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Optimization of Multi-channel Intramuscular EMG (iEMG) Signal Simulator

MRes Final Oral Presentation (Viva)

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Contents

PART 1 Introduction

- Physiological Background
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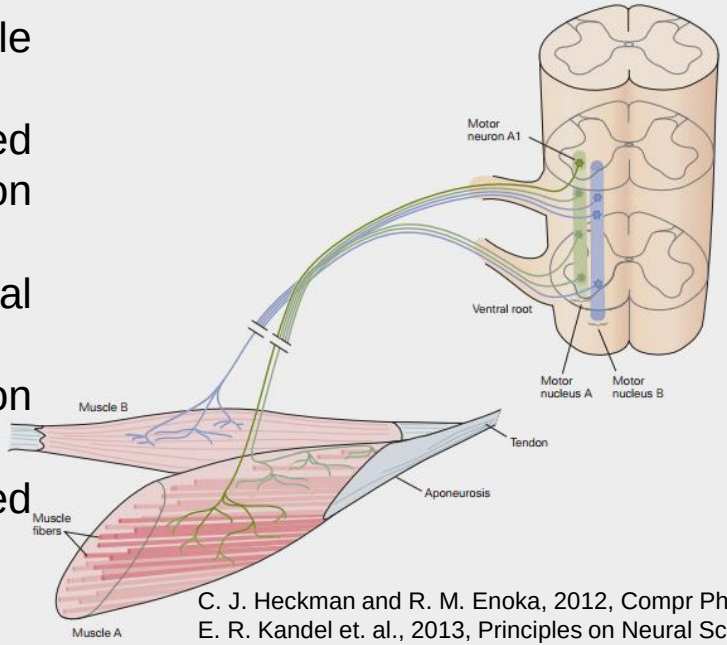
Physiological Background

- **Motor Unit:** Consist by a motor neuron and muscle fibres it innervate.
- **Recuritment Threshould:** A value if recerived excitations are larger than it in each MU, action potential will generate.
- **Single Fibre Action Potential:** The electrical activities on a muscle fibre.
- **Motor Unit Action Potential:** The linear summation of single fibre action potential spatical and temproal.
- **Spike Train**: A 0/1 time sequence of APs generated by a MU.



C. J. Heckman and R. M. Enoka, 2012, Compr Physiol.
E. R. Kandel et. al., 2013, Principles on Neural Science, pp. 749

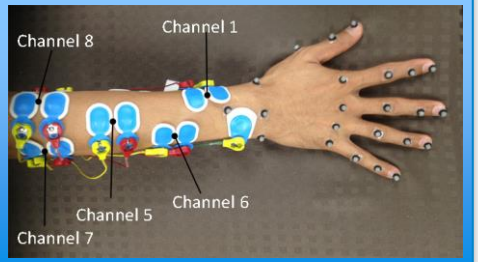
EMG Signals - Types

- EMG signal is the recording of the electrical activities causing the muscles contraction.

Surface EMG (sEMG)

- Electrodes are locating on the skin.
- Recording global activities of shallow level muscles.
- Included noise from external environment or other tissues.

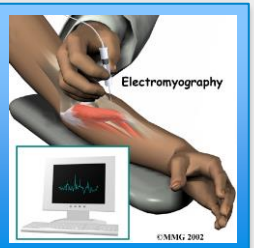
J. Nego; T. Tamei and T. Shibata, 2014, IEEE



Intramuscular EMG (iEMG)

- Electrodes are insert into muscle.
- Recording activities in specific area.
- Noise will only from internal.

F. Stival, 2015



iEMG Models

- iEMG decomposition model: The iEMG signals can be represented as the convolution of MUAPs and their spike trains.
- As a decomposition model, above model lack of simulating the physiological structure of MU.
- Dr Konstantin proposed a novel iEMG model based on above decomposition model but resolves the limitations of above model.

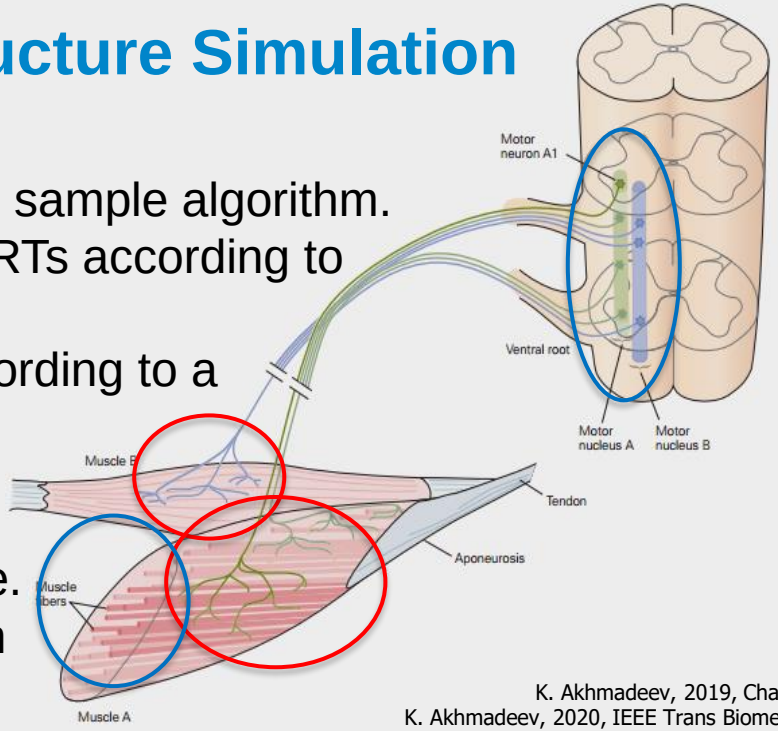
iEMG Model – Physiological Structure Simulation

MNs and MFs Pool

- Centres are generated from farthest point sample algorithm.
- MN innervation size are generating from RTs according to Henneman‘s principle.
- Assignment of MF to specific MN are according to a probability.

