Myoelectric prosthesis controlling algorithm based on Motor Imagery recognition by a Spiking Neural Network

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Supervisor: Dr. Husam

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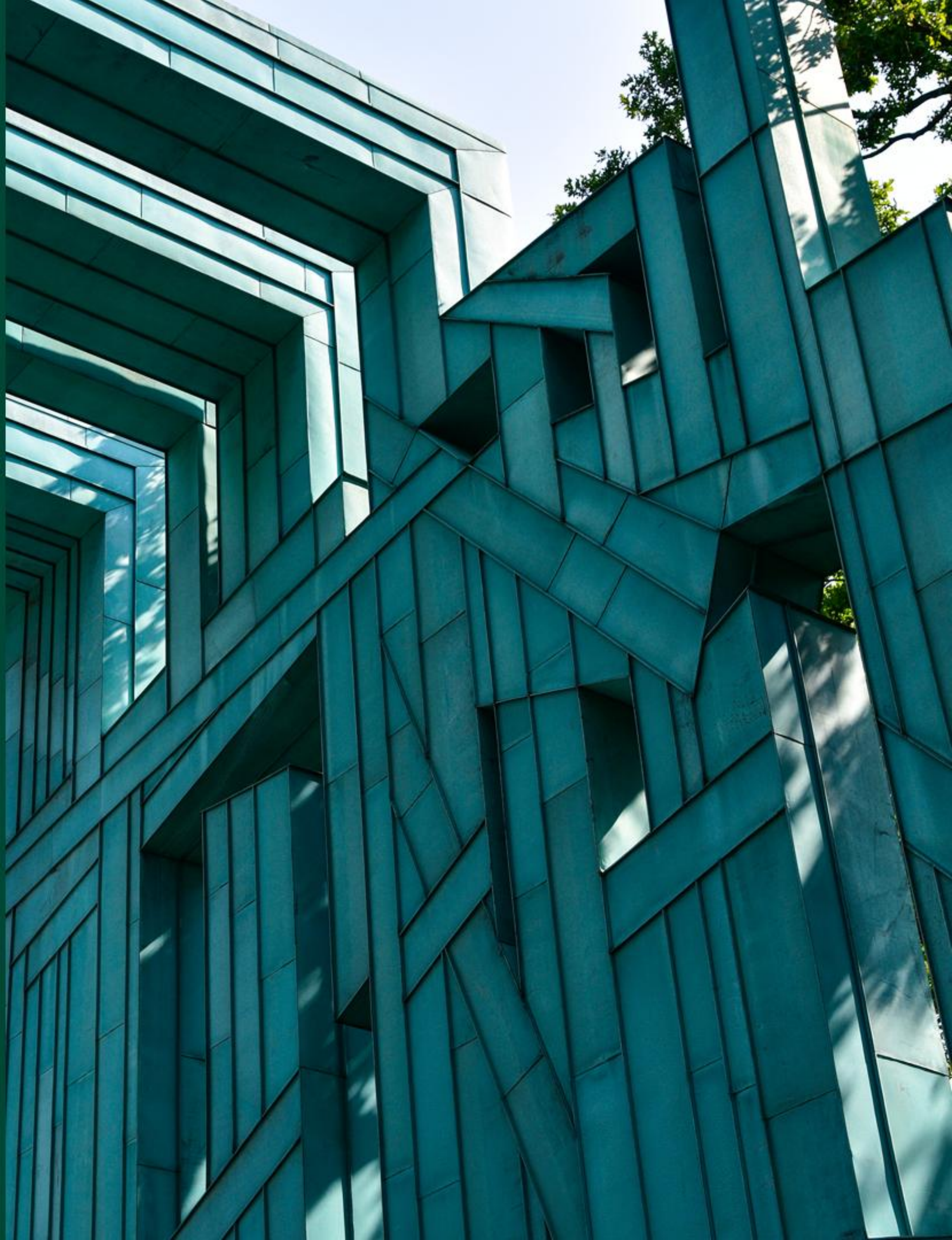

Outline

- Myoelectric Prosthesis
  - Problem - Prosthetic control
  - What does the title mean? (MI, EMG, EEG, SNN)
- Proposed solution
  - Experimental setup
  - Data analysis
  - SNN training
  - Working prototype
- Conclusion
- Acknowledgement

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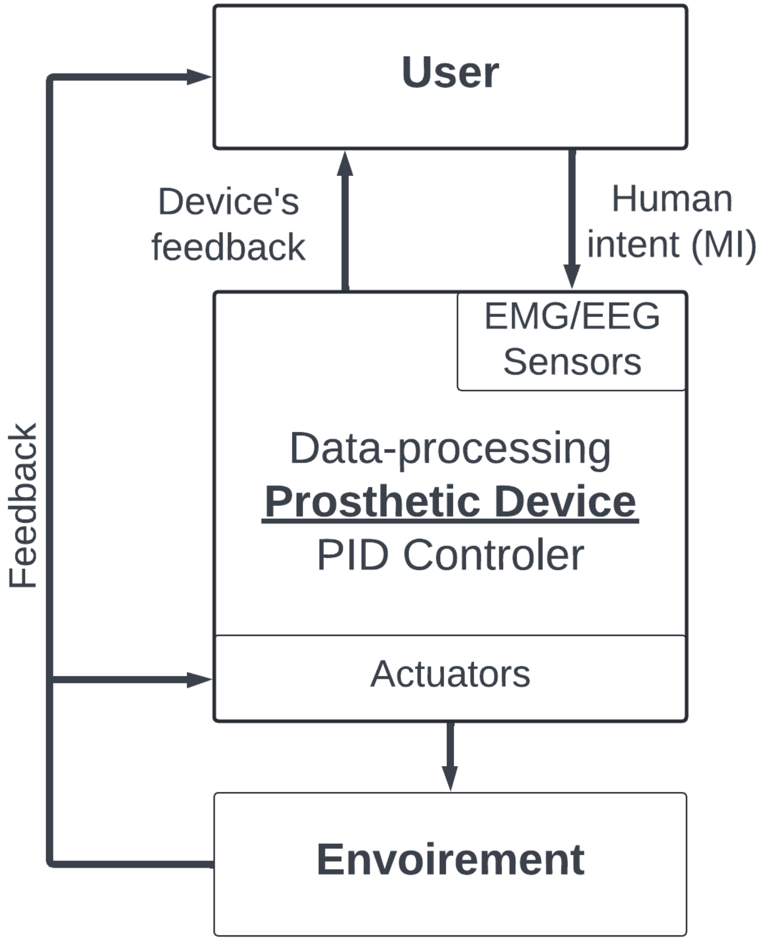
Myoelectric prosthesis

- Replace a missing limb
- Battery, motors…
- Processing unit



- Input: muscle electrical signals
- Output: desired motion
- Models: shoulder-hand, forearm-hand, hand, leg-feet, feet…

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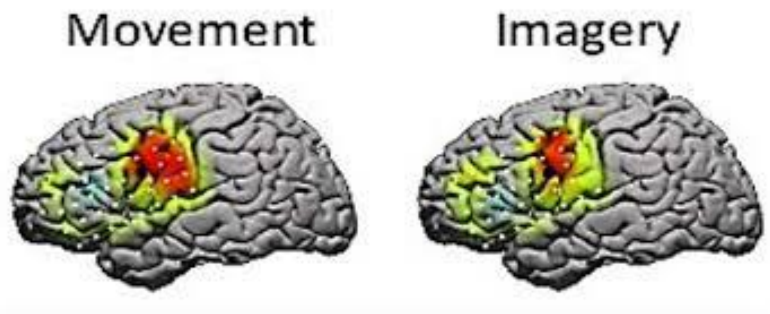
Prosthetic control - Problem

- State of the art
  - Unintuitive – Proportional Control (Cordella et all)
  - Poor accuracy (Altaheri et all)

Proposed technique:

"**Motor Imagery** is the **mental simulation** of a movement without any **muscle contraction.**"



