LEARNING IN SPIKING NEURAL NETWORKS FOR BIOINSPIRED MOTION CONTROL

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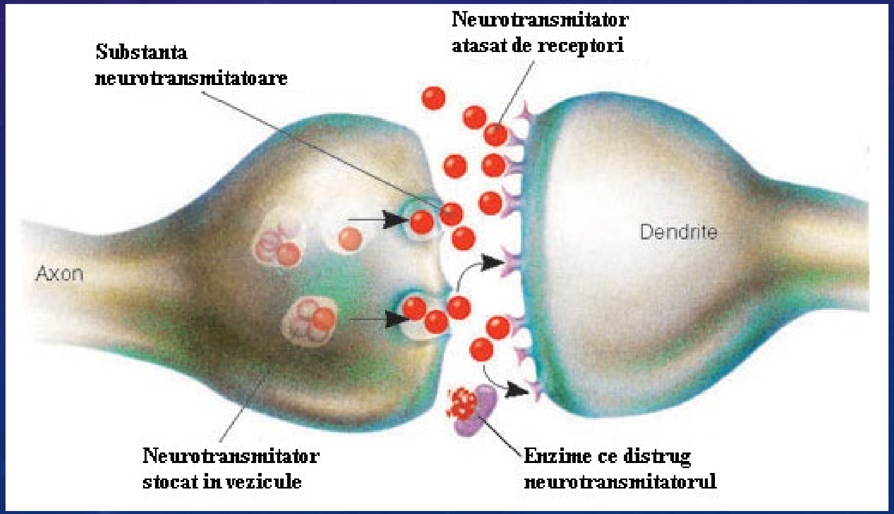
SPIKE TIMING DEPENDENT PLASTICITY (STDP)

- Is related to learning in our brains
- Depends on the moments of neurons activation
- Is related to the degree of concurrence of PRE and POST neurons.
- Includes long-term potentiation and long-term depression.

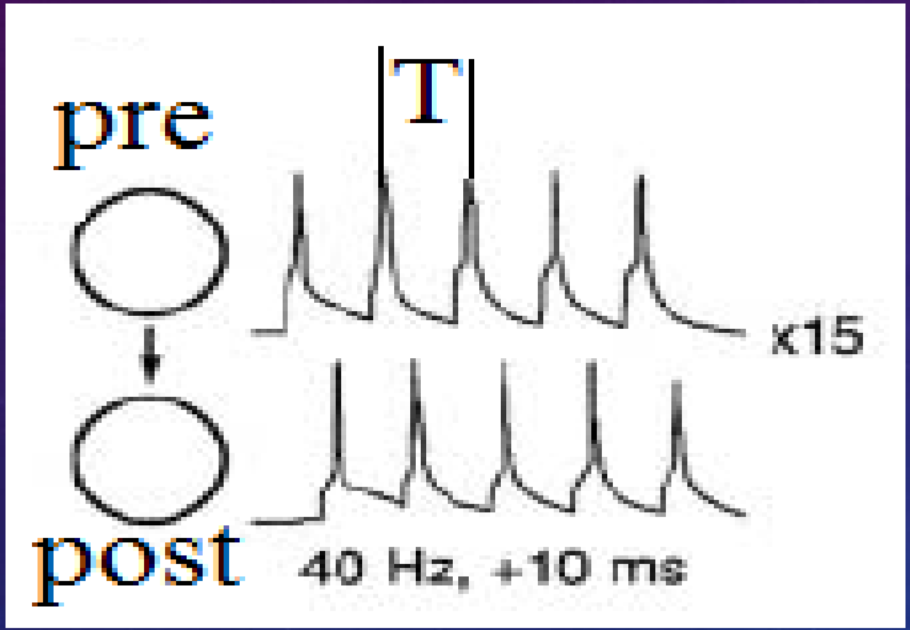
Presynaptic



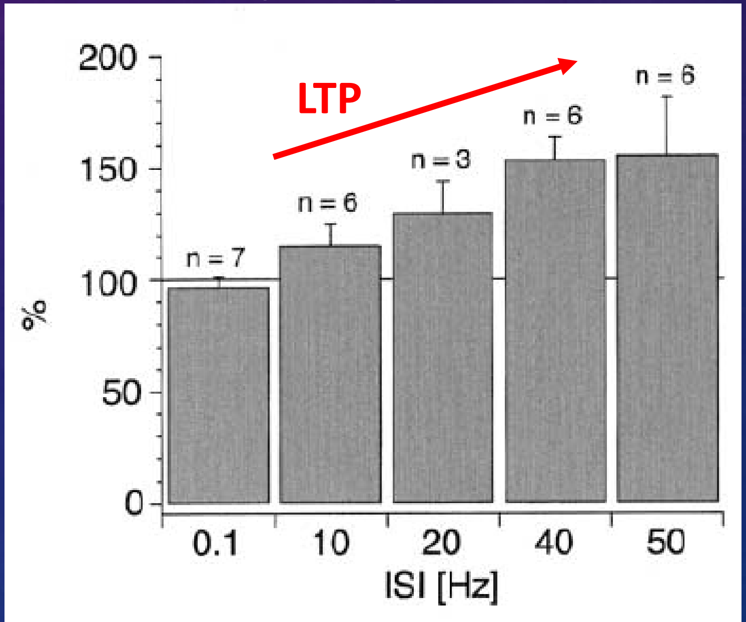
Postsynaptic

LTP AND LTD DEPENDS ON THE FREQUENCY OF ACTIVATION

Pair of stimuli *pre-post*



LTP increases with the spiking rate



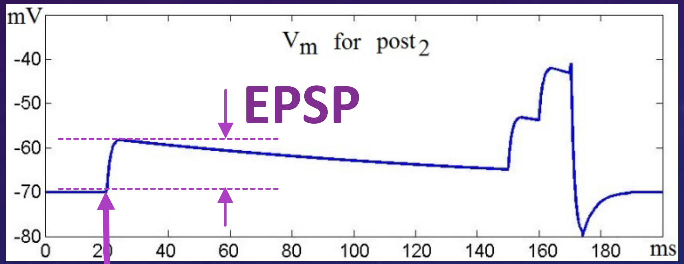
Sjostrom, et. al.

