Gated recurrent unit network for decomposition of synthetic high-density surface Electromyography signals

Content

- Motivation and Objective
- Biological Background of EMG
  - Generation
  - Decomposition
  - Recording
- Methods and Neural Network Implementation with results
  - First method with motor unit activation labels
  - Second method with raw innervation pulse train
- Conclusion and Future scope

Project Motivation

Motivation: Humans preform many tasks using Neuro-Muscular system with precise controls

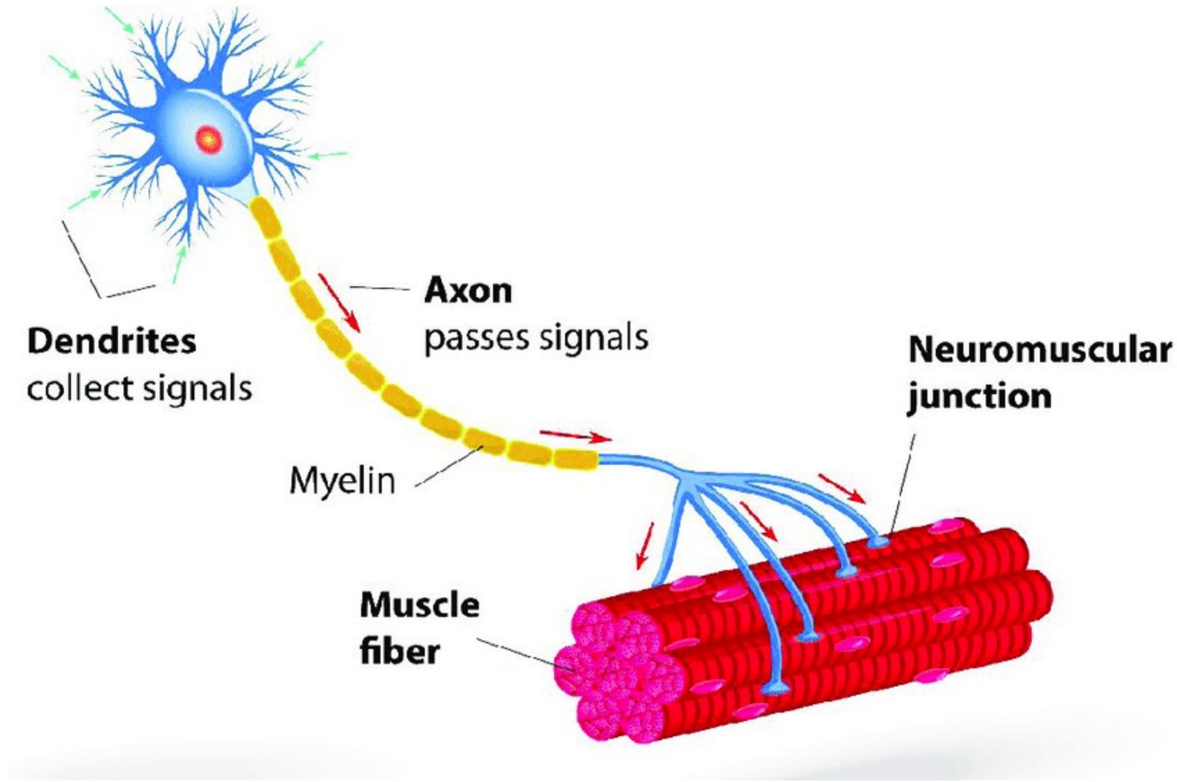
- Field of sports
- Prosthesis control using EMG signal
- Hand gesture recognition

Project Objective

With recent advancement in EMG decomposition using deep learning as mentioned in work by A.K.Clarke[8]

- The main objective of this study is to decompose the high-density surface EMG using supervised learning
- Different methodology for robust outcome
- Qualitative and Quantitative analysis and validation of sEMG decomposition using various metrics

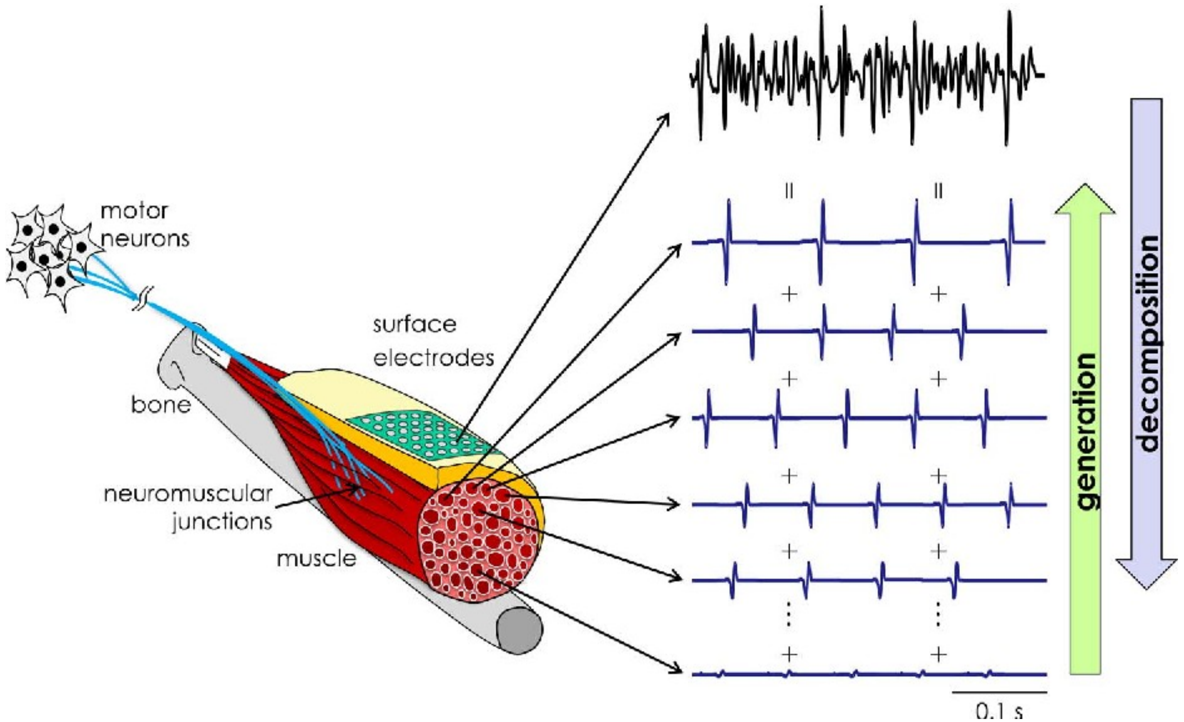
Biological background: Motor unit



A motor unit, Source [2]

- Action potential in neurons creates action potential in muscle fiber
- One MU innervating five muscle fibers : Innervation number