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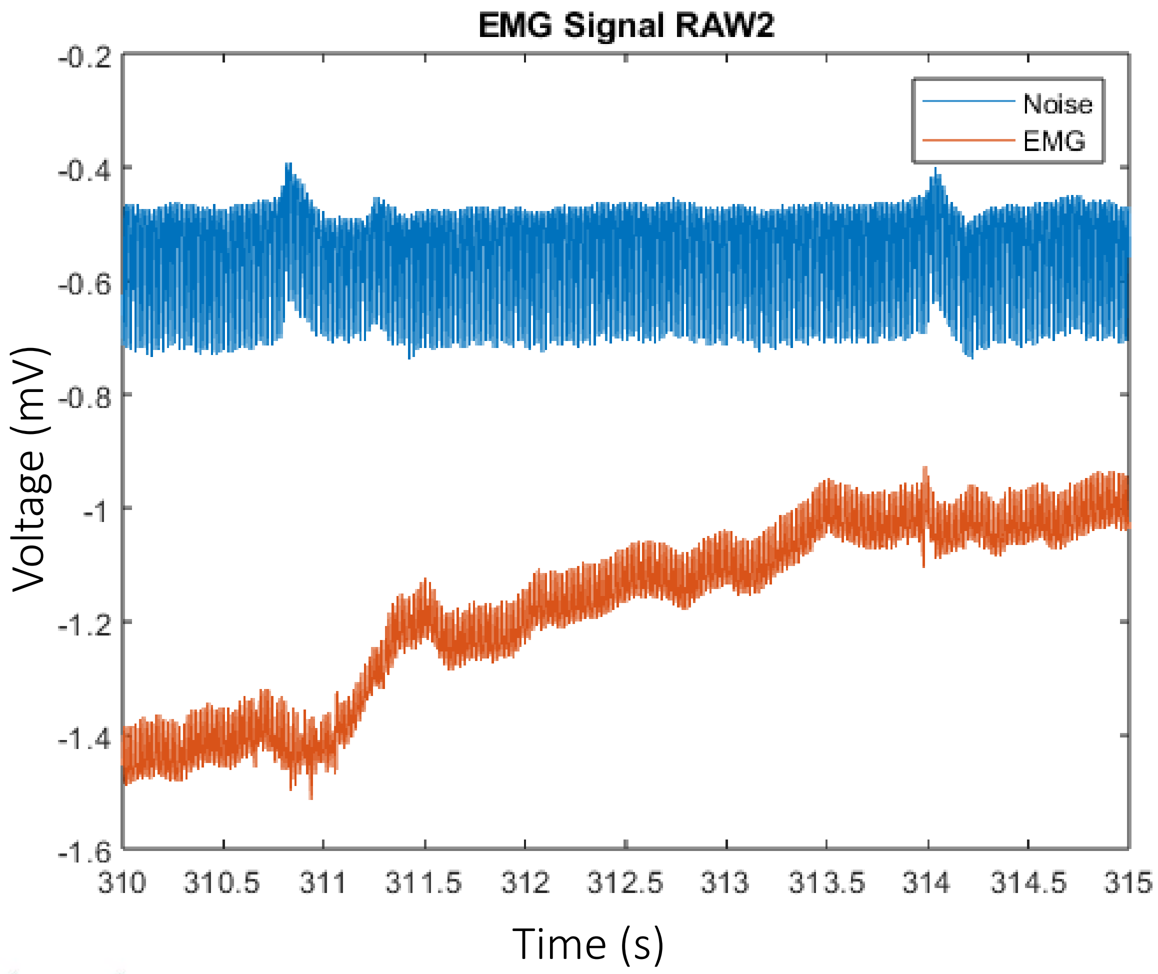
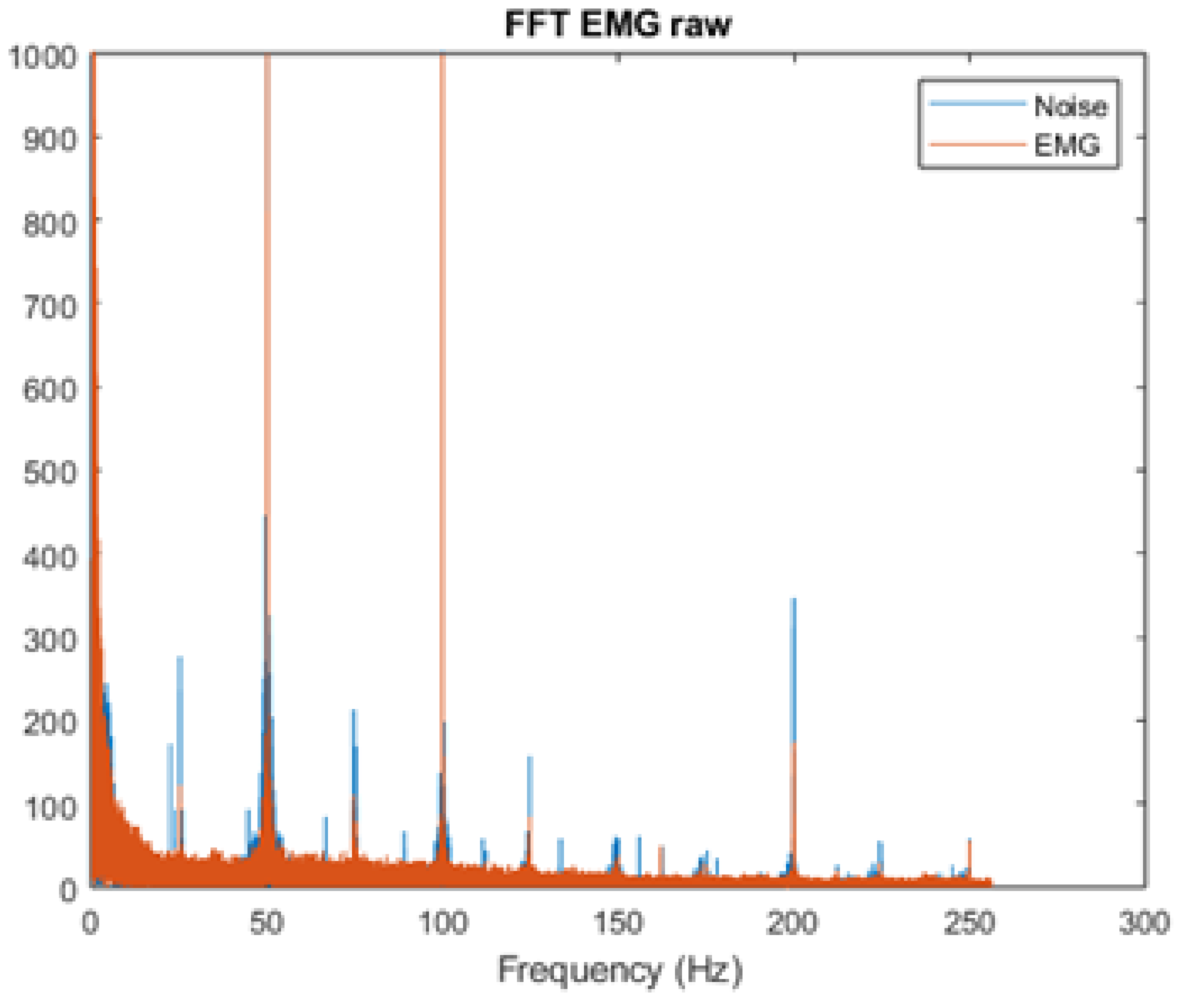
The Electroencephalographic (**EEG**) signal **pattern changes** during its practice.

EMG Data





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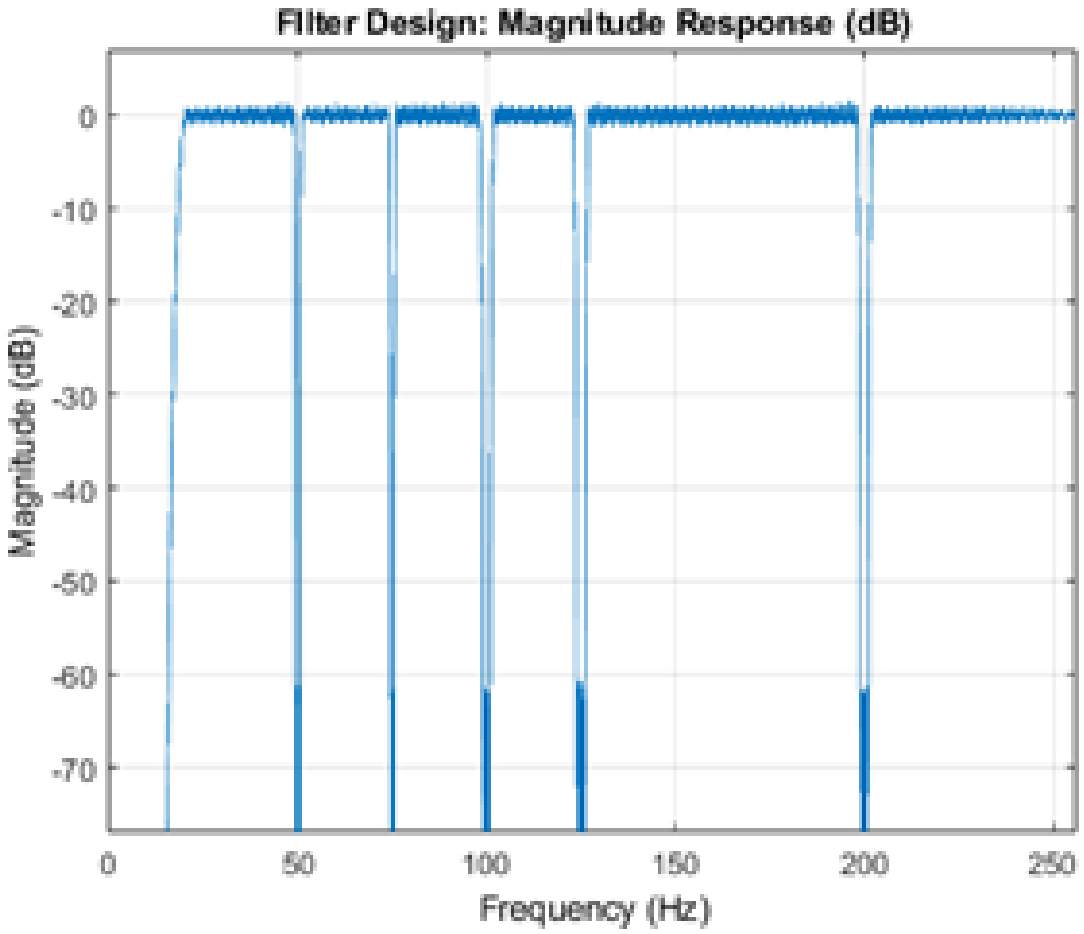
EMG Data