- For low stimulation frequency (0.1 Hz) LTP IS NOT observed for ***pre-post***
- Value of LTP increases with the frequency of stimuli

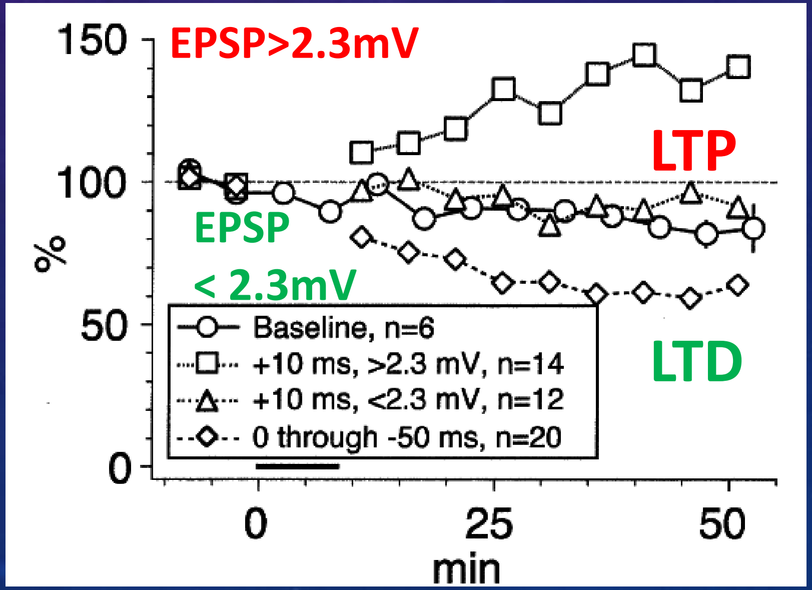
POSTSYNAPTIC RESPONSE

2. LTP DEPENDS ON THE EPSP VALUE

- The synapses are potentiated by **LTP** if:
  - The value of **EPSP > 2.3 mV** even if the activation frequency is low
  - Pre-post succession
- Succesion post-pre detemines **LTD**



PRE activation



If **EPSP<2.3mV** then **no LTP**

LTP is not produced at low values of EPSP

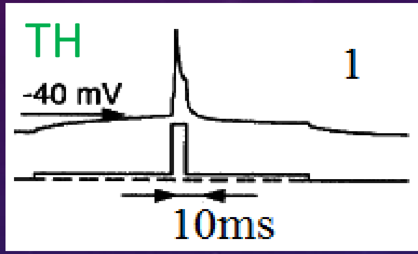
3. LTP-LTD DEPENDS ON INITIAL DEPOLARIZATION

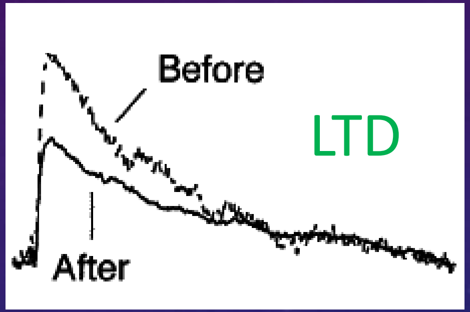
Initial depolarization

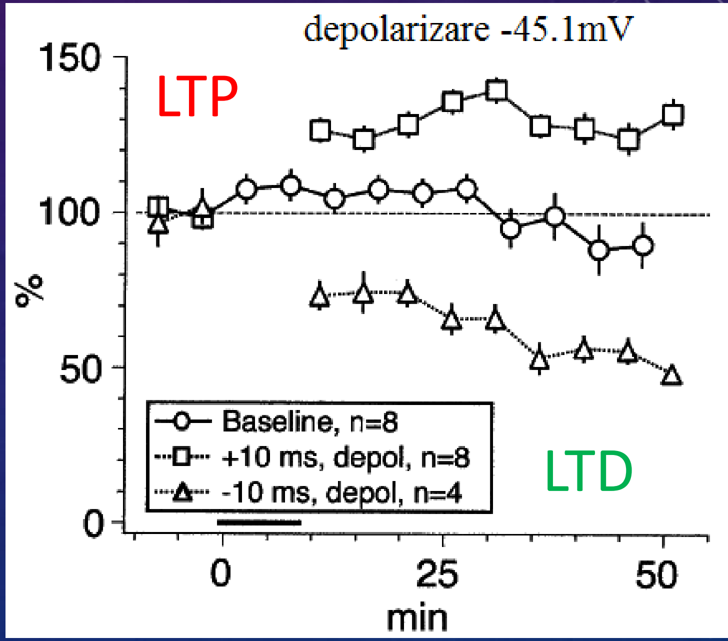
EPSP

Normal behavior for far depolarization

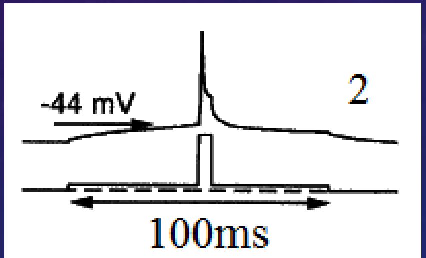
Just below the threshold (LTD)

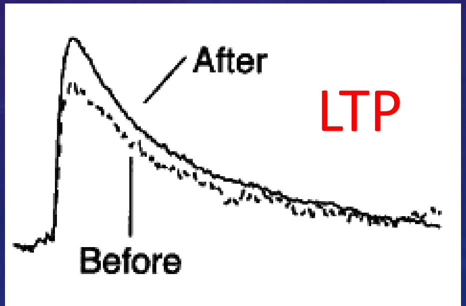






Above the threshold (LTP)





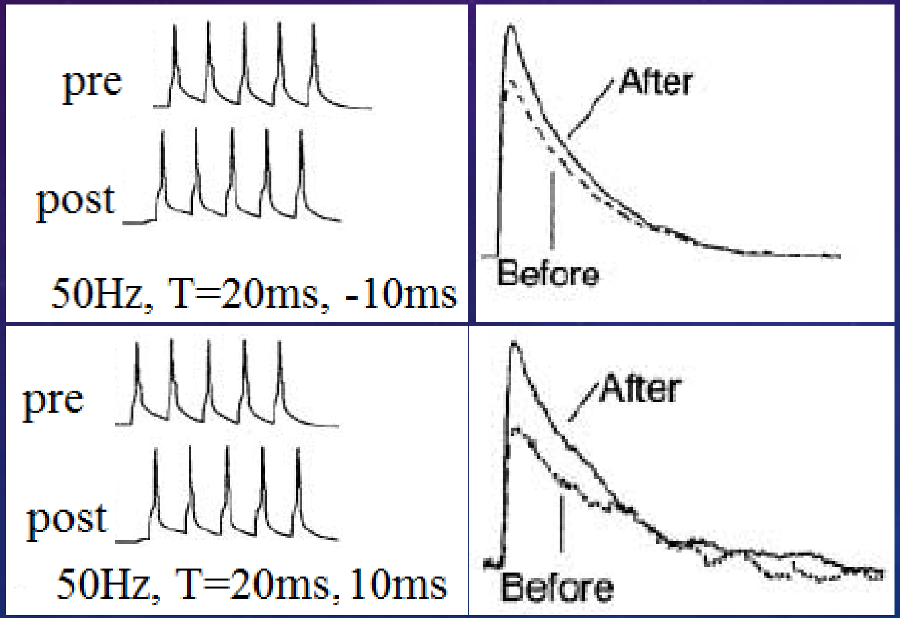
Sjostrom, et. al.