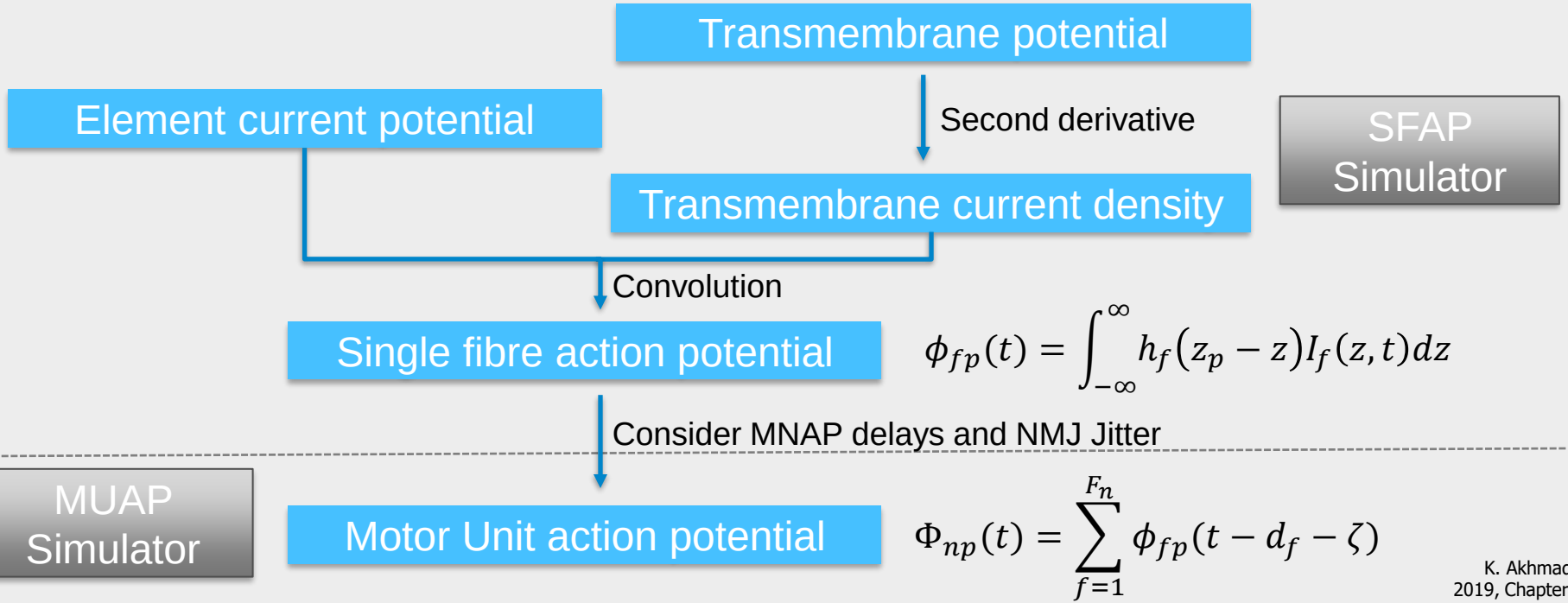
Neuromuscular Junction

- End of axons are simulated to break twice.
- MNAP delays are calculated separately in each parts and finally summed up.



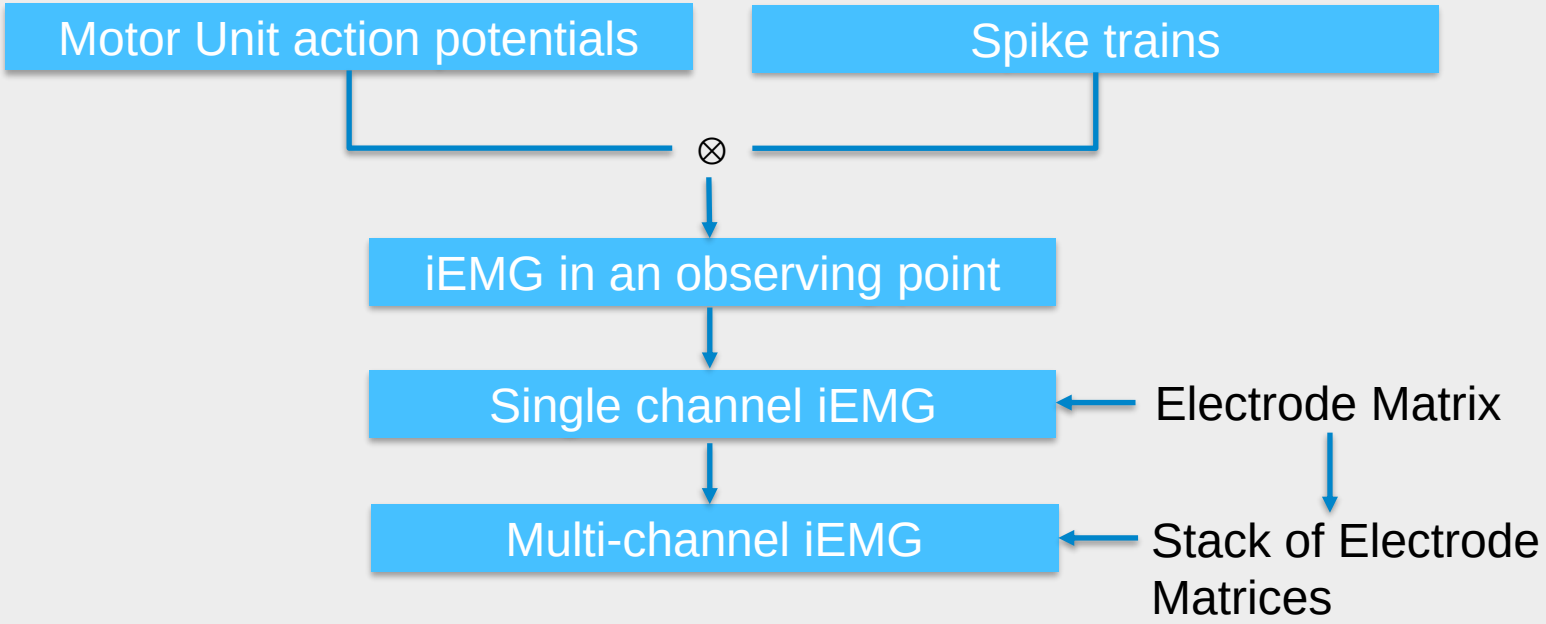
K. Akhmadeev, 2019, Chapter 4
K. Akhmadeev, 2020, IEEE Trans Biomed Eng
A. J. Fuglevand et al., 1993, J. Neurophysiol.
E. Henneman et al., 1965, J. Neurophysiol.

iEMG Model – MUAP Simulation



K. Akhmadeev, 2019, Chapter 4, 5

iEMG Model – iEMG Signal Simulation



K. Akhmadeev, 2019, Chapter 4, 5

Objective

- Dr. Konstantin's multi-channel iEMG simulator includes all relevant biophysical and physiological parameters for simulating motor unit (MU) activity. But some critics have pointed out that the model lacks authenticity since the signal it simulated was not compared with clinical iEMG signals.