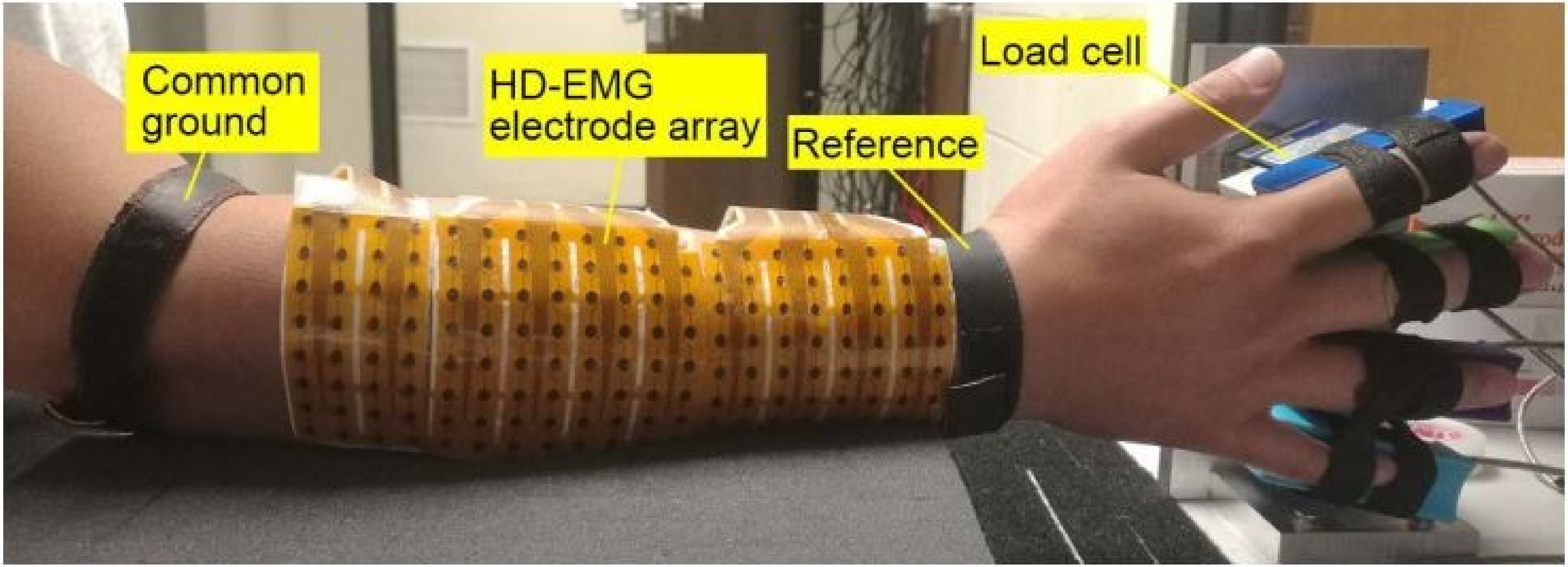
EMG signal generation and decomposition



EMG Generation and Decomposition, Source [3]

- MUAP – Motor unit action potential
- Superposition of MUAP to form EMG signal

Recording EMG signals



Surface EMG Recording – Non invasive [7]

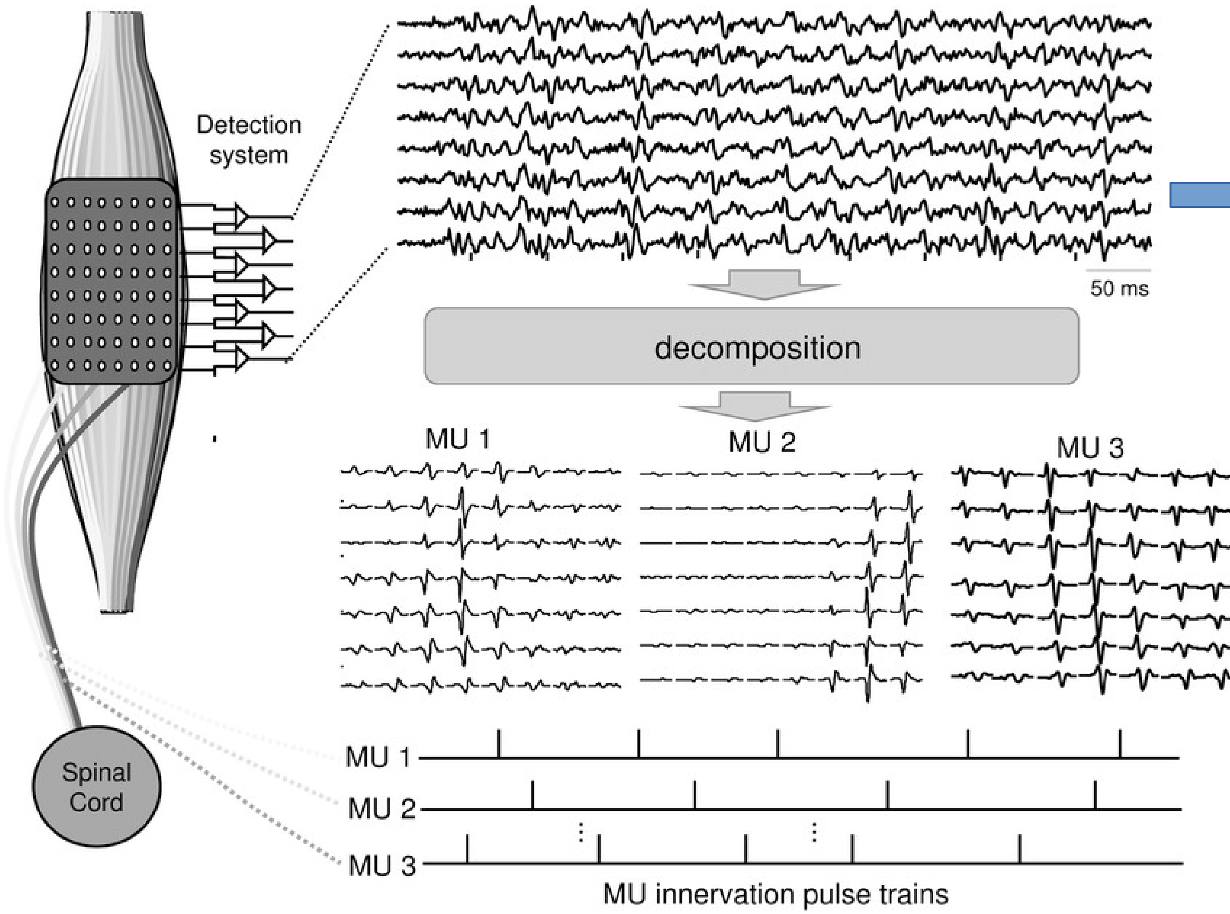
- Invasive or Indwelling
- Non-Invasive

Existing EMG decomposition methods

- Template matching approach
  Clustering based on Shape of MUAP (Invasive)