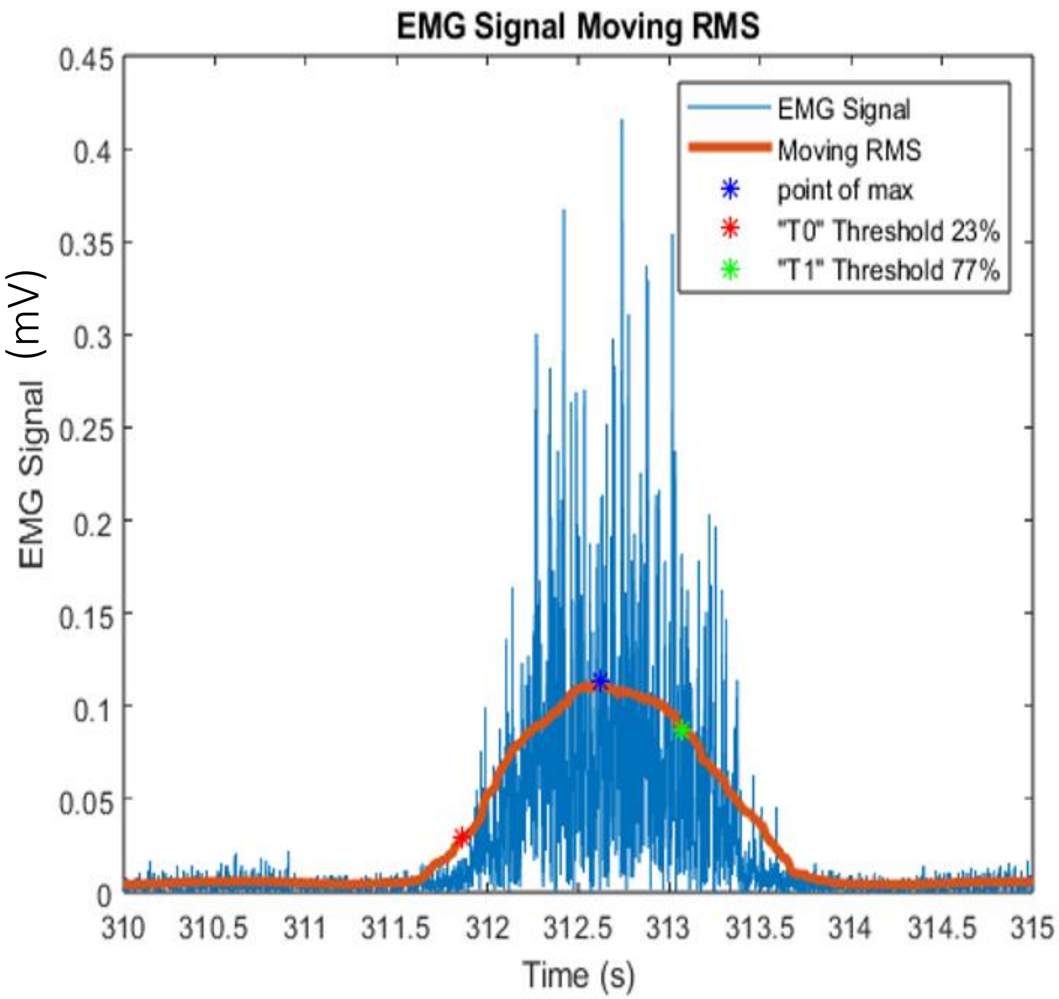


Figure 3. Representative chart of the EMG signal of the biceps contraction. Definition of times T1 and T2 as 23% or maximum amplitude and T3 as 77% of the maximum amplitude after reaching the peak.

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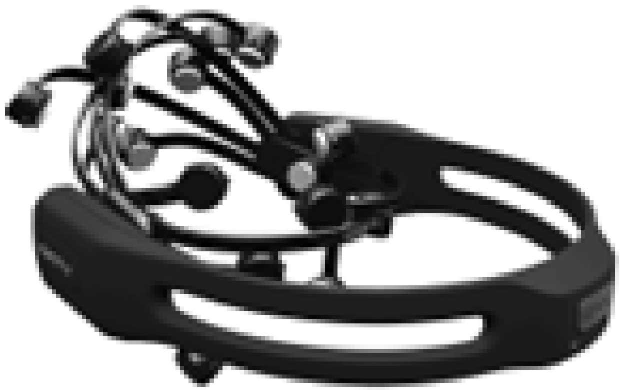
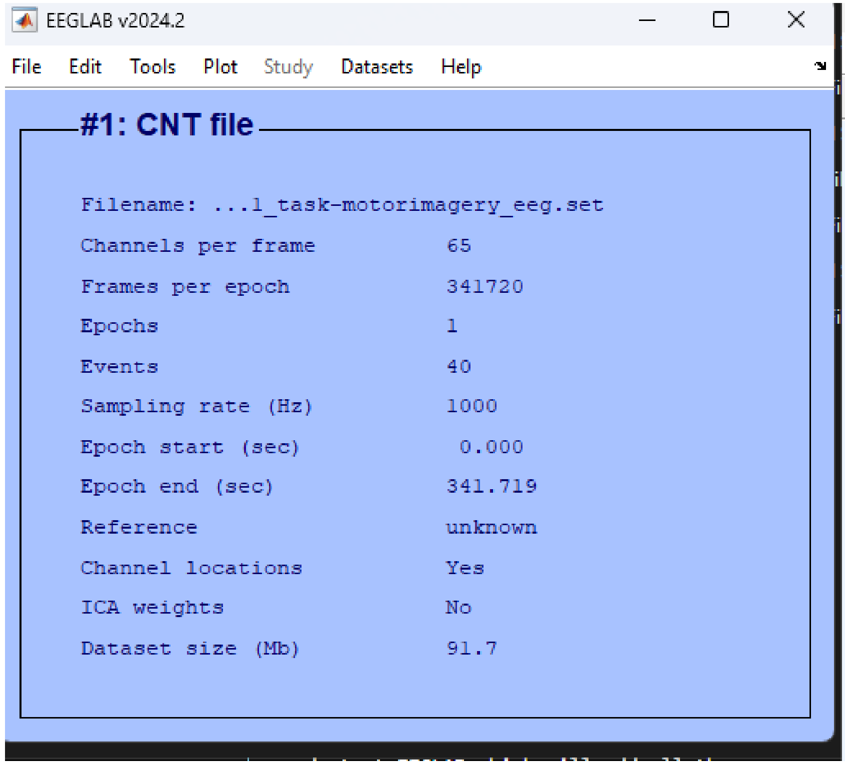
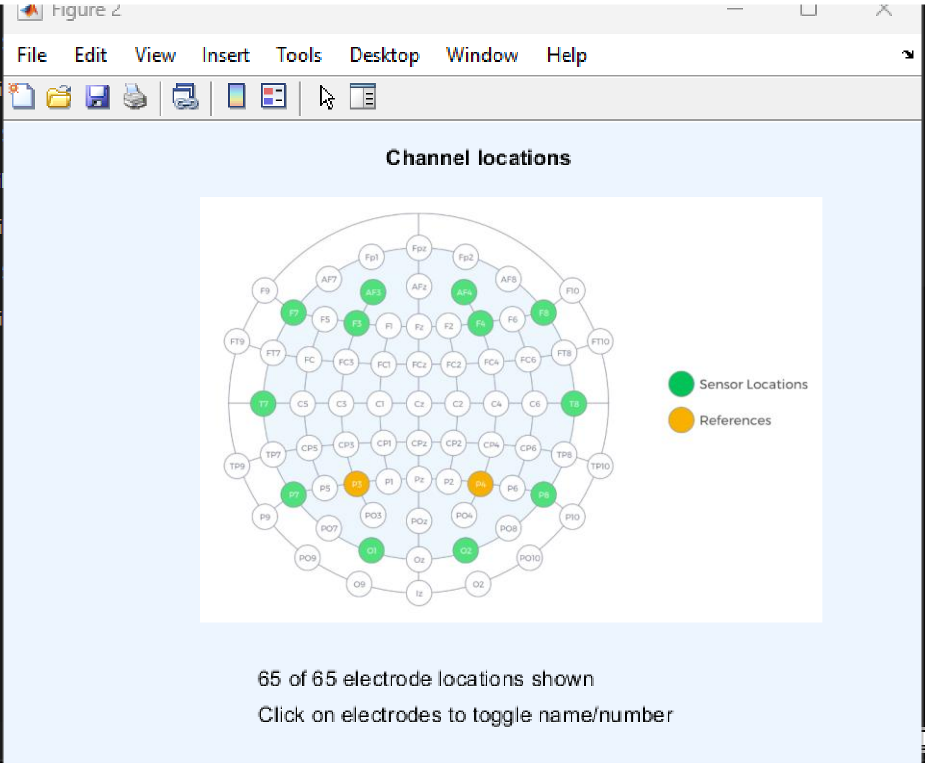
EEG Data