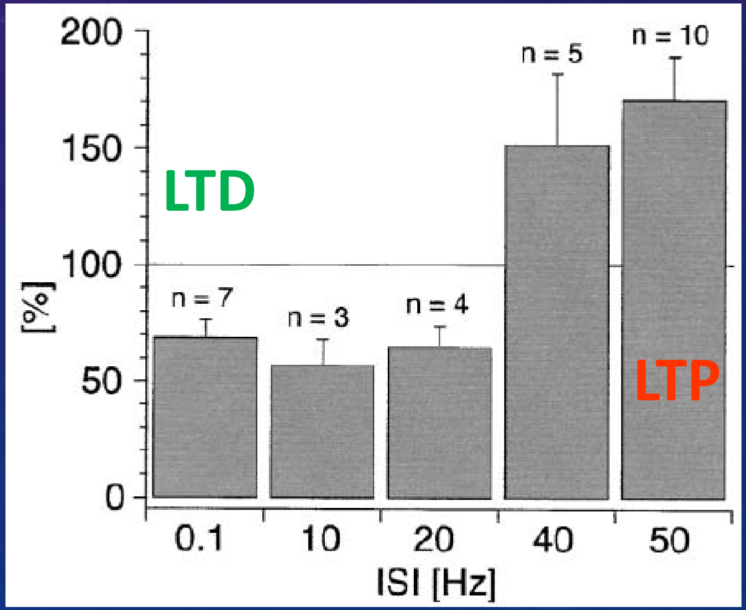
The initial depolarization should be far from the activation threshold to produce **LTP.** Otherwise **LTD** is produced.

LTP and LTD depends also on the residual depolarization (data not shown)

LTD (DEPRESSION) PRODUCES FOR LOW FREQUENCIES

- For frequency **below 20 Hz the LTD** is produced and it does not depend on the **frequency of activation**
- For frequency **above 40 Hz** only **LTP** is produced
- Note that **LTP** occurs when the frequency of ***post-pre*** is above 40 Hz





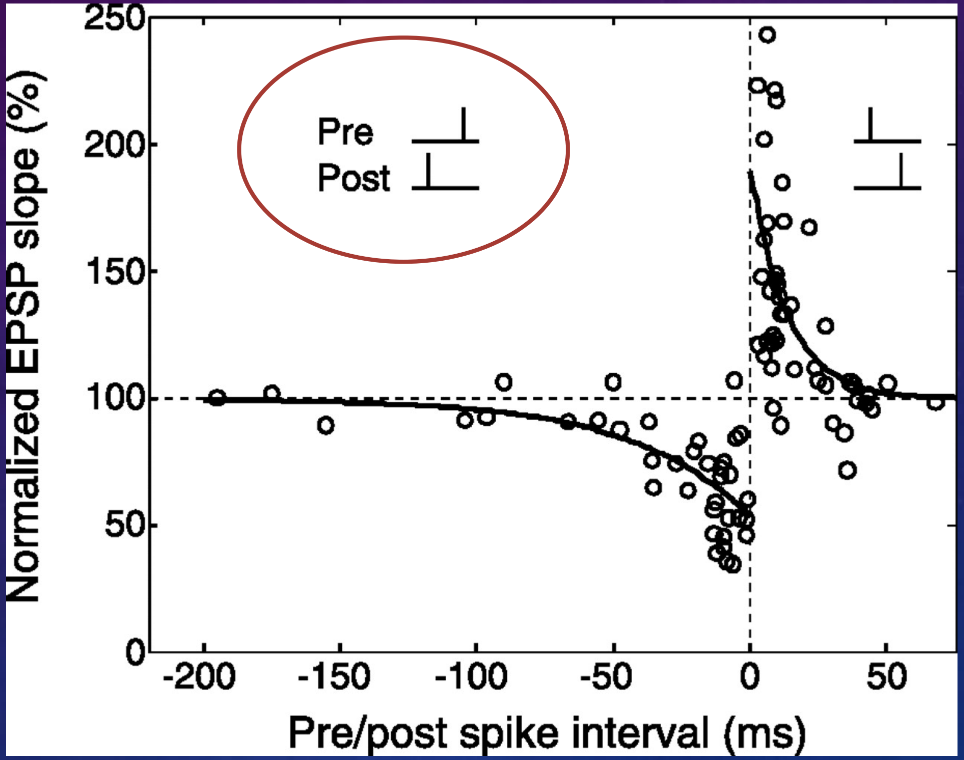
The synaptic plasticity **depends on the initial value** of the weight only for **LTP** and not for **LTD**.

THE REAL STDP WINDOWS

For high frequencies Hebbian learning occurs because of LTP

LTD

Post → pre



LTP

Pre → post

- The LTP window is shorter but LTP is more powerful then LTD for short time intervals
- LTP dominates the LTD

CONSTRUIREA MODELULUI PENTRU T-STDP

- For the synaptic transmission we consider the following **variables:**
  - **r_1, r_2** – detectors of presynaptic events
  - Possible biological meaning:
    - **The quantity of NMDA** that stimulates the postsynaptic membrane
    - The number of NMDA receptors that are activated
  - Time constants for the variation of presynaptic detectors: τ_+, τ_x