- Gradient Convolution Kernel Compensation. (gCKC) (Non-invasive)

Simulated data set

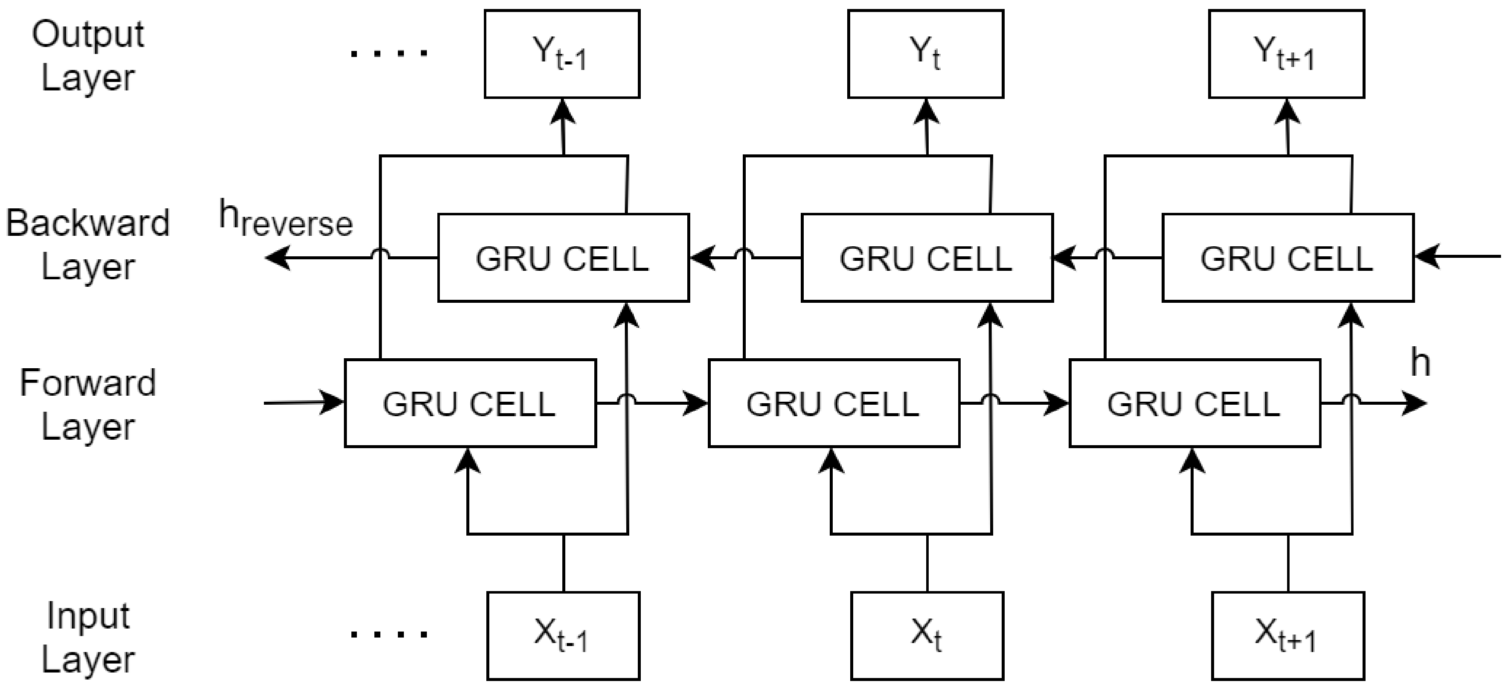


Input signal
HD-sEMG

HD-sEMG, Source [4]

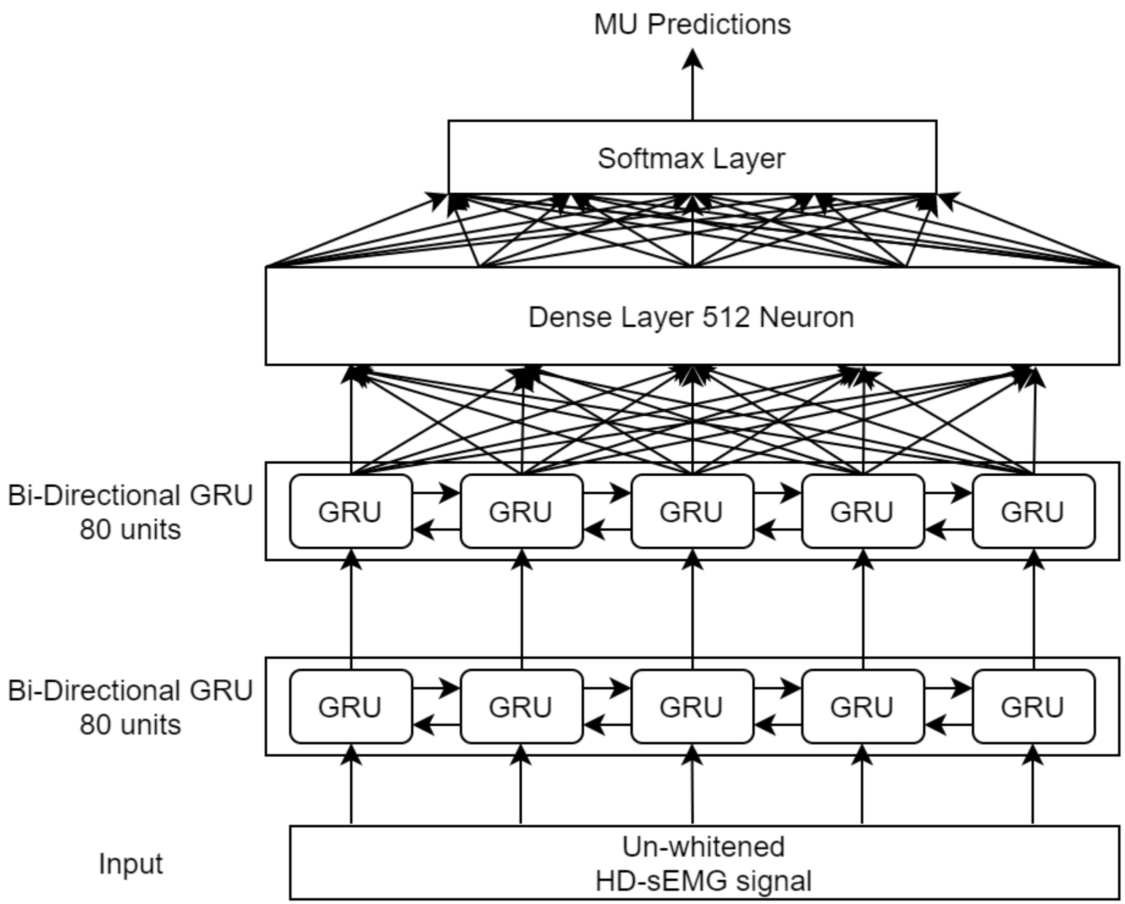
- Synthetic datasets with varying configurations
- Output or Label : 1) Discharge time or ground truth
  2) gCKC output IPT signal