- **Bioelectrical** signals



EPOC X EEG device





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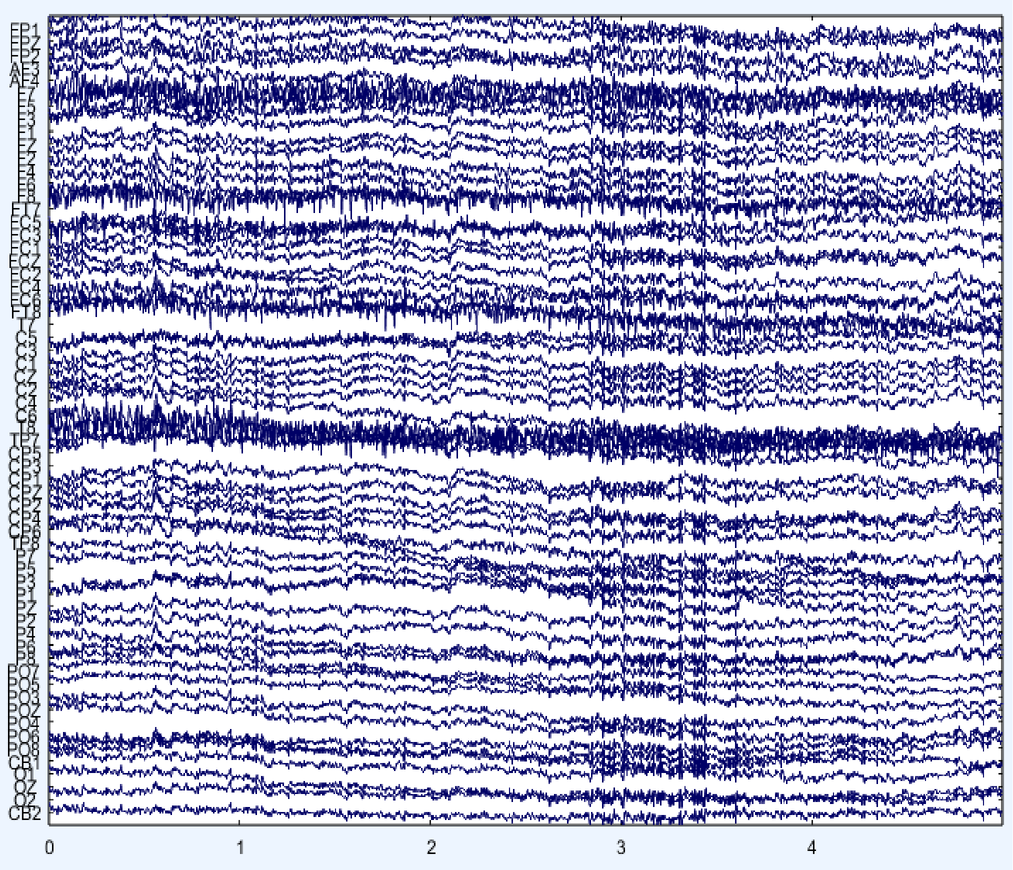
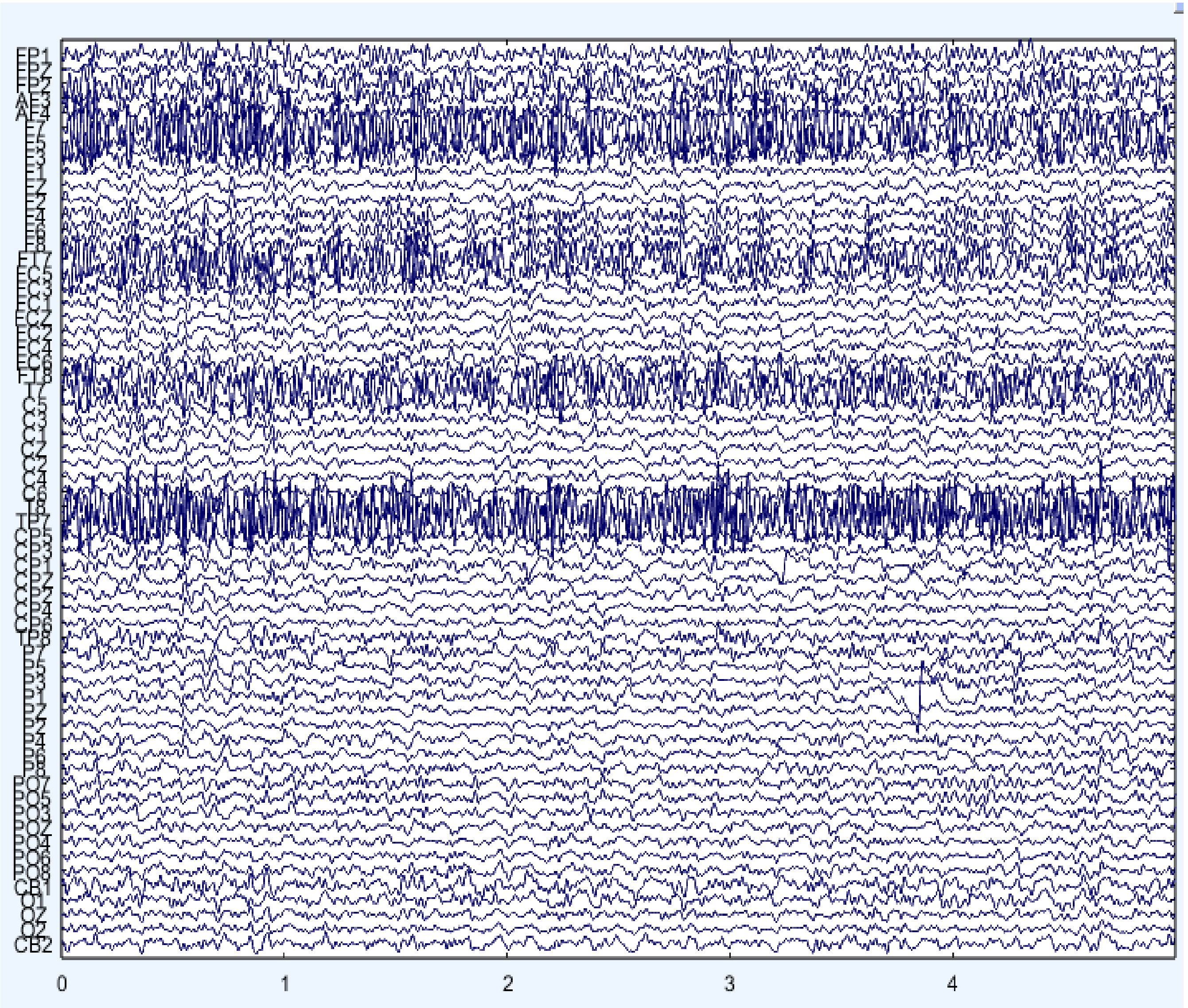
EEG Data

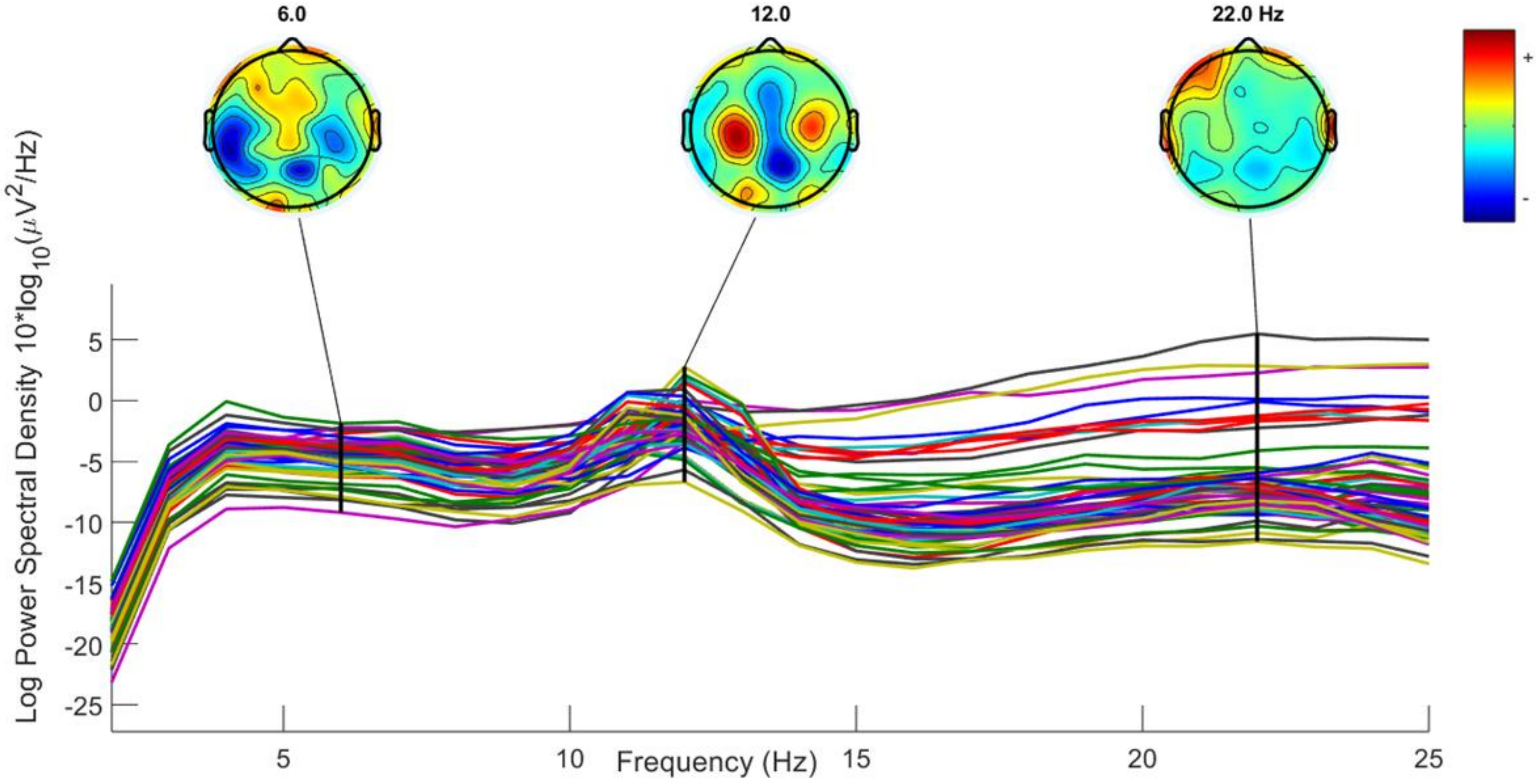


Raw data



Preprocessed data

EEG Data



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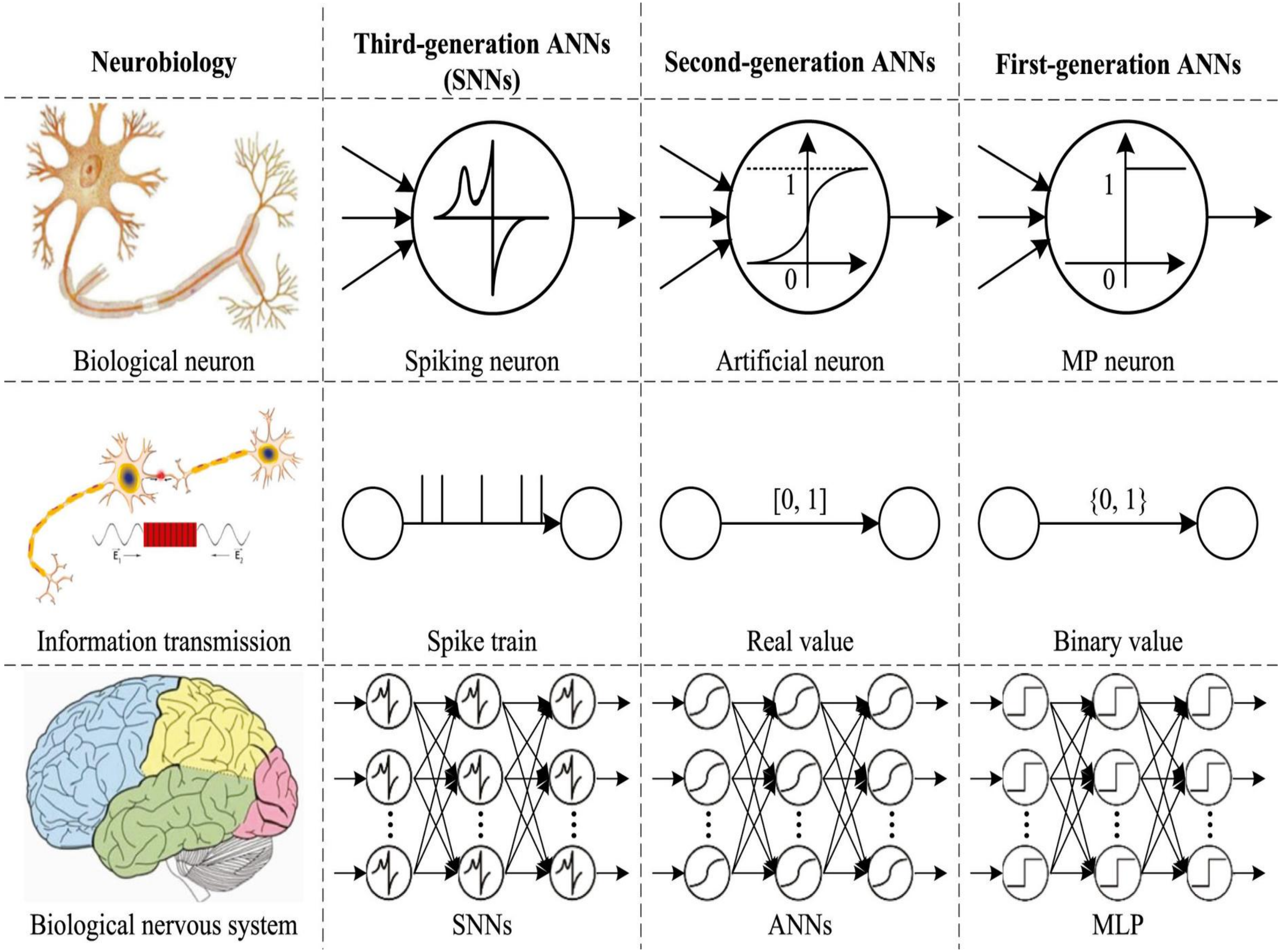
Pattern recognition – Spiking Neural Networks