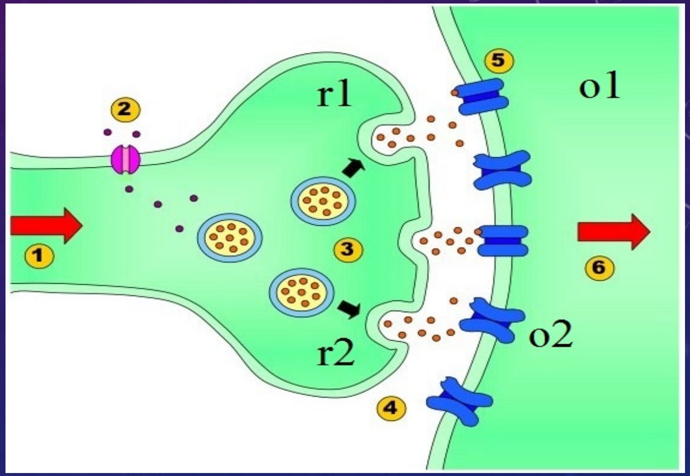
  - **o_1, o_2** – detectors for postsynaptic events
  - Biological plausibility
    - **The flux of** Ca^{2+} ions through the NMDA channels.
    - **The electric field** which is determined by the retro-propagation of the action potential.
  - Time constants for the variation of the postsynaptic detectors: τ_-, τ_y

VARIATION OF $R_{1,2}$ AND $O_{1,2}$ DURING NEURON ACTIVATION

Variation of detectors for neurons activation:

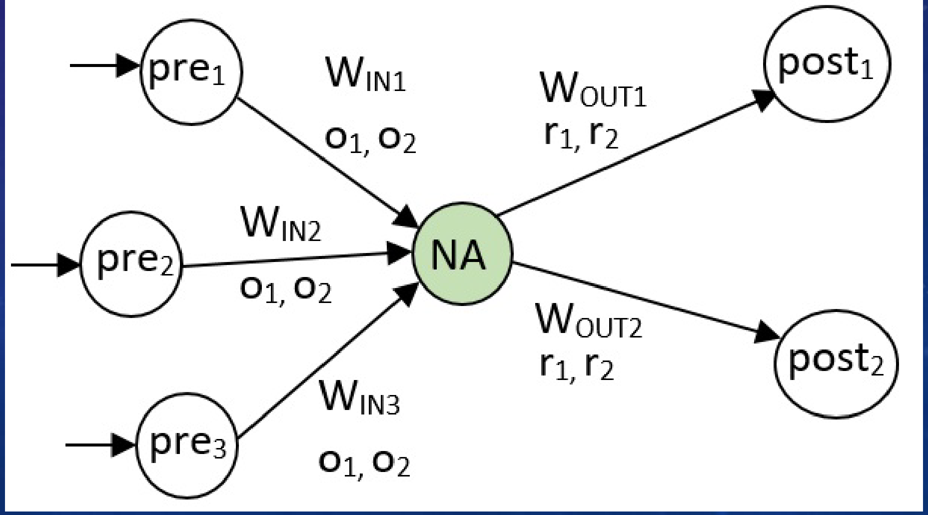
pre: $\text{if } t = t^{\text{pre}}, \text{ then } r_{\text{i}} \rightarrow r_{\text{i}} + 1$

post: $\text{if } t = t^{\text{post}} \text{ then } o_{\text{i}} \rightarrow o_{\text{i}} + 1$



	pre	post
Inactivation	$\frac{dr_{\text{i}}(t)}{dt} = -\frac{r_{\text{i}}(t)}{\tau_{+,\text{x}}}$	$\frac{do_{\text{i}}(t)}{dt} = -\frac{o_{\text{i}}(t)}{\tau_{-,\text{y}}}$

When NA is activated r si o are activated for the adjacent synapses

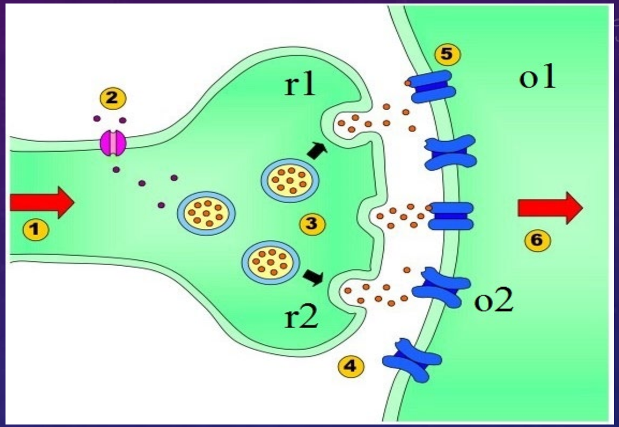


POTENTIATION AND DEPRESSION OF THE SYNAPSES

Variation of activation detectors:

pre: $\text{if } t = t^{\text{pre}}, \text{ then } r_{\text{i}} \to r_{\text{i}} + 1$

post: $\text{if } t = t^{\text{post}} \text{ then } o_{\text{i}} \to o_{\text{i}} + 1$



Inactivation

pre

$$\frac{dr_{\text{i}}(t)}{dt} = -\frac{r_{\text{i}}(t)}{\tau_{+,\text{x}}}$$

post

$$\frac{do_{\text{i}}(t)}{dt} = -\frac{o_{\text{i}}(t)}{\tau_{-,\text{y}}}$$

- LTD: w decreses for *post* that are activated previously

$$w(t) \to w(t) - o_1(t)[A_2^- + A_3^- r_2(t - \epsilon)] \text{ if } t = t^{\text{pre}}$$

  - Depends on o_1 – (principal post) si r_2 – prior to activation of pre

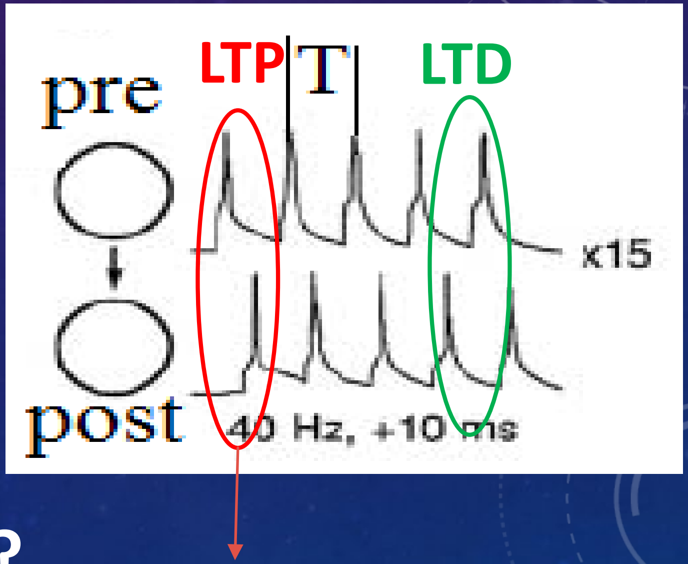
- LTP: w increases for *pre* activated previously

$$w(t) \to w(t) + r_1(t)[A_2^+ + A_3^+ o_2(t - \epsilon)] \text{ if } t = t^{\text{post}}.$$

  - Depends on r_1 – (principal pre) si o_2 – prior to post activation

QUESTION ?