- This project aims at optimizing the model parameters (electrode position, recruitment thresholds etc.) in order to best match experimental data (inverse modelling).

- Some parameters in simulator are selected from experiential data of the first dorsal interosseous of a 22-year-old man in Feinstein's paper (Acta Anat 1955;23:127–142)

PART 2 Methodology and Result

- Overview
- Optimization of Electrode Position
- Optimization of Motor Unit Territories and Muscle Fibre Innervation via Recruitment Threshold Parameters
- Complete Optimization Model
  - Integrated Optimization Model
  - Simplification Optimization Model

Overview

Input constants

MFs' centers position (X_{mf}, Y_{mf}, Z_{mf})

MNs' centers position (X_{mn}, Y_{mn}, Z_{mn})

Number of MN N

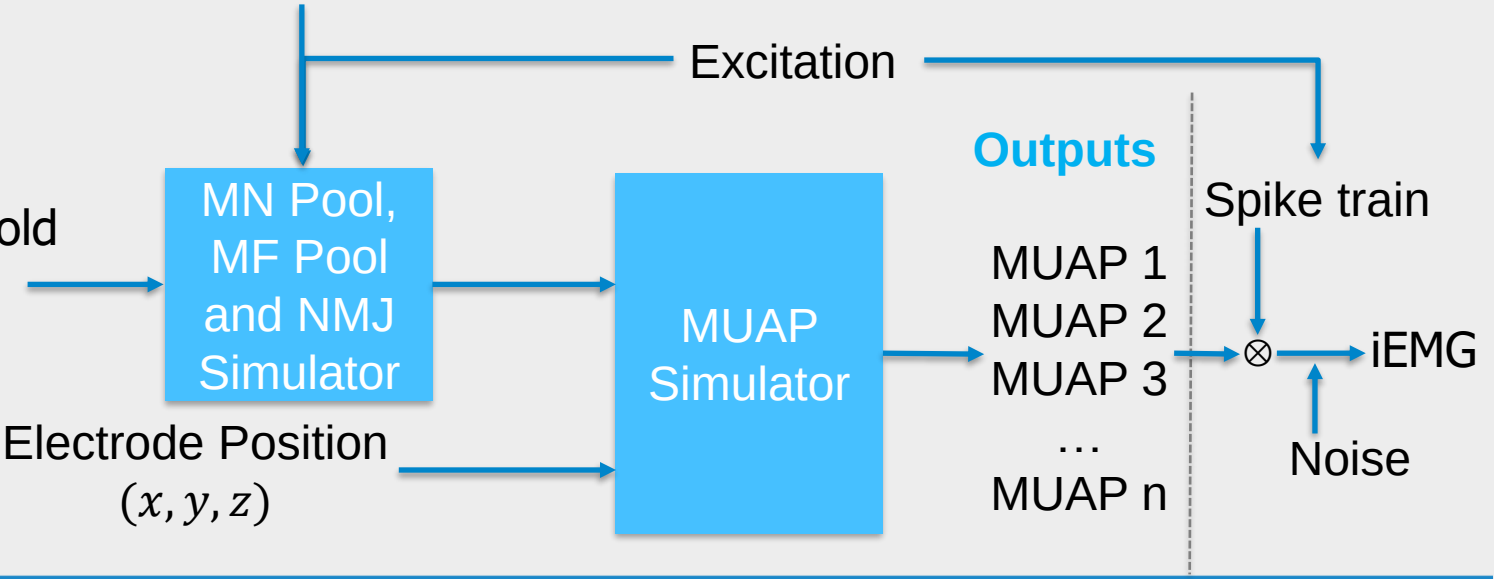
$$R = \frac{r_1}{r_N}$$

$$M = r_N$$

Input variables

Recruitment threshold parameters (R, M)

Electrode Position (x, y, z)



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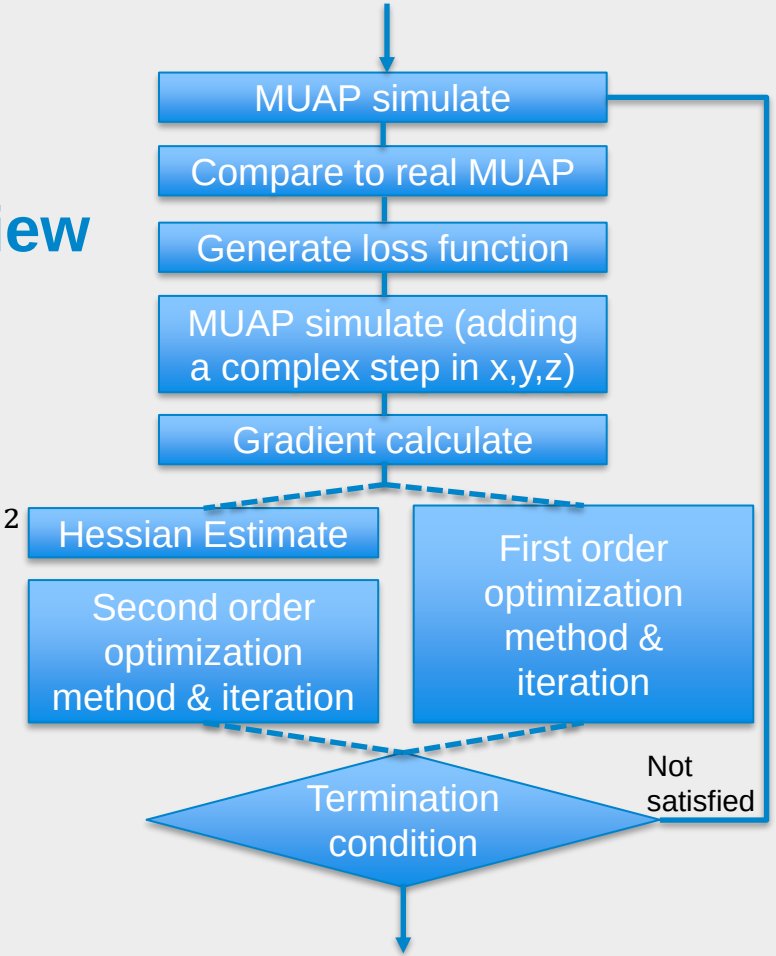
Optimization of Electrode - Overview

$$\arg\min_{x_p, y_p, z_p} \sum_{t=1}^{T_s} \left(\Phi_{np\_real}(t) - \Phi_{np\_sim}(t - d_f, x_p, y_p, z_p) \right)^2$$