- Biologically inspired
- Rich temporal encoding
- Event-driven / Power Efficient



[Wang et all, 2020]

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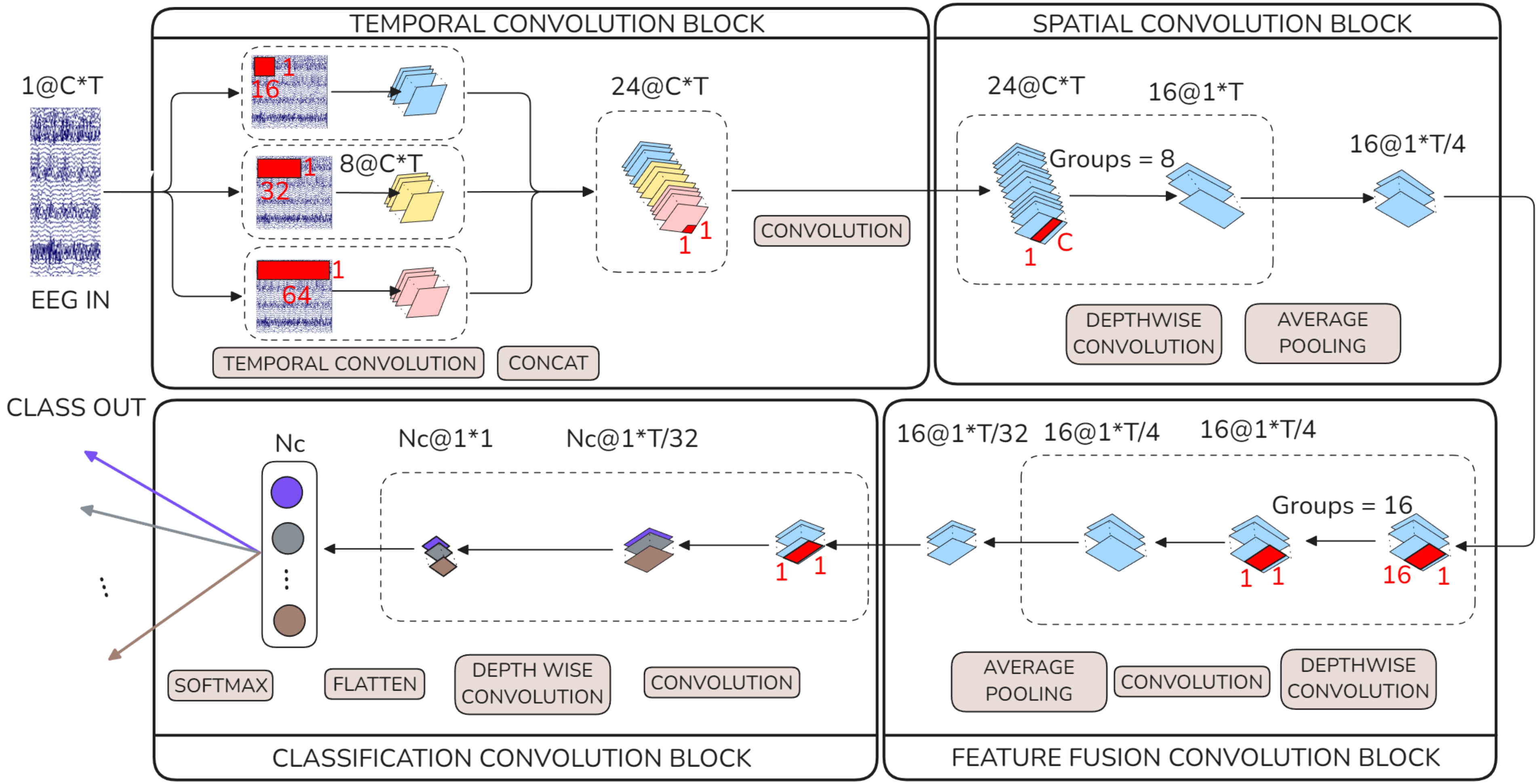
Training a CNN



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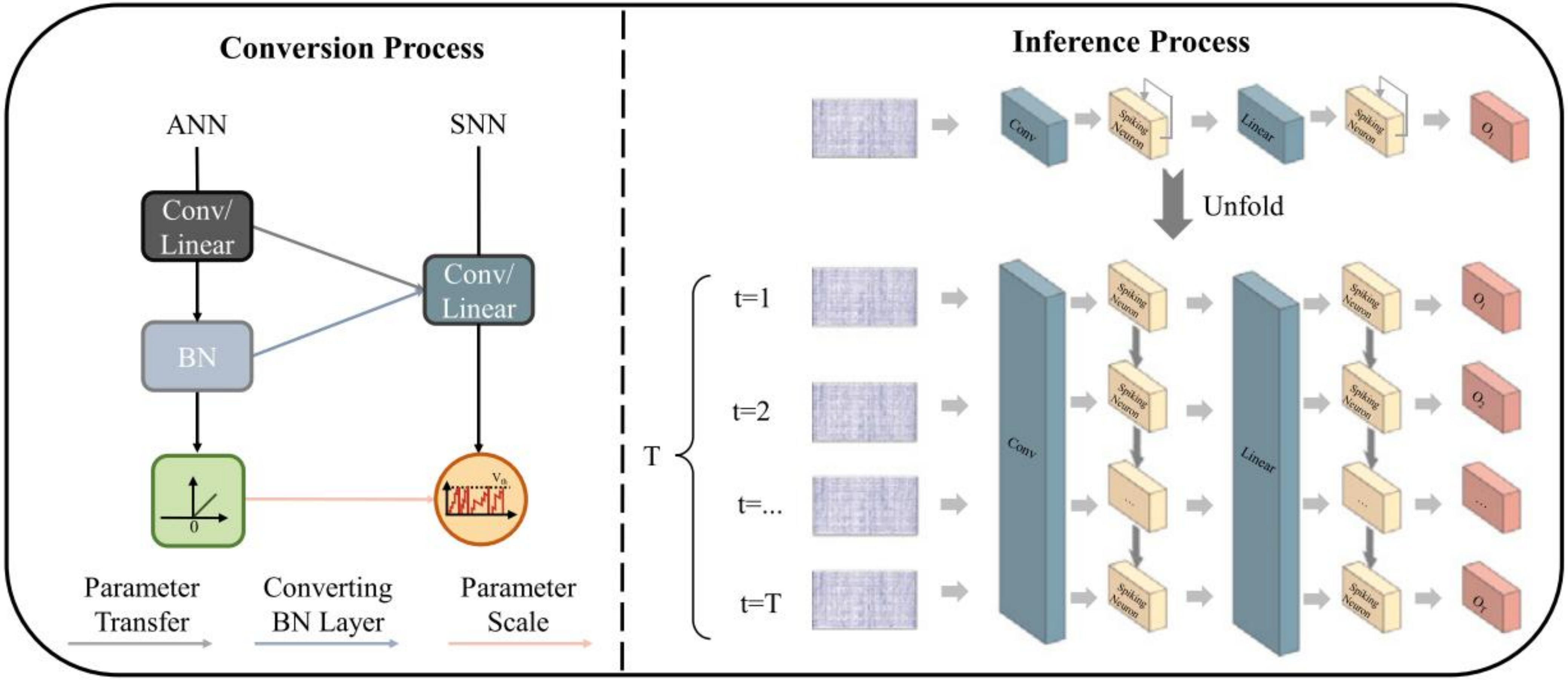
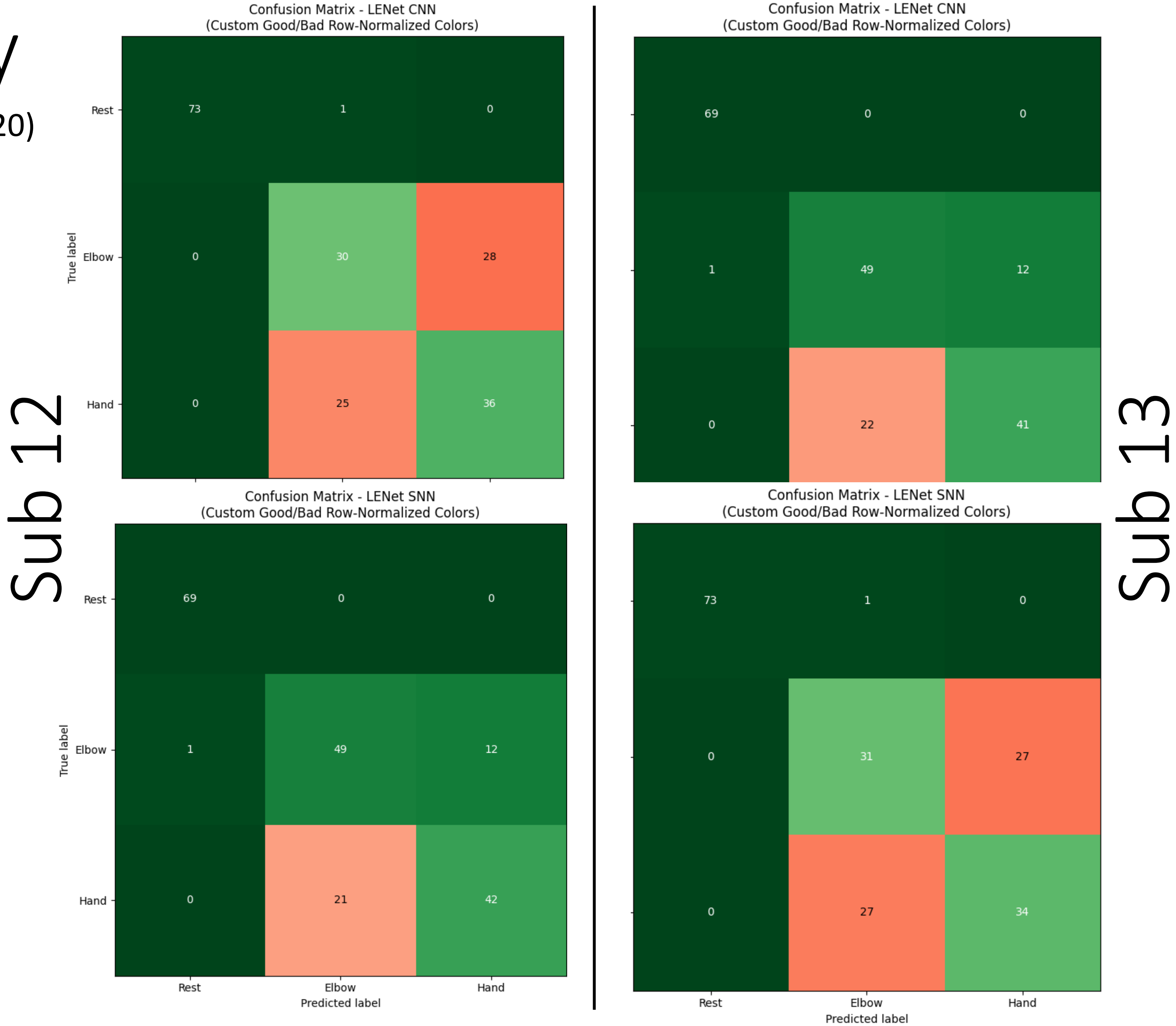
Converting from ANN to SNN