- The effects of STP and LTP seems antagonistic
- This rises the question:
- STP and LTP compensates each other on long term?

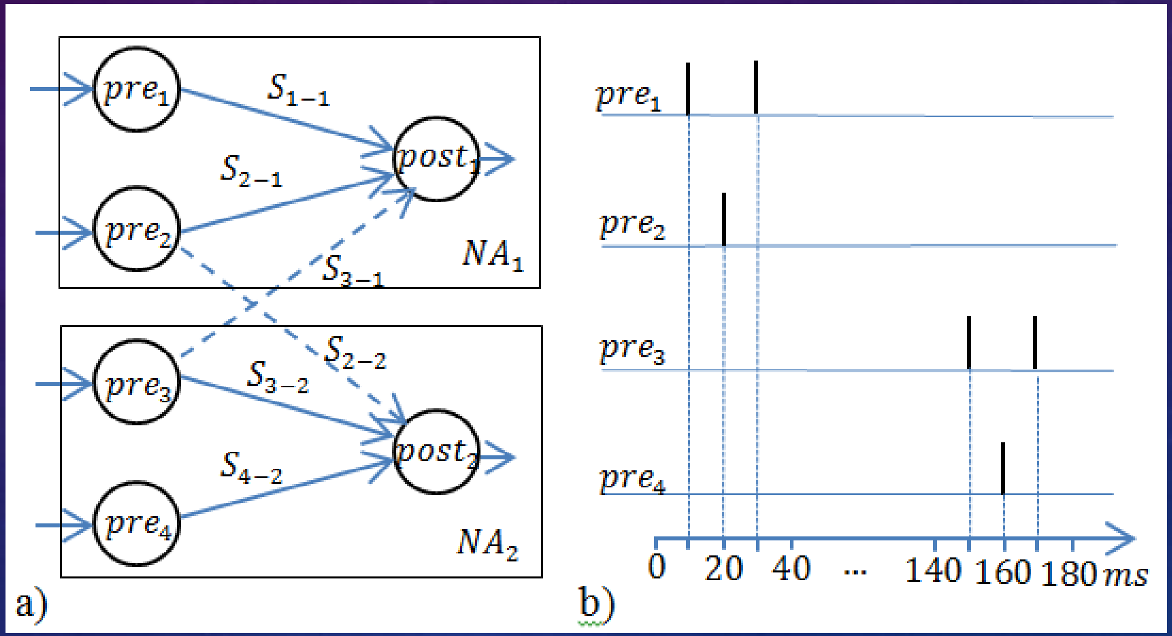


NEURAL NETWORK STRUCTURE

- Allow evaluation of the synaptic weights variation
- Main principle for the weights adjustment
  - Causality
    - potentiate the synapses that participates to the neuron action potential (activated before *post*)
    - Depress the synapses that did not participate to postsynaptic neuron activation (activates after post)
  - Triplets and quadruplets interaction
    - *Pre-post-pre* and *pre-post-post-pre* produces depression or leave the synaptic weights unchanged
    - *Post-pre-post* and *post-pre-pre-post* produces potentiation

TESTING THE NEURON MODEL

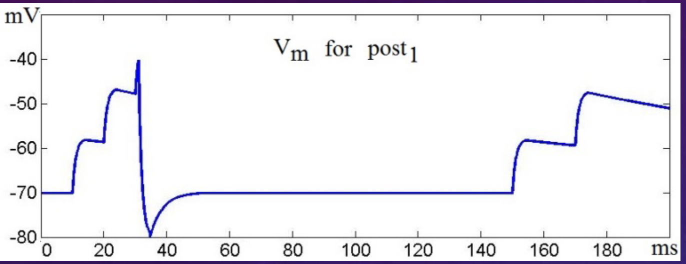
- Simple neural network structure
- Input pattern of stimuli

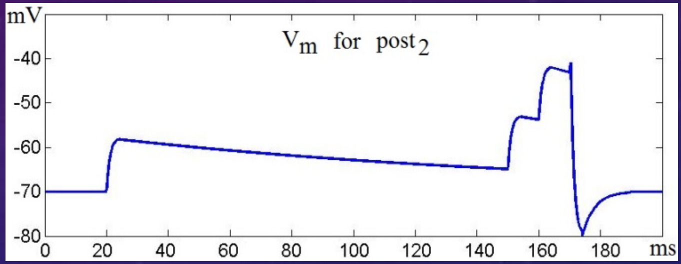


- The Neural Network is split in two areas

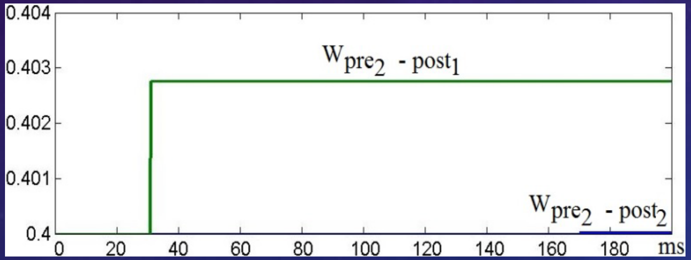
NETWORK RESPONSE FOR THE COMBINATION OF STIMULI

