
1															
2															
3															
4															
5															
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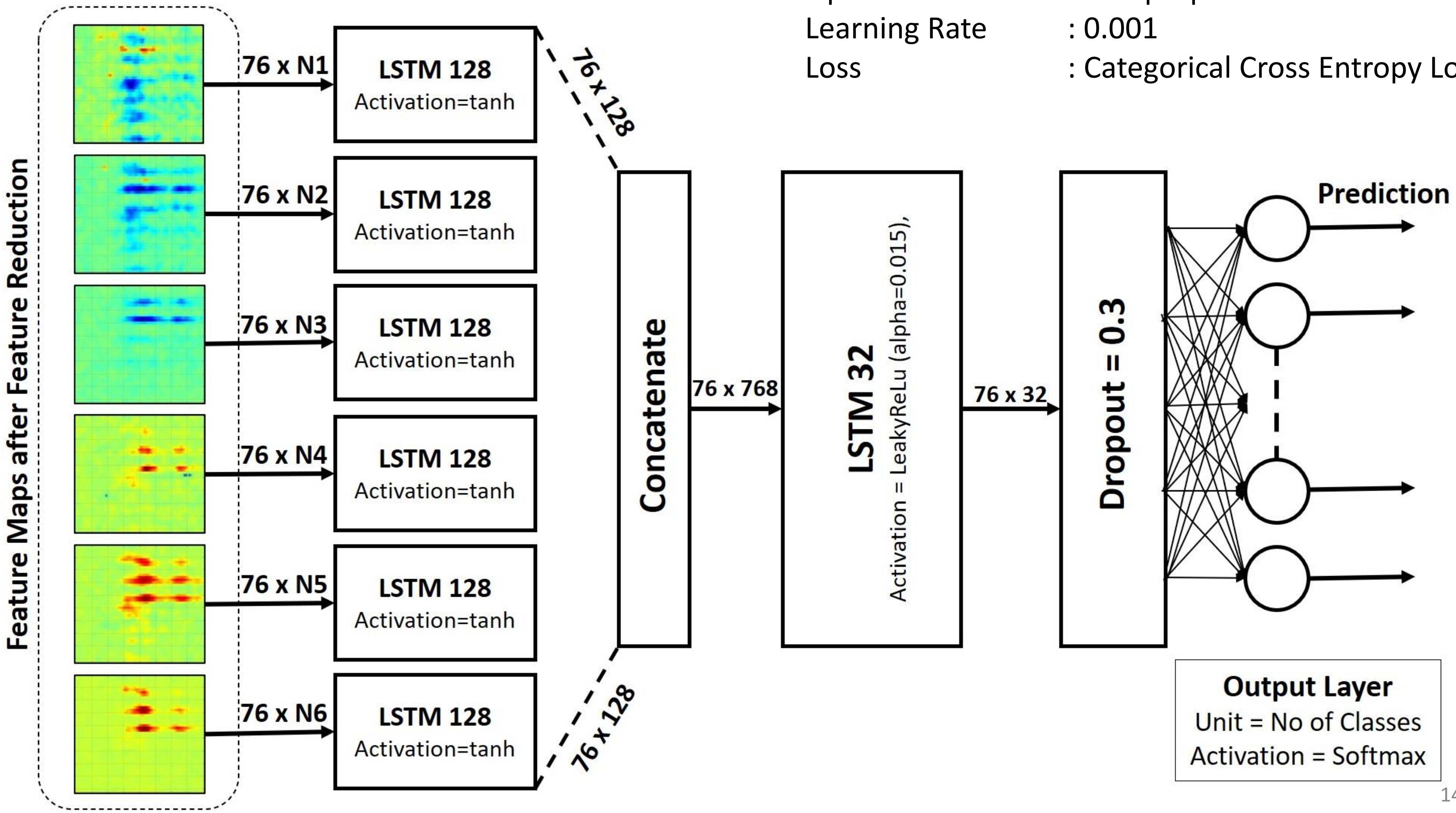
Gesture Classification

Optimizer : RMSprop
Learning Rate : 0.001
Loss : Categorical Cross Entropy Loss



Results and Discussion

- Stratified 10-fold cross validation accuracy
- Gruenwald et al [1]
  - For 7 subjects : 79.6
- Onaran et al [2] :
  - For first 3 subjects : 86.3%
- Proposed Method:
  - With PCA : 77.0%
  - With Statistical Channel Selection : 82.4 %

Table : Classification Accuracy

Code	Gruenwald et al, 2019 [1]	Proposed architecture with PCA	Proposed architecture with statistical channel selection
bp	89.4 ± 1.3	82.6±10.3	89.8±6.7
cc	82.8±1.2	83.7±7.2	85.4±6.7
zt	85.7±1.2	84.9±7.2	86.6±9.2
Average (bp,cc,zt)	85.9	83.7	**87.3**
jp	77.3±2.0	70.4±11.3	79.2±12.1
ht	64.5±3.2	66.1±8.6	69.7±6.5
wc	80.1±1.7	71.4±11.8	79.7±6.0
jc	77.5±1.7	80.2±7.5	86.7±4.2
Average (All)	79.6	77.0	**82.4**

[1] J. Gruenwald, A. Znobishchev, C. Kapeller, K. Kamada, J. Scharinger,and C. Guger, “Time-variant linear discriminant analysis improves hand gesture and finger movement decoding for invasive brain-computer interfaces,” Front. Neurosci., vol. 13, no. Sep, 2019.

.[2] Onaran, N. Ince, and A. Cetin, “Classification of multichannel ECoG related to individual finger movements with redundant spatial projections,” 2011 Ann. Int. Conf. IEEE Eng. Med. Biol. Soc., 2011.

Conclusion

- ✓ LSTM based novel deep neural network architecture
  - ✓ To provide equal importance for each frequency band
- ✓ Experimented with two feature reduction approaches
  - ✓ PCA and statistical based channel selection approaches
- ✓ Achieved accuracy better than state-of-the-art methods.

References

[1] Yanagisawa et al., “Real-time control of a prosthetic hand using human electrocorticography signals: Technical note,” J. Neurosurg.,vol. 114, no. 6, pp. 1715-1722, 2011.

[2] G. Pan et al., “Rapid decoding of hand gestures in electrocorticography using recurrent neural networks,” Front. Neurosci., vol. 12, no. Aug,2018.

[3] J. Gruenwald, A. Znobishchev, C. Kapeller, K. Kamada, J. Scharinger,and C. Guger, “Time-variant linear discriminant analysis improves hand gesture and finger movement decoding for invasive brain-computer interfaces,” Front. Neurosci., vol. 13, no. Sep, 2019.

[4] C. Kapeller et al., “Single trial detection of hand poses in human ECoG using CSP based feature extraction,” 36th Ann. Int. Conf. IEEE Eng.Med. Biol. Soc., 2014

Thank You

Our code is available at:
https://github.com/Jathurshan0330/Decoding-of-Hand-Gestures-from-Electrocorticography-with-LSTM-Based-Deep-Neural-Network

Further Inquires :

Jathurshan Pradeepkumar
Department of Electronic and Telecommunication,
University of Moratuwa, Sri Lanka.
jathurshanpradeepkumar@gmail.com
+94777150631