[Liao et al. 2025]

Inference accuracy

3 class MI-EEG dataset (Ma, Qiu, and He 2020)



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Comparison with State of The art

Table 1: accuracy benchmark comparison with other SoA models for the same dataset

Model	Accuracy (%)	STD (%)
CAMLP-Net	77.44	0.57
$\boldsymbol{LENet_{CCB}}$	**77.23**	4.99
$\boldsymbol{SNN_{CCB}}$	**77.23**	5.50
MLP-Mixer	76.51	0.77
Corr+CNN	75.03	3.37
DeepConvNet	73.07	1.44
TSception	71.97	0.82
EEGNet	70.44	1.18
FBCSP+SVM	68.68	2.44

Energy consumption comparison

$$\boldsymbol{E_{ANN}} = E_{MAC} \sum_{l=1}^{L} \mathrm{FLOPs_{MAC}}(l) \quad (1)$$

$\mathbf{E_{MAC}}$ is the energy consumed per MAC operation (4.6 pJ)

$\mathrm{FLOPs_{MAC}}(\mathbf{l})$ number of floating-point MAC operations in layer l.

$\mathbf{L}$ is the total number of layers in the network.

$$\boldsymbol{E_{SNN}} = E_{MAC} \cdot \mathrm{FLOPs_{MAC}}(1) + E_{AC} \sum_{l=2}^{L} fr \cdot T \cdot \mathrm{FLOPs_{MAC}}(l) \quad (2)$$

E_{AC} is the energy consumed per AC operation (0.9 pJ)

Table 2: Energy consumption for inference

Total MACs	ANN Energy (μJ)	SNN Energy (μJ)	Consumption Reduction (%)
33,973,008	156.28	93.15	**59.6**

*Constants used: $EMAC$=4.6 pJ, EAC=0.9 pJ. SNN parameters: T=100, Assumed Average Firing Rate fr=2%.

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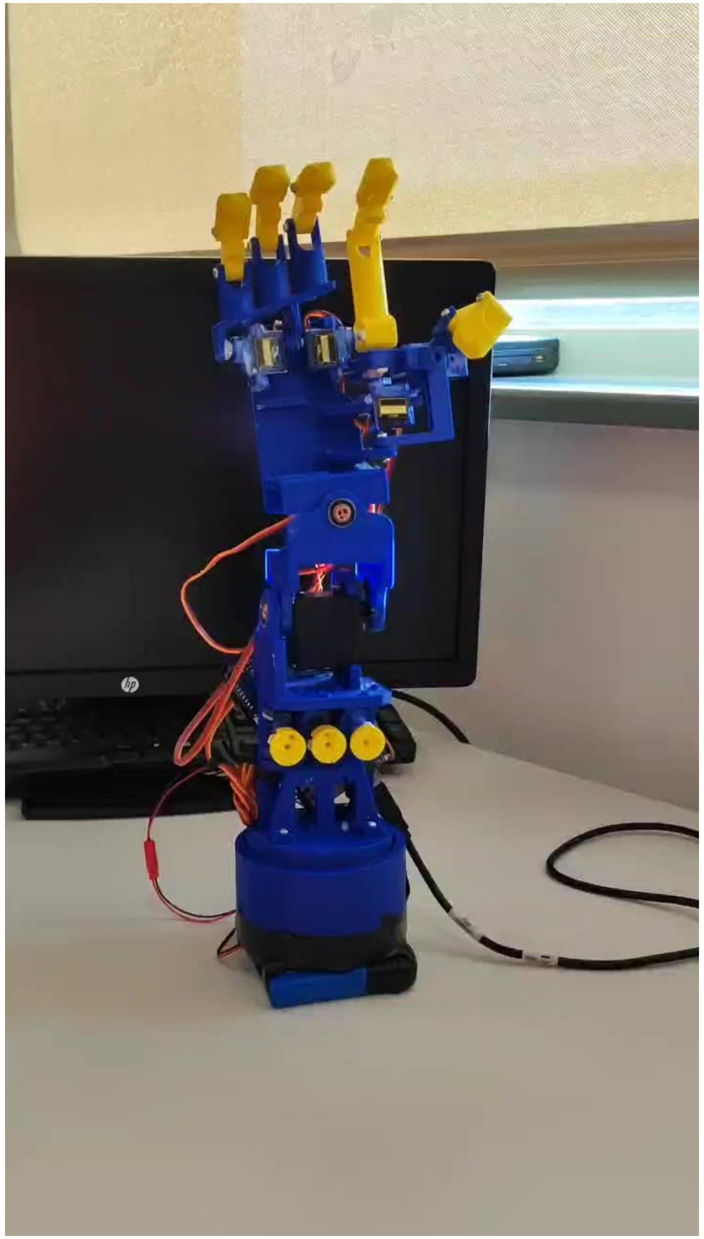
Test prototype with 3 classes



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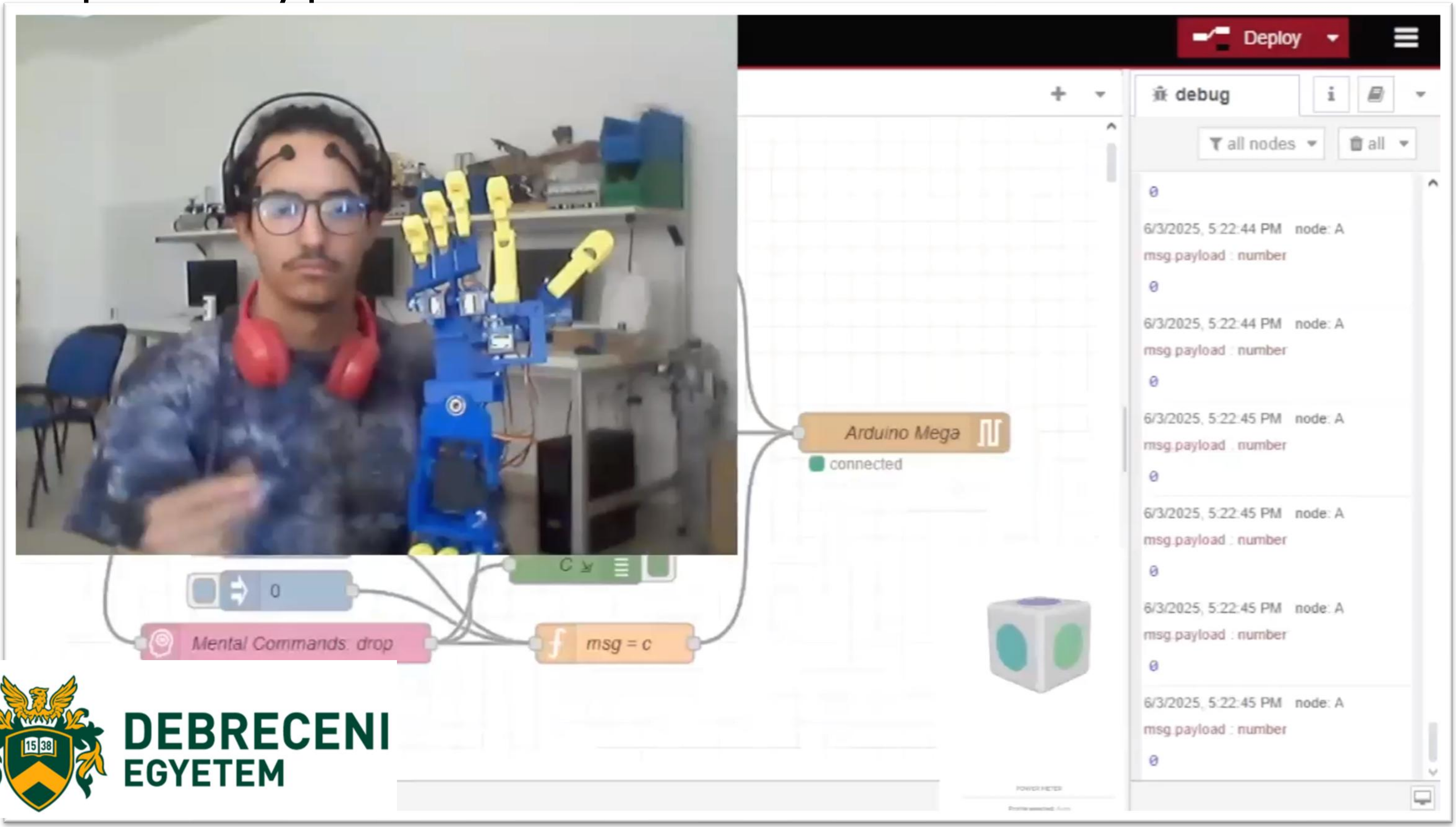
Test prototype with 3 classes