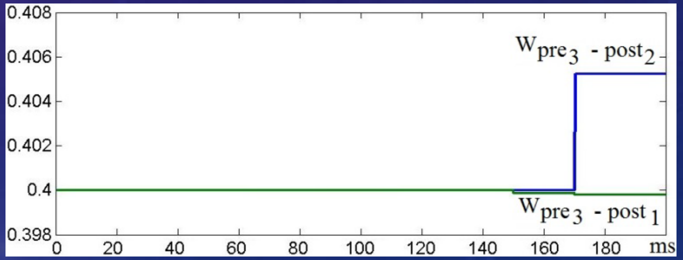
- Membrane potential variation





- Synaptic weights adjustment





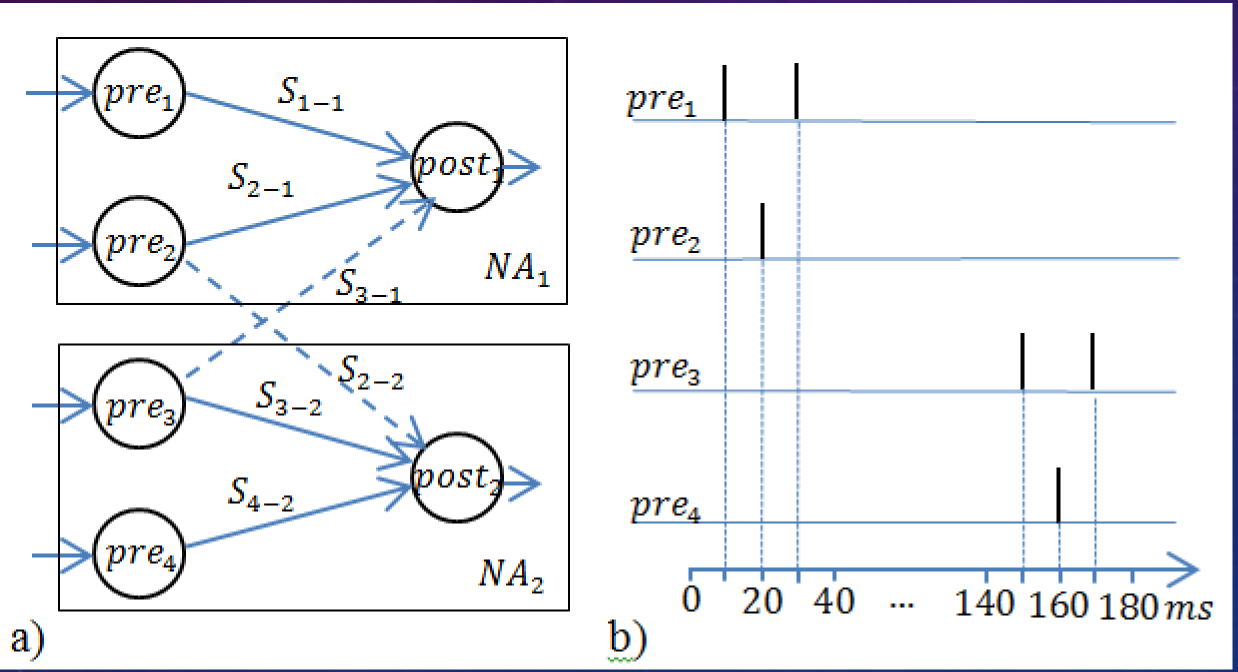
	Weights (initial value is 0.4)					
Patt. rep.	S1-1	S2-1	S2-2	S3-1	S3-2	S4-2
1	0.4047	0.4028	0.4000	0.3998	0.4053	0.4029
5	0.4246	0.4146	0.4000	0.3989	0.4265	0.4146
10	0.4273	0.4338	0.4001	0.3980	0.4529	0.4292

WEIGHTS EVOLUTION

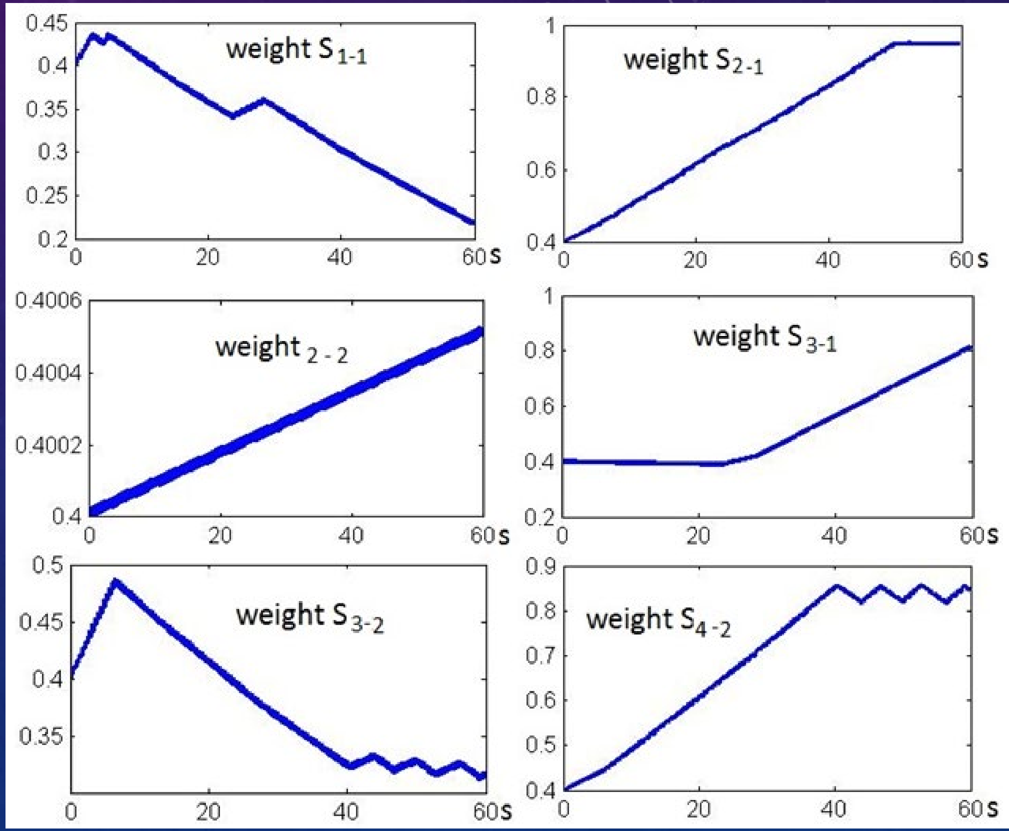
- Weights variation during the first 60 seconds