subject to

$$x_p^2 + y_p^2 \leq R_{muscle}^2$$

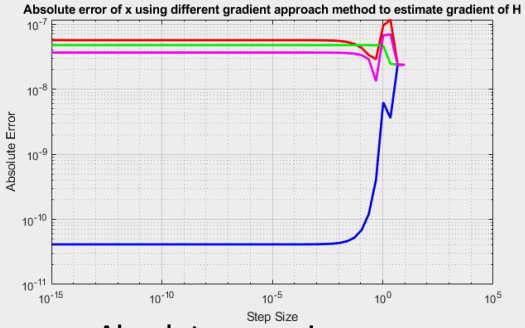
$$0 \leq z_p \leq L_{muscle}$$



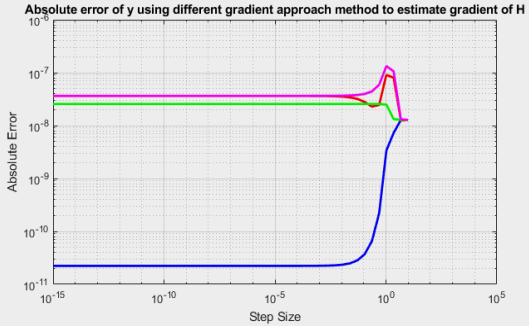
Optimization of Electrode – Method Chose

- Since there is no stochastic processes here, so traditional method using gradient or Hessian are applicated here.
- Here we choose 4 optimization methods to compare: Gradient Descent; Adaptive moment estimation (ADAM); Quasi-Newton (DFP approach); Quasi-Newton (BFGS approach)
- The gradient are calculated by complex step method, since it use a single function to evaluate the gradient by taking an imaginary step. Furthermore, it has the best performance compare with other methods when the step size is small.

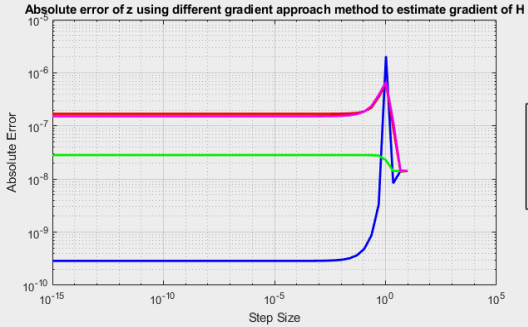
Optimization of Electrode – First Order Method



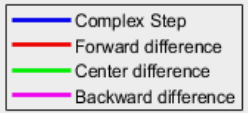
Absolute error in x



Absolute error in y



Absolute error in z



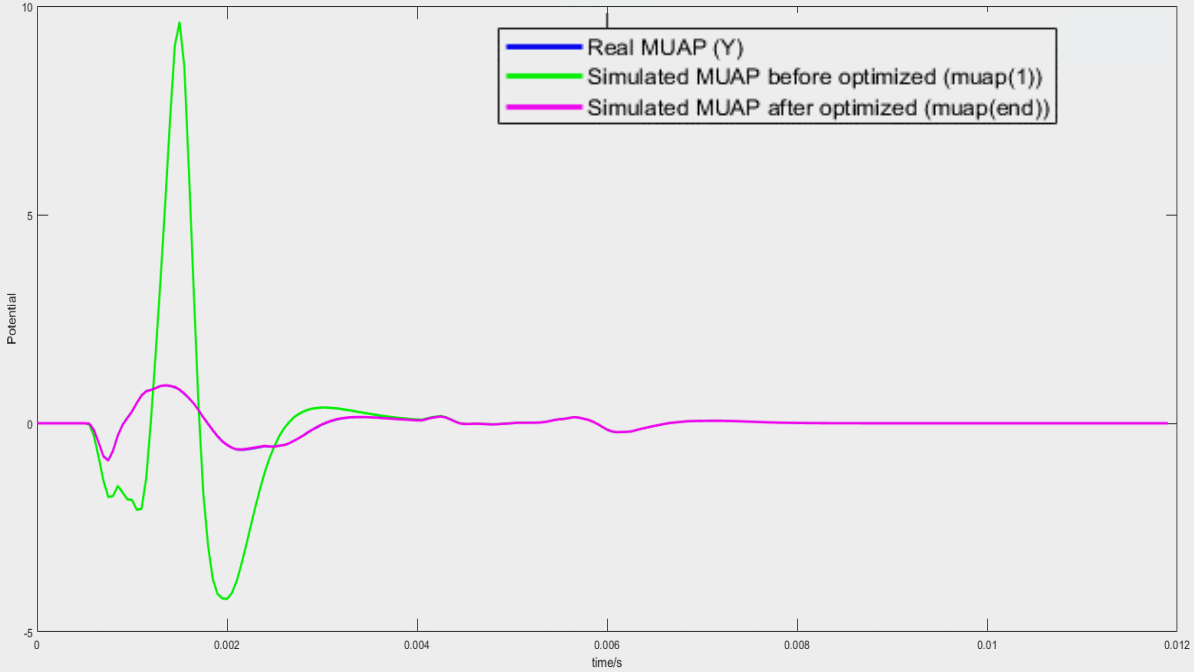
Optimization of Electrode – Different Method Comparison

Method	Final loss function	Iteration	Opti. time	Termination condition
Gradient Descent	0.28	2070	503.884s	(1)
ADAM	0.00105	3547	1062.324s	(2)
Quasi-Newton (DFP)	8.1898	36	11.550s	(3)
Quasi-Newton (BFGS)	14.9304	8	2.9761s	(3)

- The termination condition:
  (1) Convergence in a interval.
  (2) Objective function smaller than limitation.
  (3) The electrode poison is out-of-boundary.

Learning ratio $\alpha = 0.005$

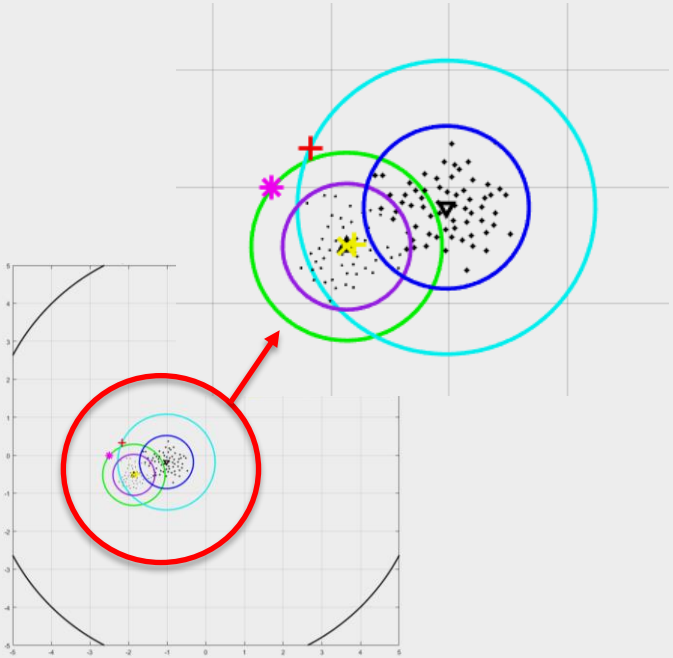
Optimization of Electrode – Results



Initial position: (-1.8,-0.5,15)
Final position: (-2.49,-0.01,14.98)
Iteration: 3547
Opti. Times: 1062.324s
Method: ADAM
Final loss function: 0.00105