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Conclusion & Future work

- **SNN Accuracy:** MI-EEG classification accuracy comparable to the SoA.
- **Energy Reduction:** SNNs offer significant energy savings (59.6%).
- **Effective Conversion**: ANN-to-SNN conversion successfully preserved discriminative features for MI classification.
- **Future Validation:** Requires evaluation on larger subject cohorts and real-world energy measurement on neuromorphic hardware.
- **Hybrid System Development:** future implementation of the proposed MI-EEG and EMG hybrid control system.

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Thank You!

AKNOWLEDGMENT:

- Presenter: Arthur Alonso
- Supervisor: Dr. Husam Abdulkareem

Evaluation Q&A

Evaluation Q&A

1. Since overall and body part accuracy ranges greatly between subjects, would more subjects be able to achieve better accuracy of the models? Based on your calculation and results, how many subjects are needed to reliably raise the accuracy to for example 80 or 90%?

- **Clarification**: The ANN training is **intrasubject**, the accuracy generally depends on the user’s ability to really concentrate and isolate the “thought” of moving the given muscle or body part.

- More subjects would give us **further validation** about the model **generalization** capability.

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Evaluation Q&A

2. Apart from more subjects, what other ways may be to make the model more accurate and robust?

The ANN training methodology can be further optimized:

- **Computational power / time limitations:**
  - Number of epochs (500) was not enough to achieve convergence in some cases.

  A dynamic epoch number could be more appropriate.
  - Down sampling used (512 to 90 Hz)

- **Further hyperparameters optimization**
  - Test different kernel sizes for the spatio-temporal convolutions
  - Drop-out ratio, Focal Loss, Number of Time stamps, grouping sizes etc.

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- **Others**
  - Data Augmentation, Wavelet transform instead of raw data, Direct SNN Training, Transfer Learning and Subject-Specific Fine-Tuning

STATE EXAM QUESTIONS

STATE EXAM

1. What passive filter circuits do you know? What components do the filter circuit include? How can calculate the cut off frequency? What is the definition of cut-off frequency? Which methods can be analyzed the filter working parameters?

Low pass, High Pass, Band pass, band stop filters

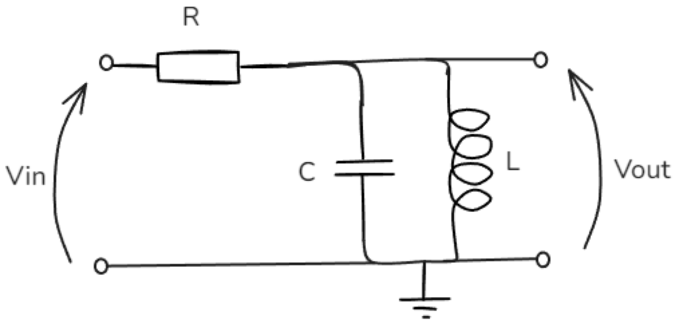
RC filter

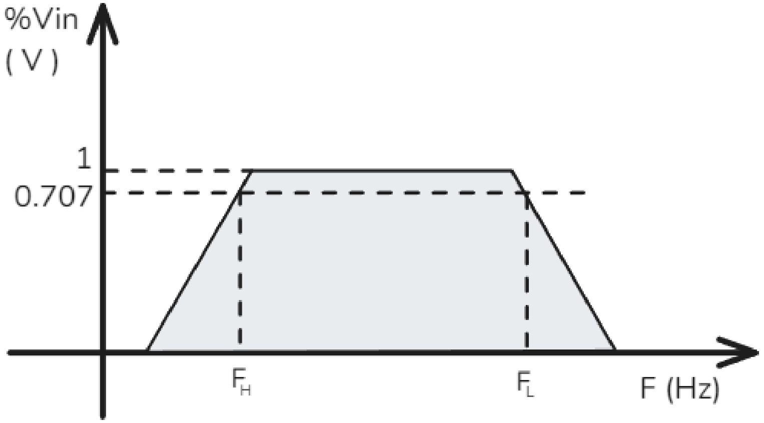
$$F_C = \frac{1}{2\pi RC}$$

RL filter

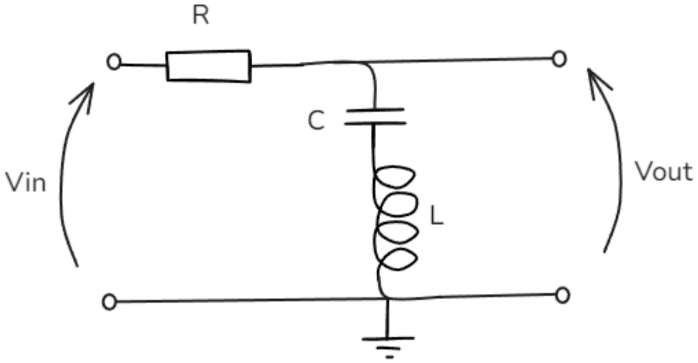
$$F_C = \frac{R}{2\pi L}$$

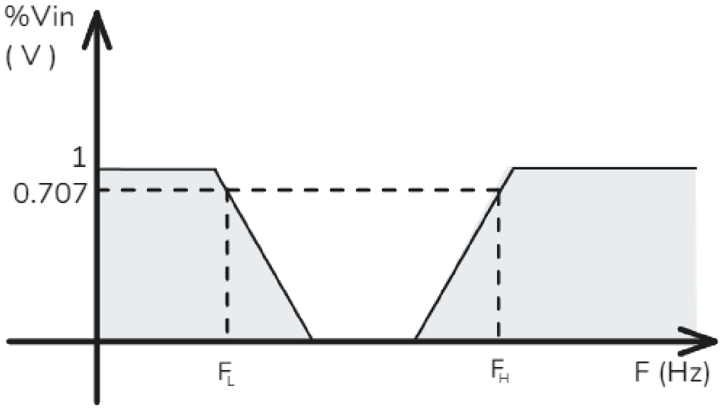
Band Pass Filter





Band Stop FIlter





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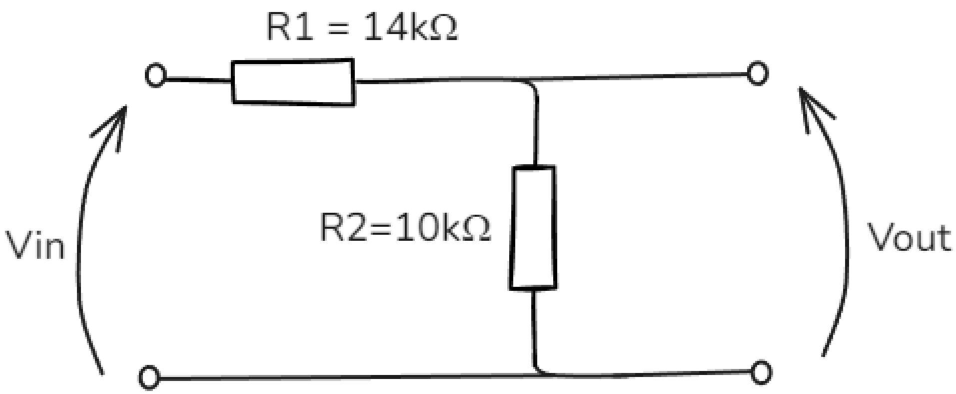
STATE EXAM

2. You would like to measure 0-24 V analog voltage and 4-20mA analog current as a sensor's output signal. Your measured system maximum input range is 0-10V. How can this problem be solved?

Mapping the 0-24V sensor output to a proportional 0-10V analog signal;

Simple hardware voltage mapping method using passive circuits: VOLTAGE DIVIDER



$$V_{out} = \frac{R_2}{R_1 + R_2} V_{in}$$

V_{in} **(V)**	V_{out} **(V)**
0.0	0.0
2.0	0.8
5.0	2.1
8.0	3.3
10.0	4.2
15.0	6.3
20.0	8.3
22.0	9.2
24.0	10.0

*14mW dissipated at 24v

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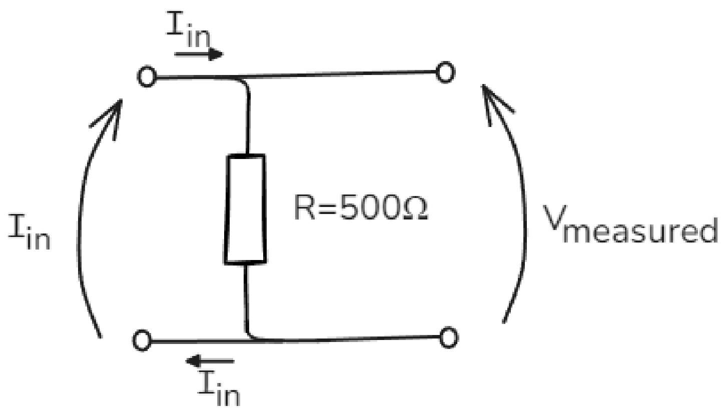
STATE EXAM

2. You would like to measure 0-24 V analog voltage and 4-20mA analog current as a sensor's output signal. Your measured system maximum input range is 0-10V. How can this problem be solved?