Gated recurrent unit (GRU)



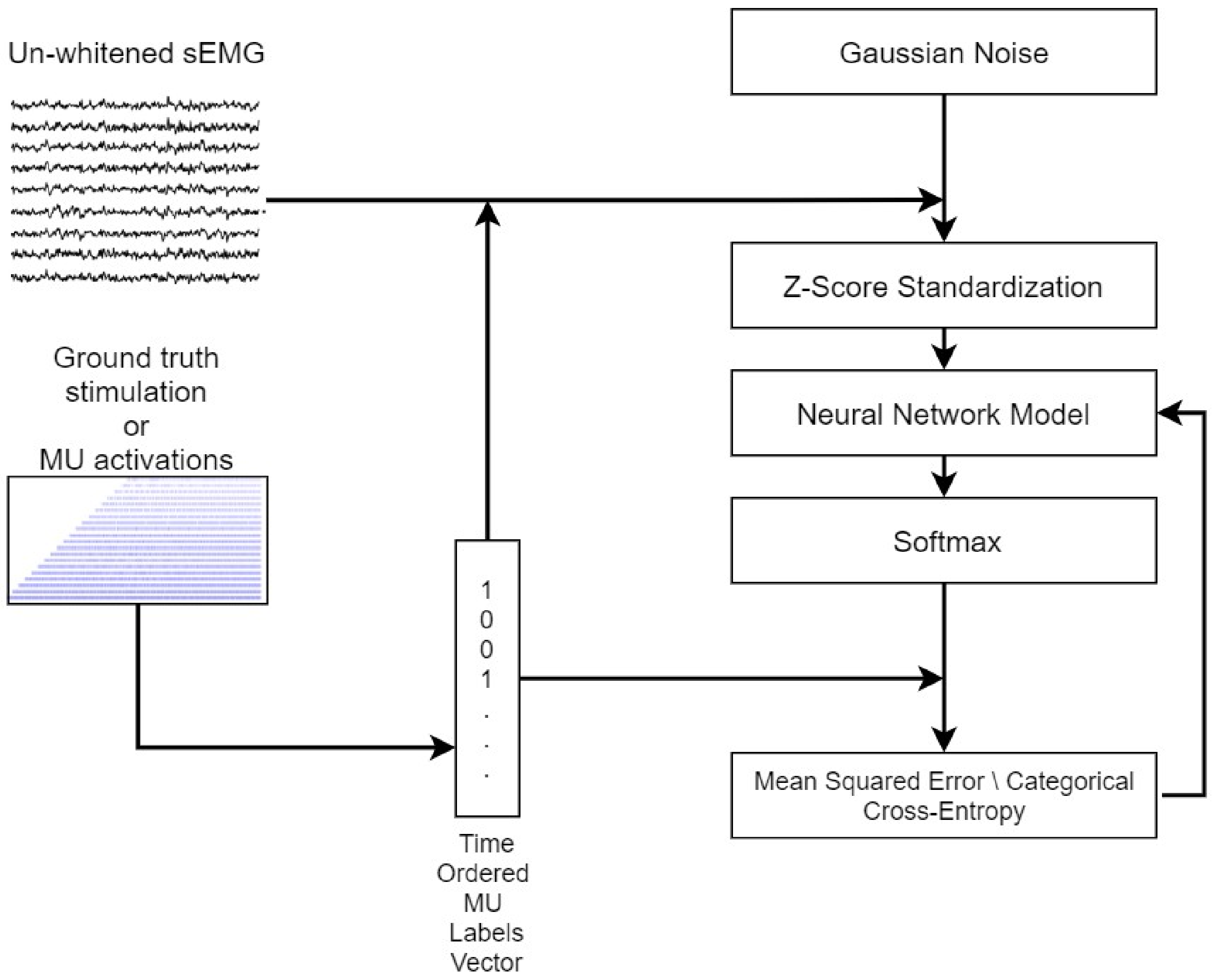
Bi-directional GRU

Neural network implementation



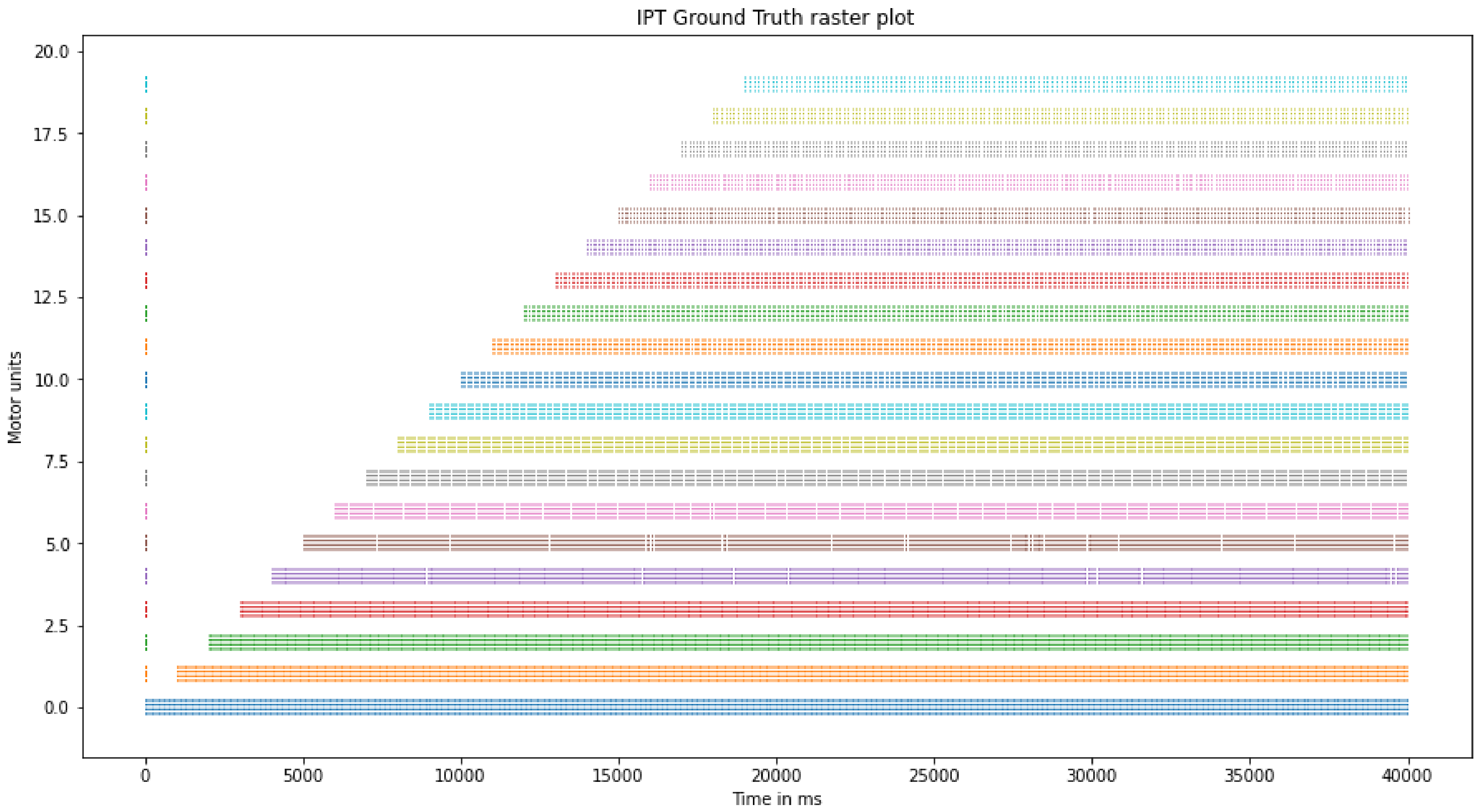
Neural Network Architecture