Optimization of Electrode – Extra Explanation

- This model can also used to test the performance of single channel iEMG decomposition algorithm by moving electrode position to generate two similar iEMG signals.
- If we simulated single MUAP, the result should be same when the electrode are putting in a circle surrounding MU (green and blue circle).
- In two intersections, the two MUAP are very similar.



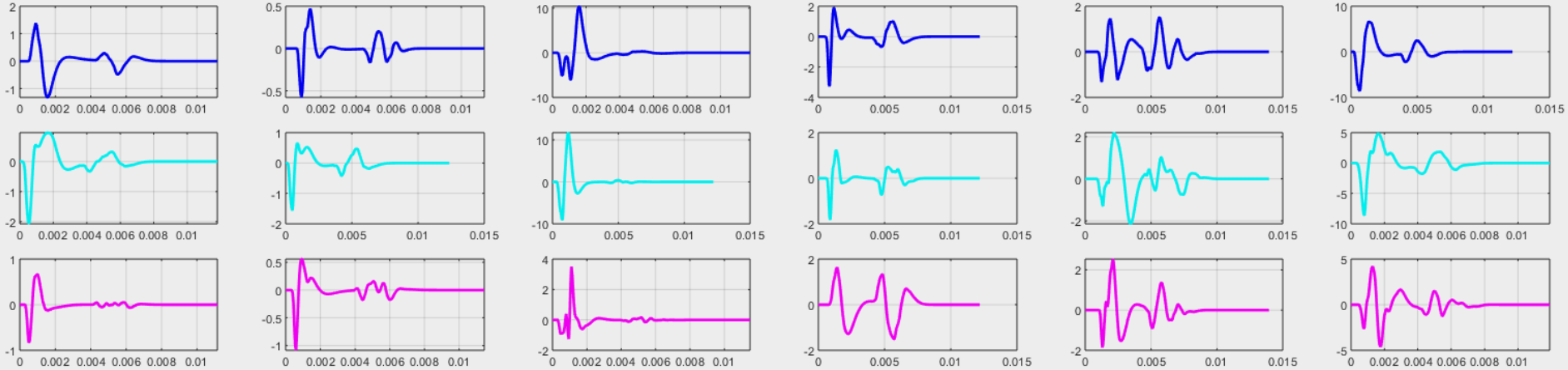
Optimization of Motor Unit Territories and Muscle Fibre Innervation via Recruitment Threshold Parameters

- Three stochastic processes exist in the MN, MF pool and NMJ simulation parts in this model. Traditional first-order or second-order method are not applicated here.

- Population-based method, as it can search a large quantity of parameters, it is more suitable to use here.

- Genetic Algorithm are chose here since it has best performances than other population method.

Optimization of Motor Unit Territories and Muscle Fibre Innervation via Recruitment Threshold Parameters



Optimization of MU Territories and MF Innervation via RT Parameters – Overview

- Loss function:

$$L_{(n)}(R,M) = \sum_{t=1}^{T_s} \left(\Phi^{(n)}_{np\_real}(t) - \Phi^{(n)}_{np\_sim}\left(t - d_f, R, M\right) \right)^2 \qquad n \in \boldsymbol{S}_{detecable\_MU}$$

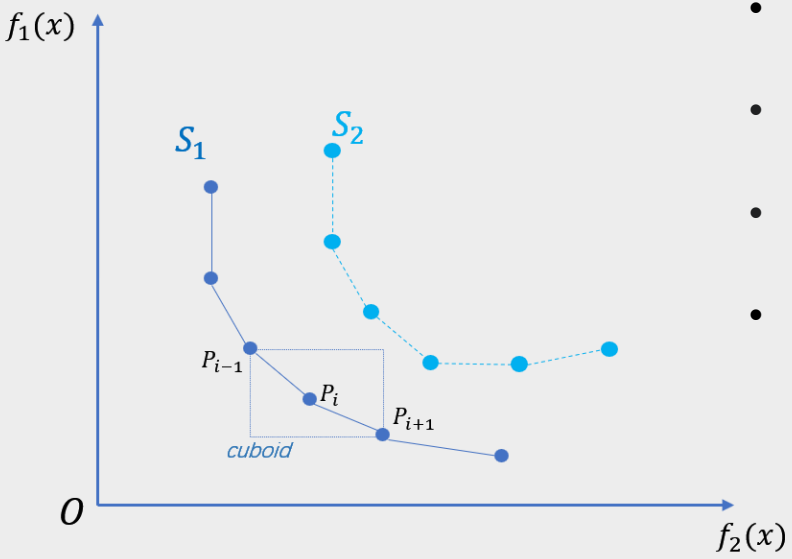
- Optimization Expression:

$$\arg\min_{R,M} \quad \left[L_{(1)}, L_{(2)}, \ldots, L_{(n)}\right]^T$$

$$\text{subject to} \quad R \geq 0$$

$$0 \leq M \leq 1$$

Optimization of MU Territories and MF Innervation via RT Parameters – NSGA-II



- **Non-domated solution:** A solution which it is optimal than other solutions for all objective.
- **Pareto optimality set:** A set for all solutions that are not dominated by any solutions.
- **Boundary Point:** the first or the last point in a pareto optimality set.
- **Crowding distance:**

$$I_i = \begin{cases} \sum_{i=2}^{N-1} \dfrac{\left| f_m^{(i+1)} - f_m^{(i-1)} \right|}{f_m^{max} - f_m^{\min}} & i \neq 1 \vee i \neq N \\ +\infty & i = 1 \vee i = N \end{cases}$$

K. Deb, 2002, IEEE Trans. Evol. Comput.
A. Konak et. al., 2006, Reliab. Eng. Syst. Saf.

Optimization of MU Territories and MF Innervation via RT Parameters – NSGA-II

- Non-domated Sorting
- Crowding Distance Computing
- Crossover
- Variation
- Diversification Genetic Pool
- Nature Selection
- Generational Optimum Selection