Spiking Neural Network

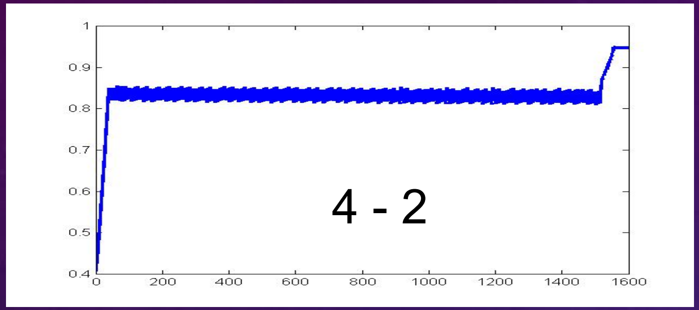
Pattern

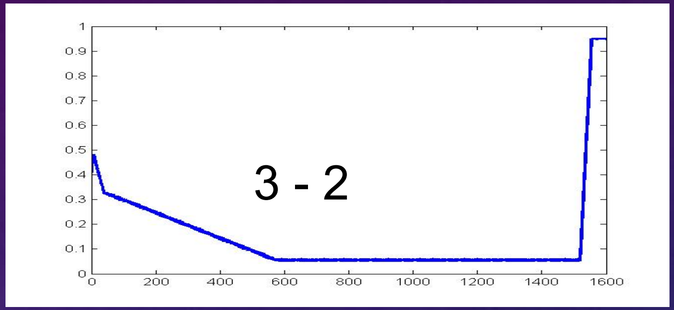


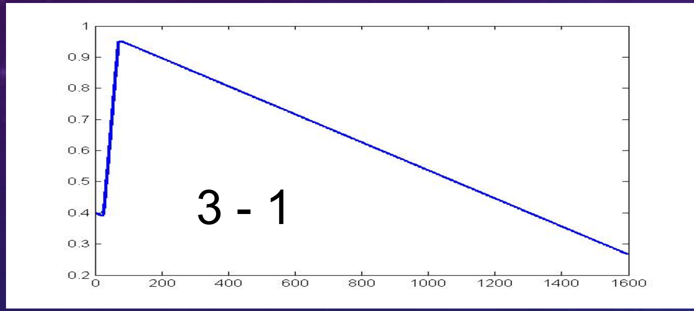
Weights variation

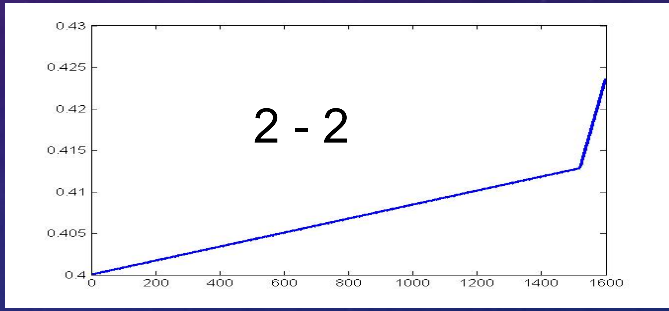


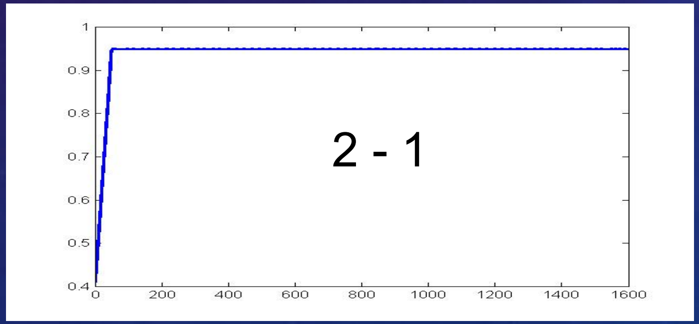
SYNAPTIC EVOLUTION

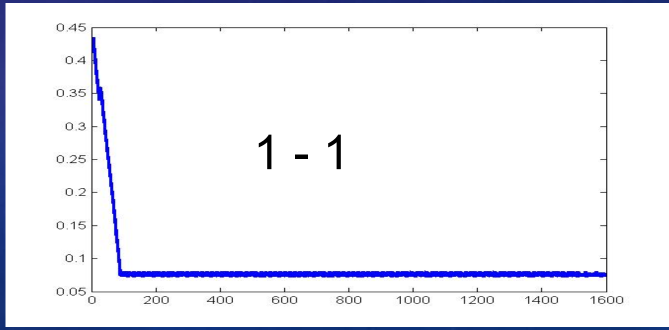












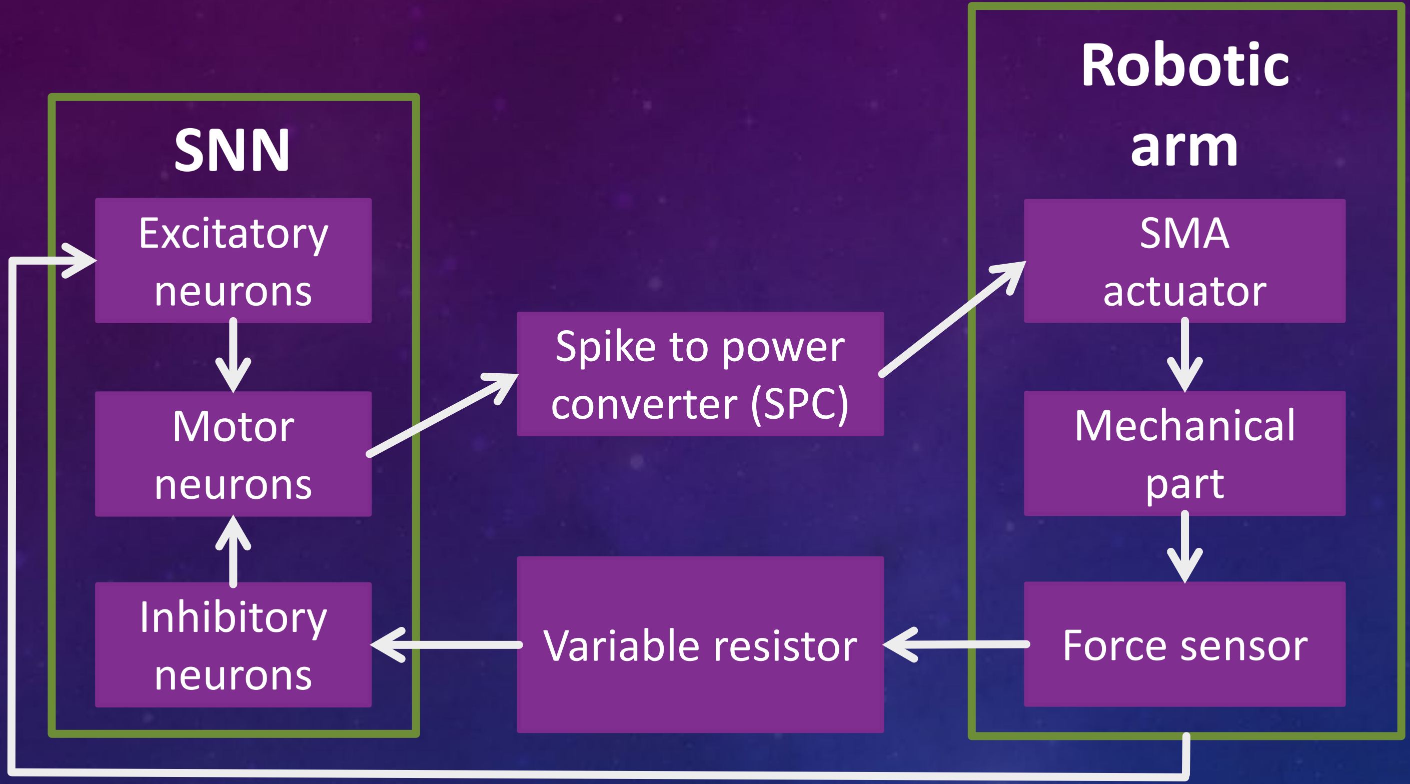
REMARKS

- Usually the weights tend to stabilize to minimum or to maximum value of the variation interval.
- In some conditions the weights tend to values that are different then the weight variation intervals limits
- Around these values the weights oscillate in small intervals
- In these cases the STP and STD effects compensate each other.