First method with MU firing labels

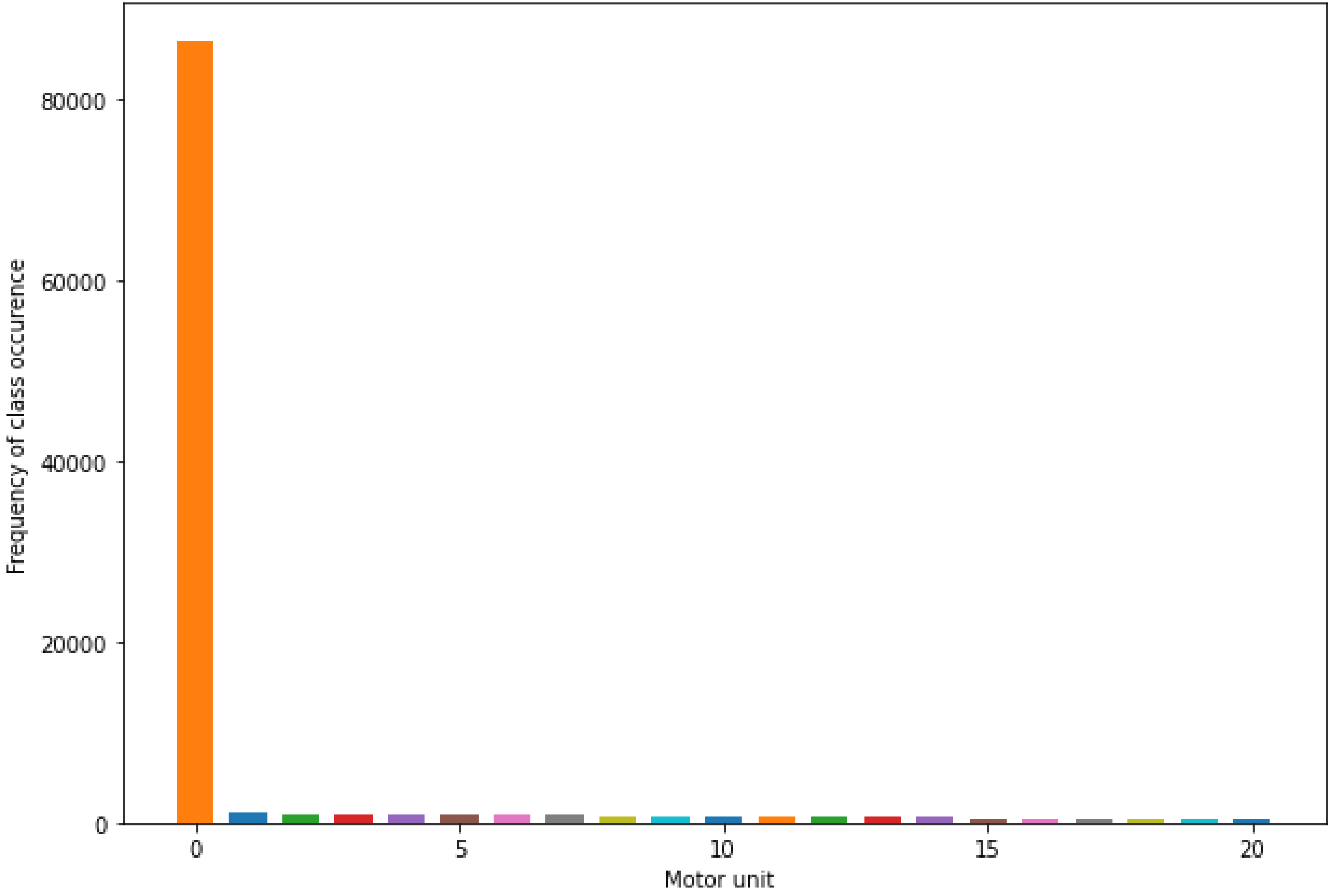


First Method

MU activation



Imbalanced data set



Metrics

$$Precision = \frac{TP}{TP + FP}$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