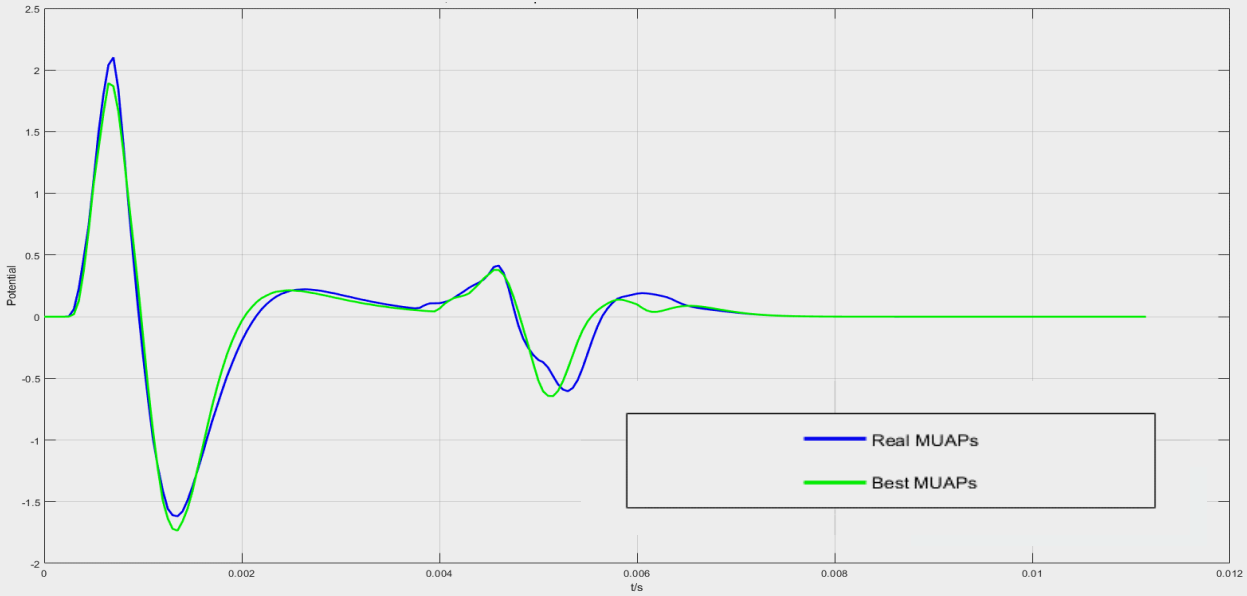
- Crossover function:

$$p_c(n) = \begin{cases} \dfrac{F_{fit}(n)^{-1}}{\sum_{i=1}^{N} F_{fit}(i)^{-1}} \cdot \dfrac{1}{l} & (n \neq 1 \vee n \neq N) \wedge (l \leq l_{lim}) \\ \dfrac{0.1}{\sum_{i=1}^{N} F_{fit}(i)^{-1}} \cdot \dfrac{1}{l} & (n = 1 \vee n = N) \wedge (l \leq l_{lim}) \\ \dfrac{0.01}{\sum_{i=1}^{N} F_{fit}(i)^{-1}} & l > l_{lim} \end{cases}$$

- Nature Selection function:

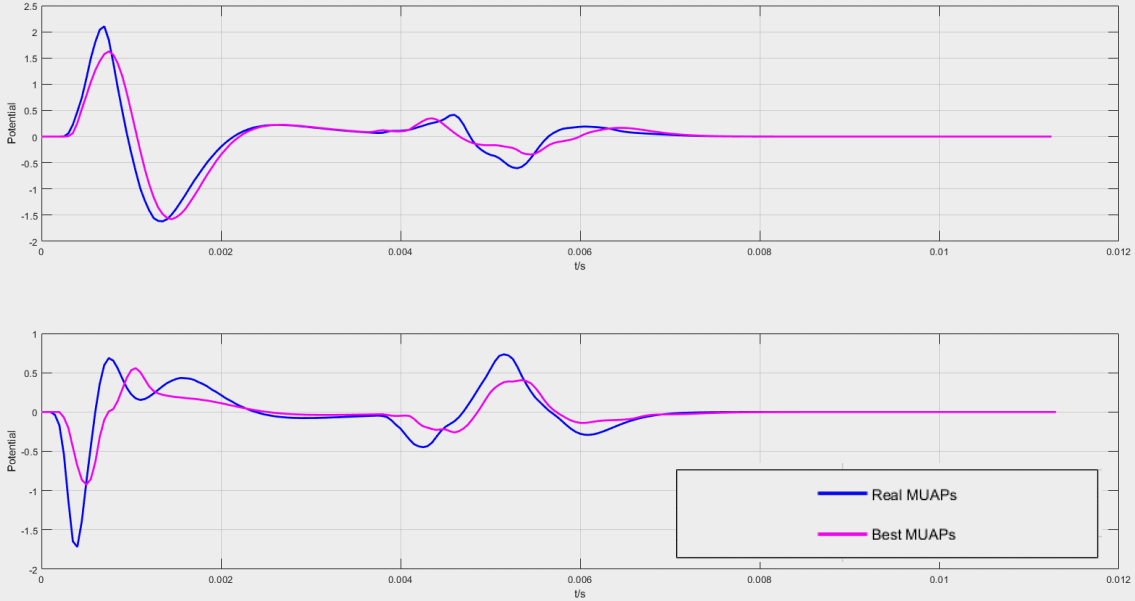
$$w_n(n) = \frac{0.7}{l} \cdot \frac{0.2F_{fit}(n)^{-1}}{\sum_{i=1}^{N} F_{fit}(i)^{-1}} \cdot 0.1I(n)$$

Optimization of MU Territories and MF Innervation via RT Parameters – Result (Single-objective)