Mapping the 4-20mA sensor output to a proportional 0-10V analog signal:

A simple high precision resistor ($R = 500\Omega$)



Ohm's law

$$V_{measured} = \mathrm{I_{in}} \cdot R$$

$$I_{in} = \frac{V_{measured}}{R}$$

I_{in} (mA)	$V_{measured}$ (V)
4.0	2.0
6.0	3.0
8.0	4.0
10.0	5.0
12.0	6.0
14.0	7.0
16.0	8.0
18.0	9.0
20.0	10.0

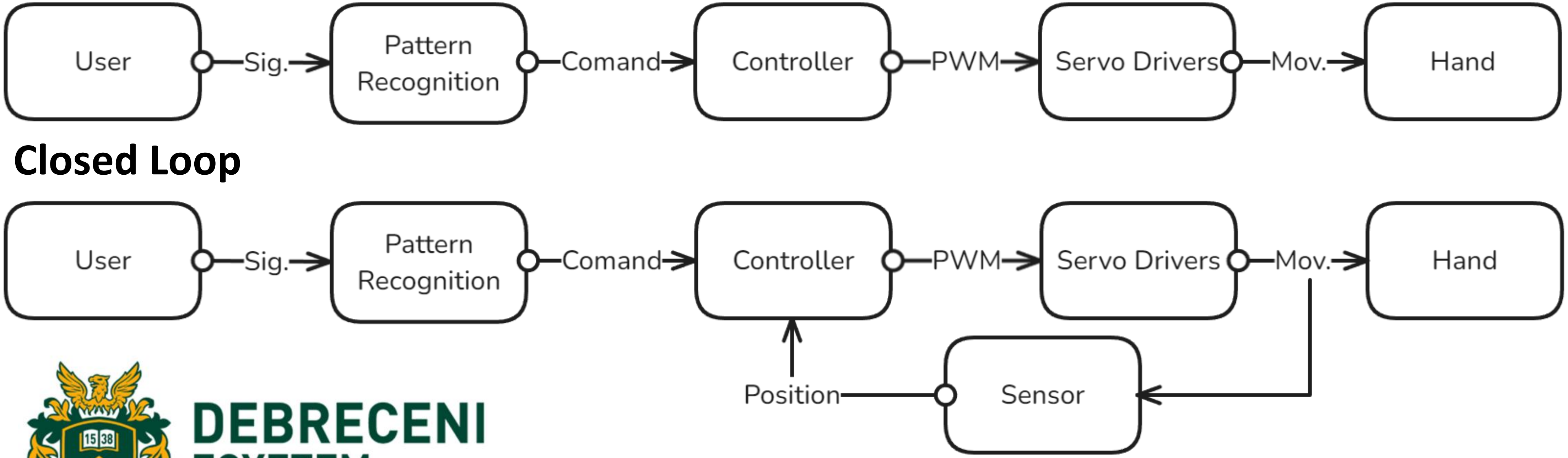
*200mW dissipated at 20mA

STATE EXAM

3. Describe the with practical examples of the open loop and feedback control! Please make an effects sketch of the processes, explain the differences. Describe different excitation signals! Example prosthetic arm grip movement:

Open Loop

Closed Loop



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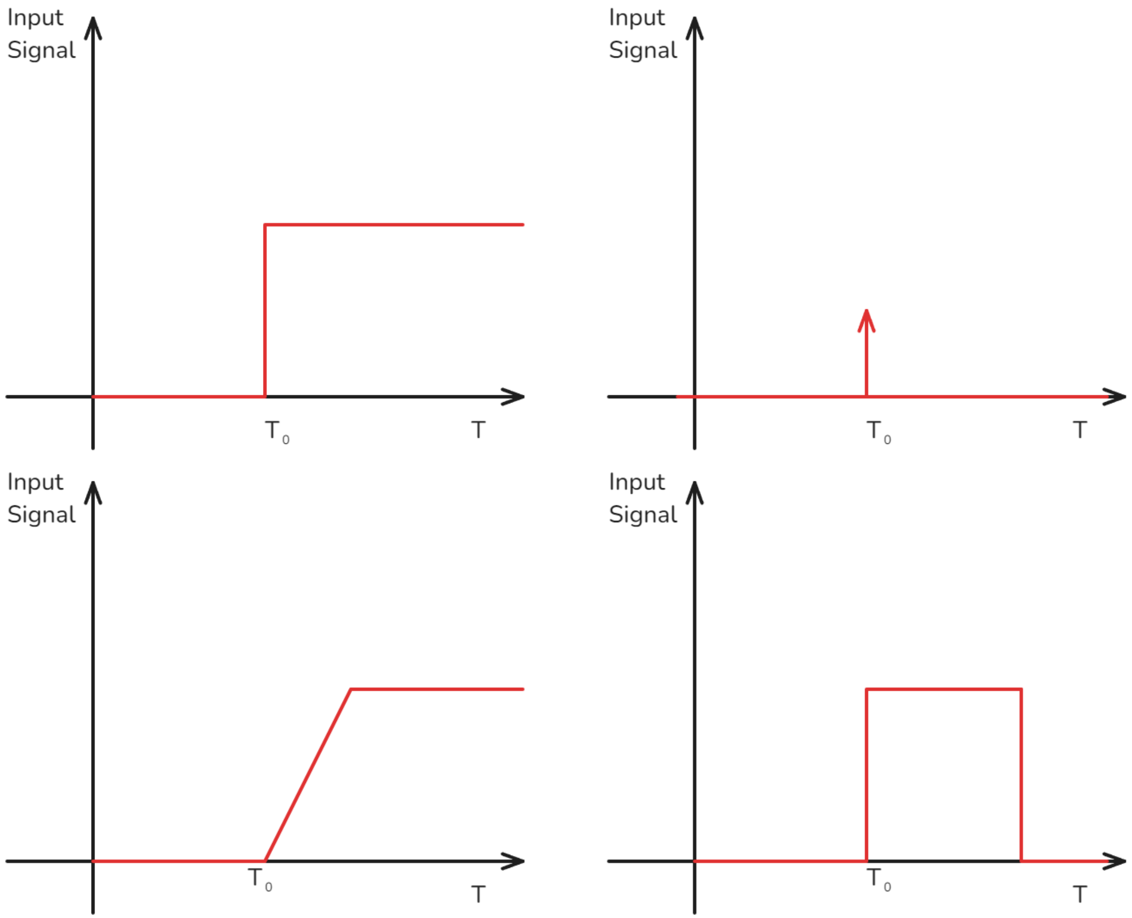
STATE EXAM

3. Describe the with practical examples of the open loop and feedback control! Please make an effects sketch of the processes, explain the differences. Describe different excitation signals!

- Step signal
- Ramp signal
- Impulse signal
- Rectangular pulse signal



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STATE EXAM

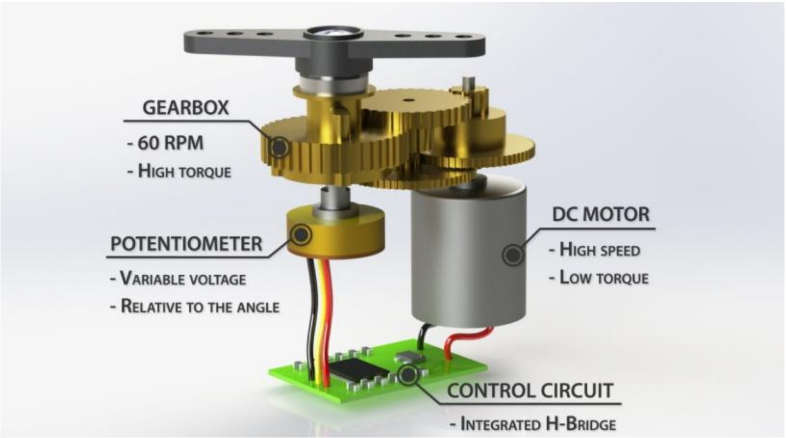
4. Servo drives: theory of operation and schematic: electrical machine, revolution sensor, power drive electronics, control electronics. How the speed and torque control can be realized? What are the important characteristics, with units?

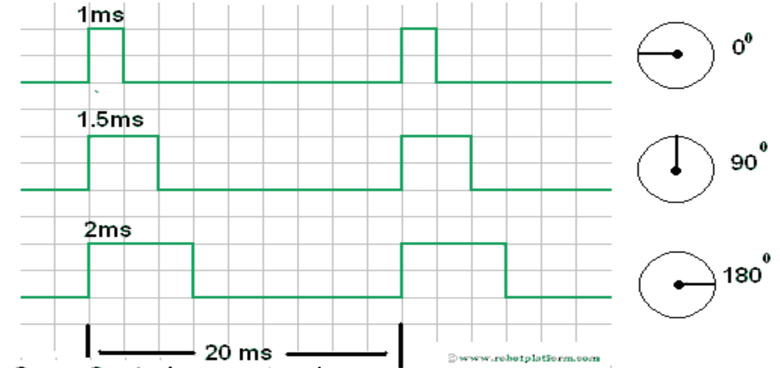
Used for precise control as it has an integrated control loop commanded by PWM inputs.

Electrical machine: **Permanent magnet brushed DC motor**
Revolution sensor: **Potentiometer** / Optical encoder / Magnetic Encoder
Power drive electronics: **H-bridge**
Control electronics: Digital Signal Processor with **PID in closed loop control**

Speed control – PWM Voltage
Torque control – Windings current

Important Parameters
Nominal voltage U_{an} (V)
No load speed Ω_{nl} (rpm)
No load current I_{anl} (mA)
Nominal speed Ω_{n} (rpm)
Nominal torque M_{n} (mNm)
Nominal current I_{n} (A)
Stall torque M_{rz} (mNm)
Stall current I_{rz} (A)
Max. efficiency η (%)





Servo Control PWM signal

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