$$Recall = \frac{TP}{TP + FN}$$

$$RoA = \frac{TP}{TP + FP + FN}$$

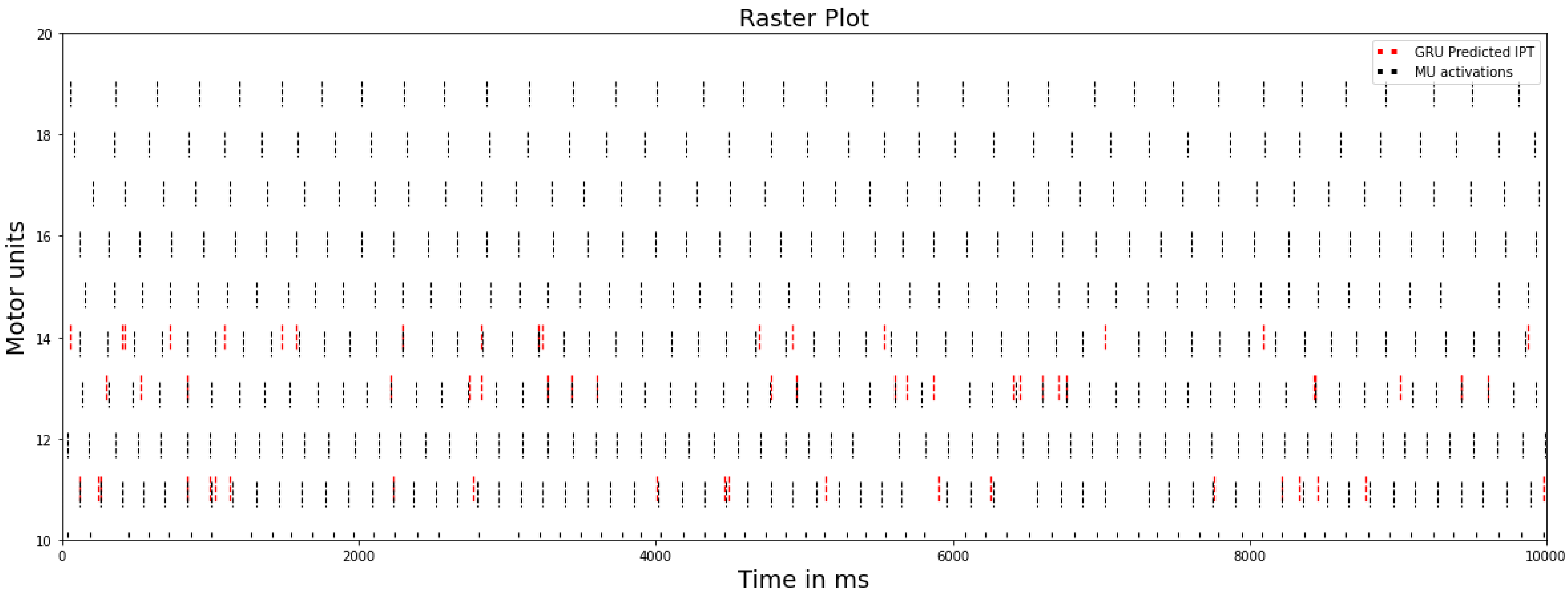
Area under ROC Curve (AUC)