Final parameters: R=90.1,M=0.5
Final loss function: 1.43

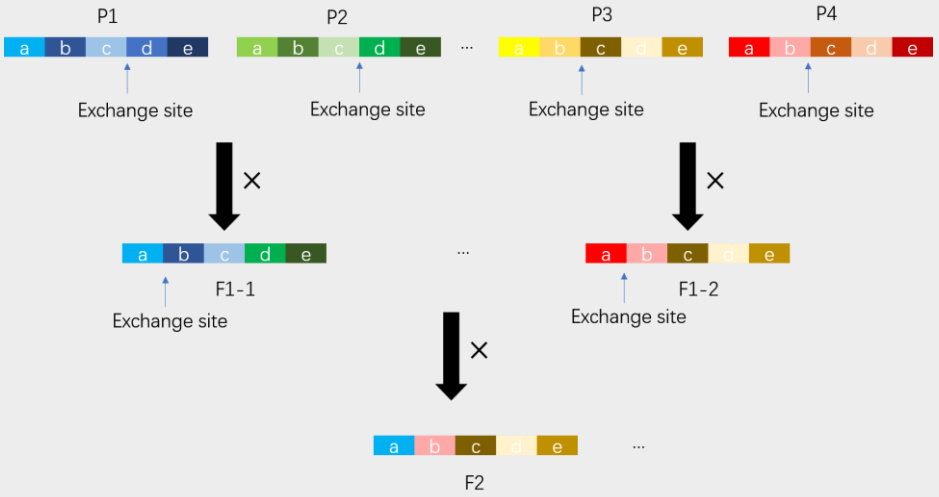
Optimization of MU Territories and MF Innervation via RT Parameters – Result (Multi-objective)



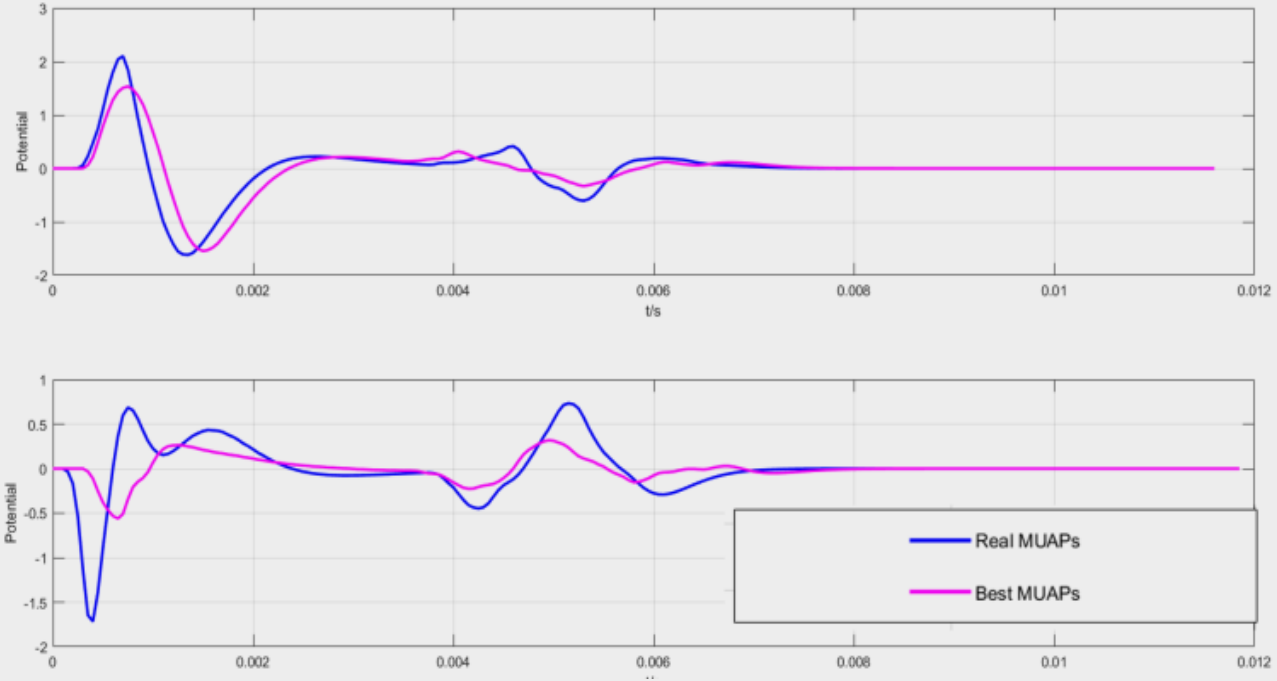
Final parameters: R=90.5,M=0.67
Final objective function: 4.76

Integrated Optimization Model

- Included both two procedures above.
- Genetic Algorithm are chose here too. Parameter vector are regarded as a chromosome here.
- Here it use single point variation, but the exchange site are randomly chosen here.



Integrated Optimization Model – Result



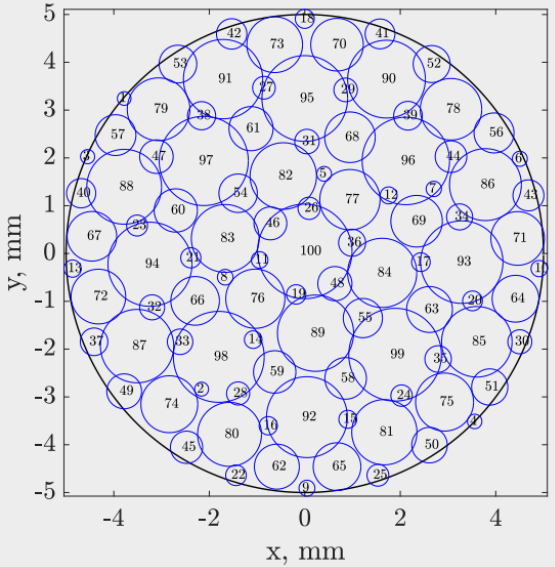
Final parameters: R=79.2,M=0.7
Final objective function: 5.31

Simplified Optimization Model

- Inspired by FPS algorithm, the generation of MUs and MFs are quasi-randomly. A MU that can simulated a simular MUAP can be found in any positions on cross-section of muscle.

- We use the distance between each MU and electrodes directly instead of applying MF positions to calculate distance.