$$TruePositiveRate = \frac{TP}{TP + FN}$$

$$FalsePositiveRate = \frac{FP}{FP + TN}$$

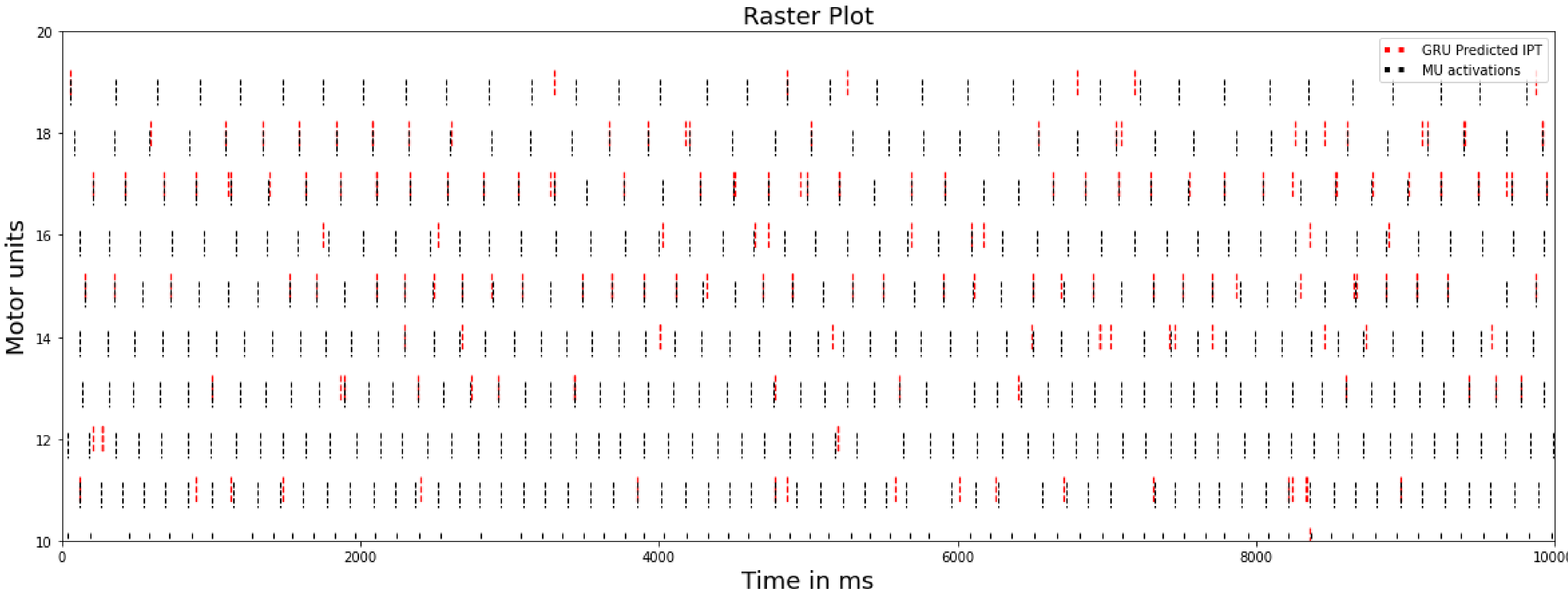
Results without class weight

Data set	Precision	Recall	AUC	F1	RoA
20MU-50Sec	86.07%	84.90%	0.93	86%	65.6%



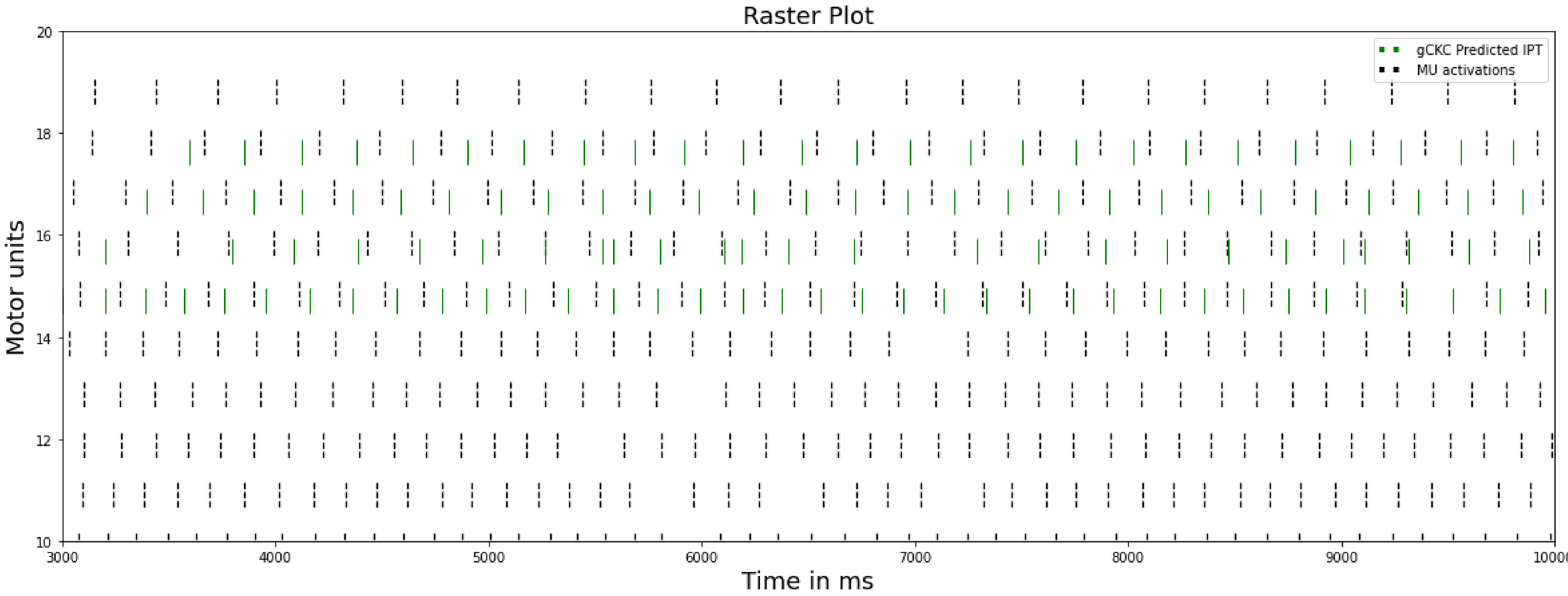
With Class weight approach

Data set	Precision	Recall	AUC	F1	RoA
20MU-50Sec	84.07%	66.04%	0.941	70.95%	75.5%



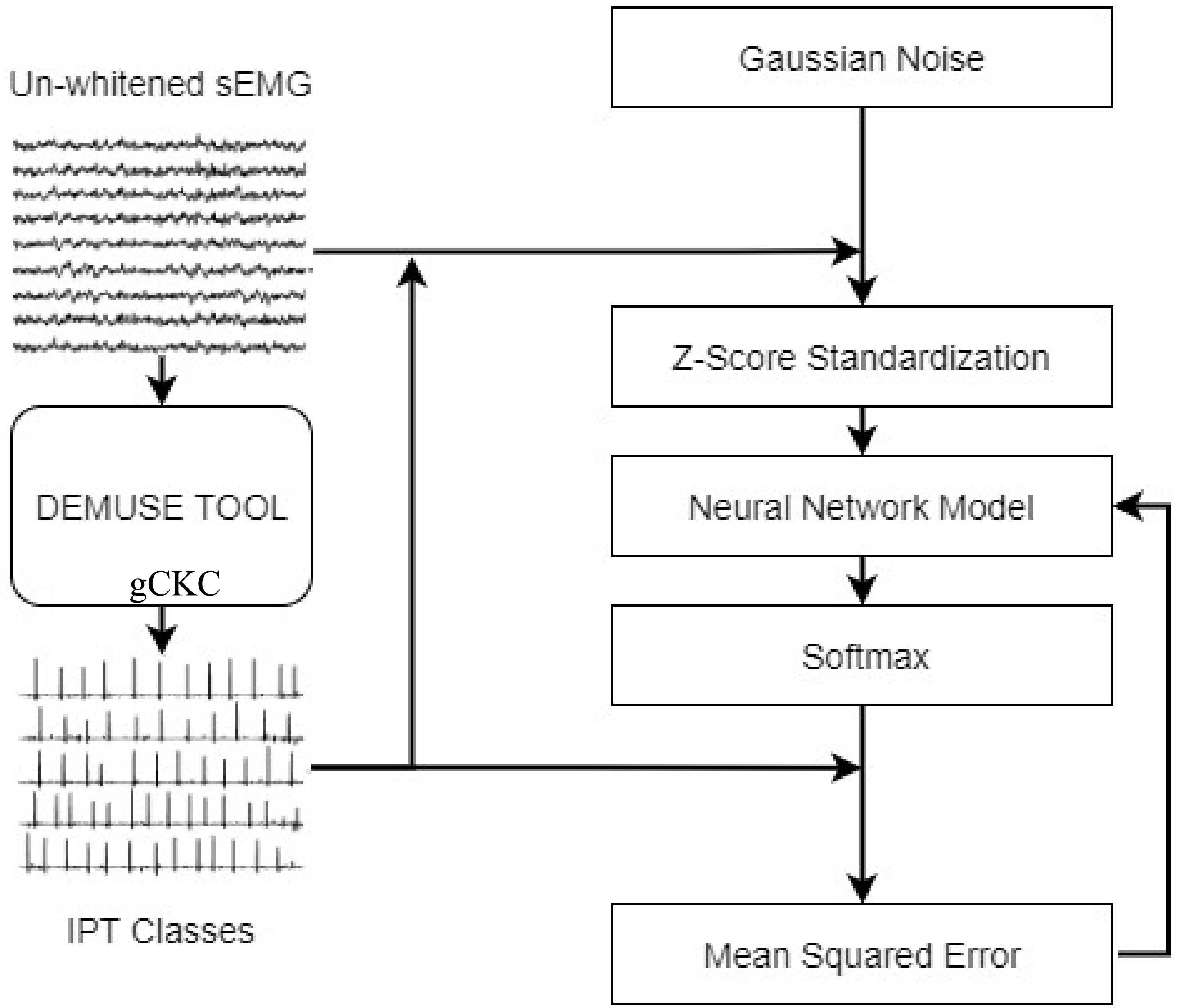
Results

20MU-50Sec



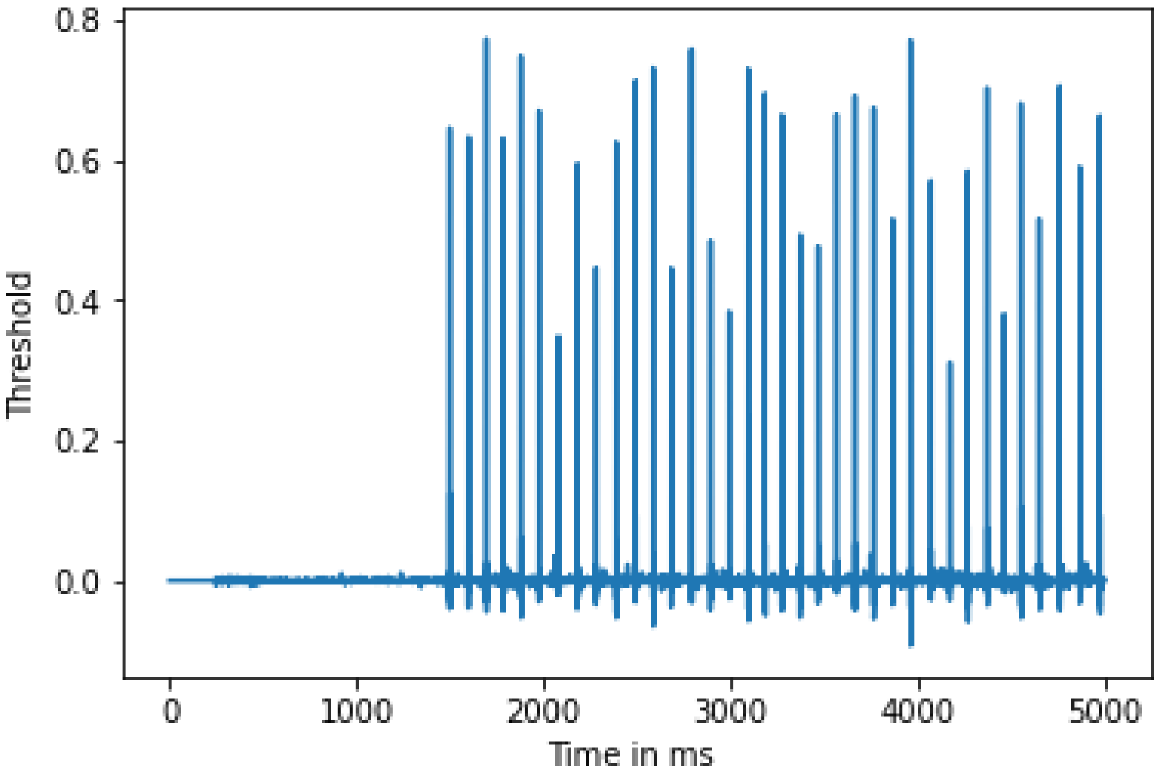
- GCKC : 4 MU

Second method with raw IPT labels



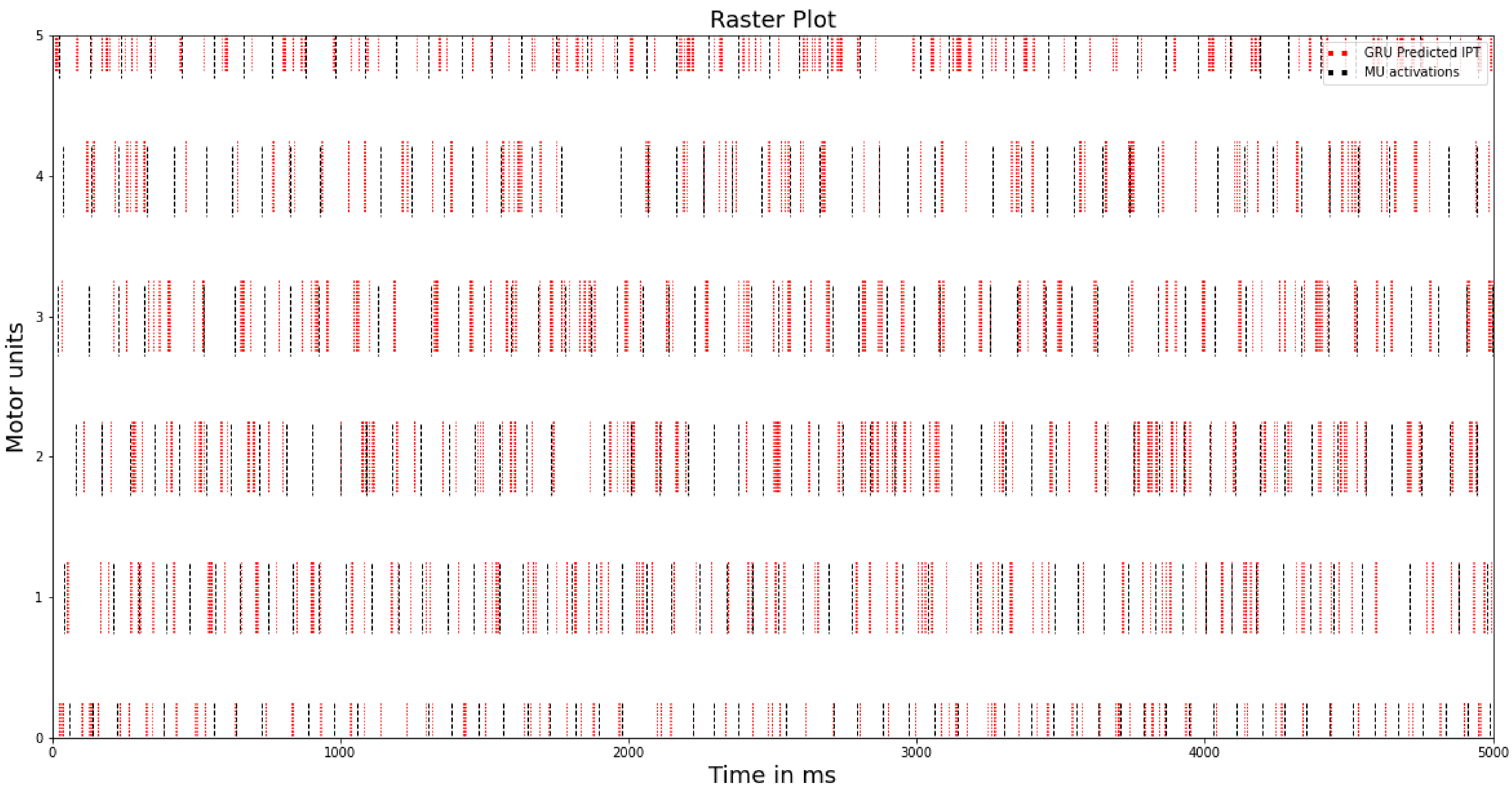
Second Method [8].

Raw IPT of MU



Raster plot

20 MU – 40 Sec



Conclusion

- GRU is a powerful neural network architecture for time series data
- GRU’s performance depends highly on outcome obtained from gCKC decomposition algorithm
- Performance of GRU also depended on the count of MU and size of MU
- Only valid for per recording and cannot be generalized
- gCKC algorithm was not able to identify all MUs
- Overfitting

Future scope

- Thoroughly searching the parameter space
- Better preprocessing and post processing steps to improve GRU performance
- Explore into methods for creating and finding larger sets of data for better generalization
- Methods to detect the shape of MUAP
- Need more robust method to detect data set with larger MU counts
- The proposed work was only validated on simulated signals but can be extended to work with actual EMG signals

Sources

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