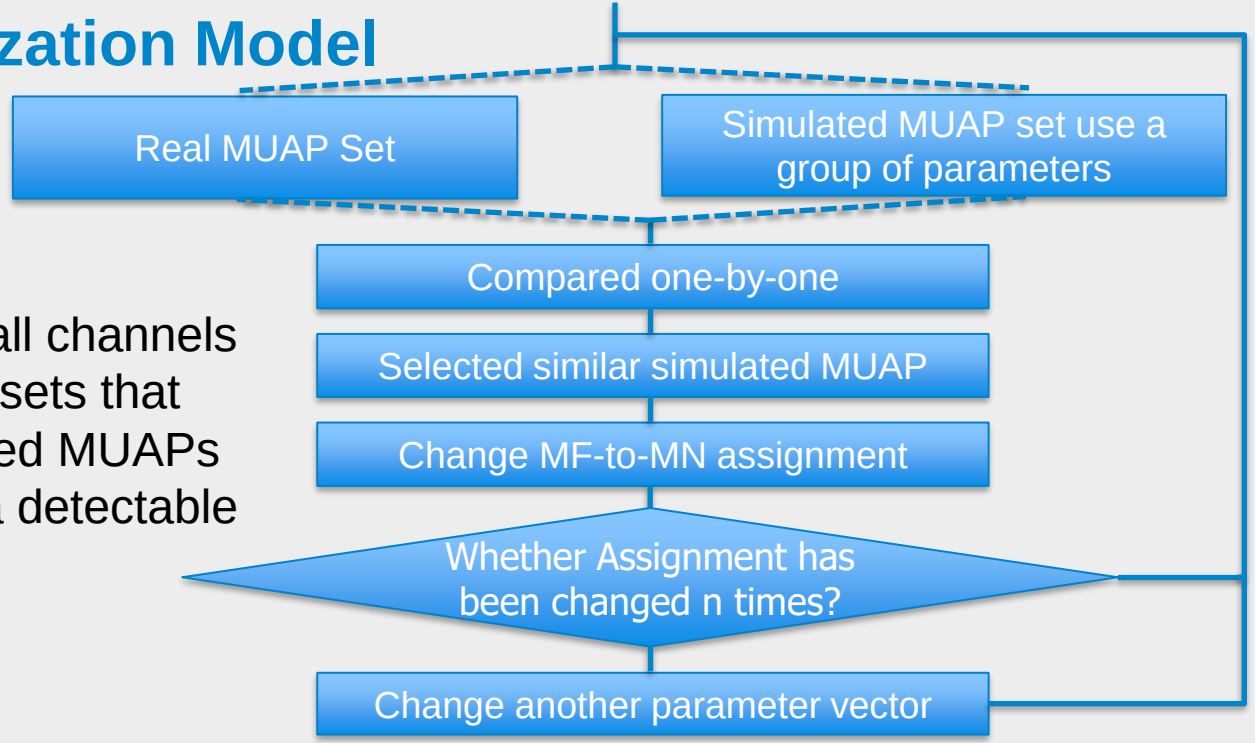
- Each real MUAP will compare to all MUAPs simulated in a muscle cross-section one-by-one, those who has a loss function smaller than 5 will be selected and save to the corrsponedenting solution sets



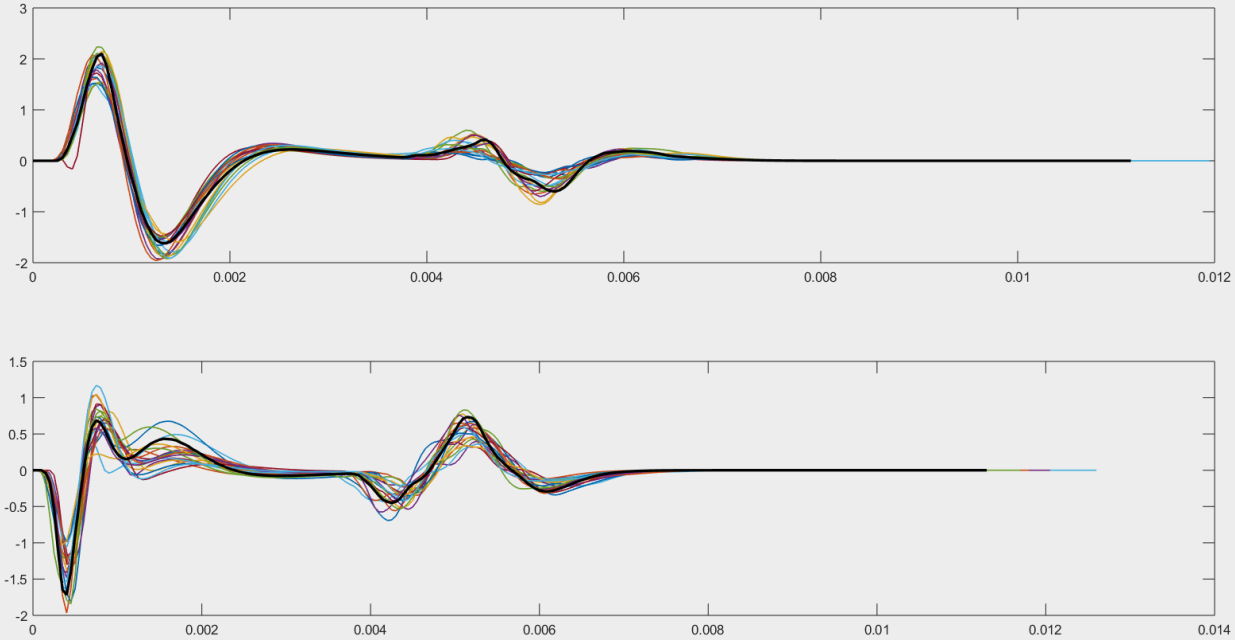
K. Akhmadeev, 2019, Chapter 4
K. Akhmadeev, 2020, IEEE Trans Biomed Eng

Simplified Optimization Model

- By simulated MUAP in all channels we can obtained serval sets that included similar simulated MUAPs for each real MUAP in a detectable area.



Simplified Optimization Model – Result



PART 3 Discussion

- **Evaluation**
- **Improvement**

Evaluation

- Due to the limitation of devices, the optimization results still has errors when use multi-objective genetic algorithm.
- The error is caused by the limit of crossover mates and population size in each iteration.
- The autheticity can still be proofed since the simplified model and single objective model has been found similar simulated MUAP.
- By applying high performance computer, a more accurate solution can be obtained.

Improvement

- Parallel computation can be used to speed up.
- For electrode optimization part, Shampoo method can be used here.
- For genetic algorithm and simplified optimization model, the structure can be redesigned to fit the parallel computation.
- We designed above two proceudre to fit parallel computation by generating simulated MUAP in multi-GPU.

PART 4 Conclusion

We reconstructing the simulator according to Dr Konstantin's paper (IEEE Trans Biomed Eng. 2020;67(7):2005-2014) and their source code in Github (https://github.com/smetanadvorak/iemg simulator).

Under the limitation of computing devices, we modified or simplified the original optimizing model and proofed the authenticity of this simulator. Meanwhile, we designed the parallel computing structure of the optimization models for further online optimization on multi-GPU devices.

PART 5 Acknowledgment

My heartfelt and deepest gratitude goes first and foremost to Professor Dario Farina and Doctor Tianyi Yu for their constant and great encouragement, guidance and supporting during my whole project period.

Q&A

If you have any question about my presentation.
Do not hesitate to ask me.

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Critical References

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Thanks for your listening