- **Future work:** These weights tend to input specific values ?

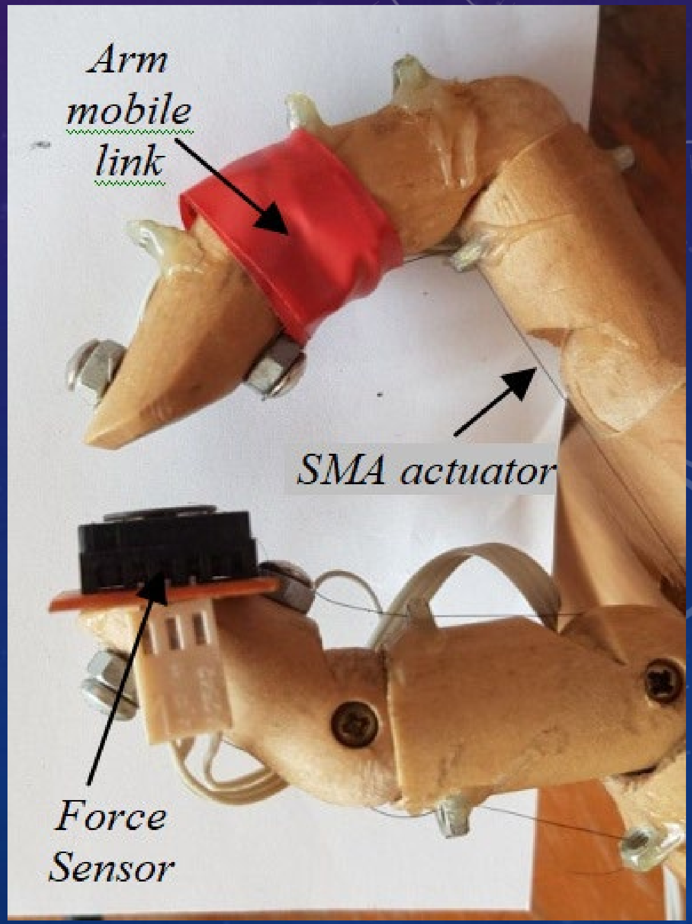
MUSCLE CONTROL
BIOLOGICAL BACKGROUND

- Muscle control is one of the most important functions of the cerebral cortex
  - Provides the organisms with the ability to mechanically interact with the external environment
- Muscle control is bidirectional (in biology)
  - Muscles contraction is determined by the spiking frequency of the motor neurons
  - Neural network receives input related to elongation and contraction force from the spindles
- Limbs movements
  - Multiple muscles are controlled by the central pattern generators (CPG)

GENERAL CONCEPT

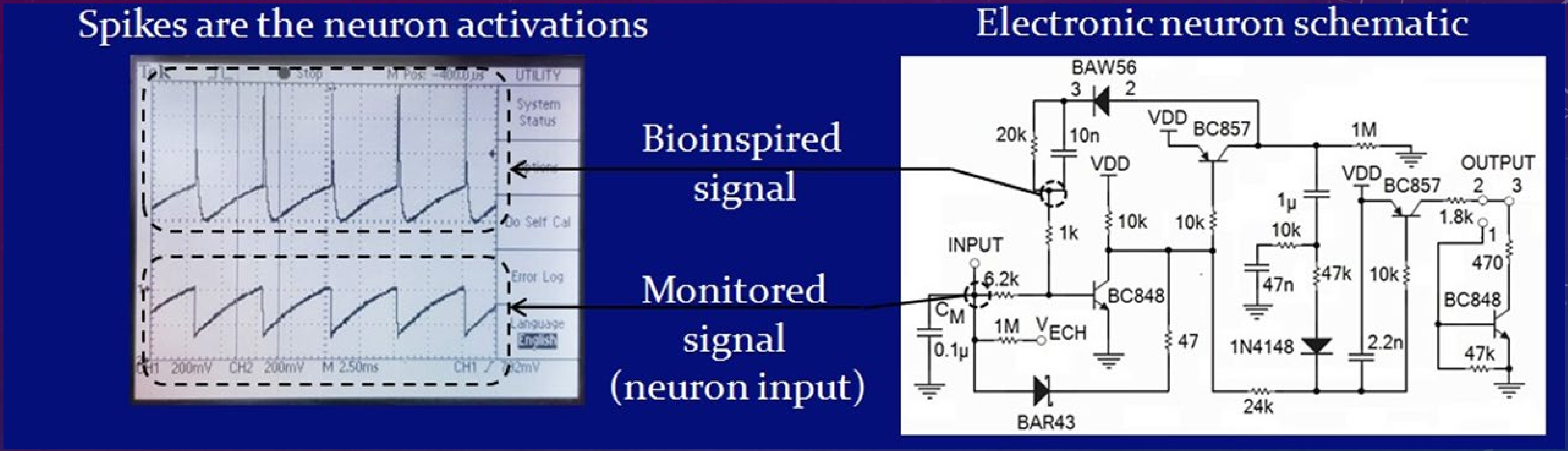


- Two opposing fingers that are actuated by SMA actuators

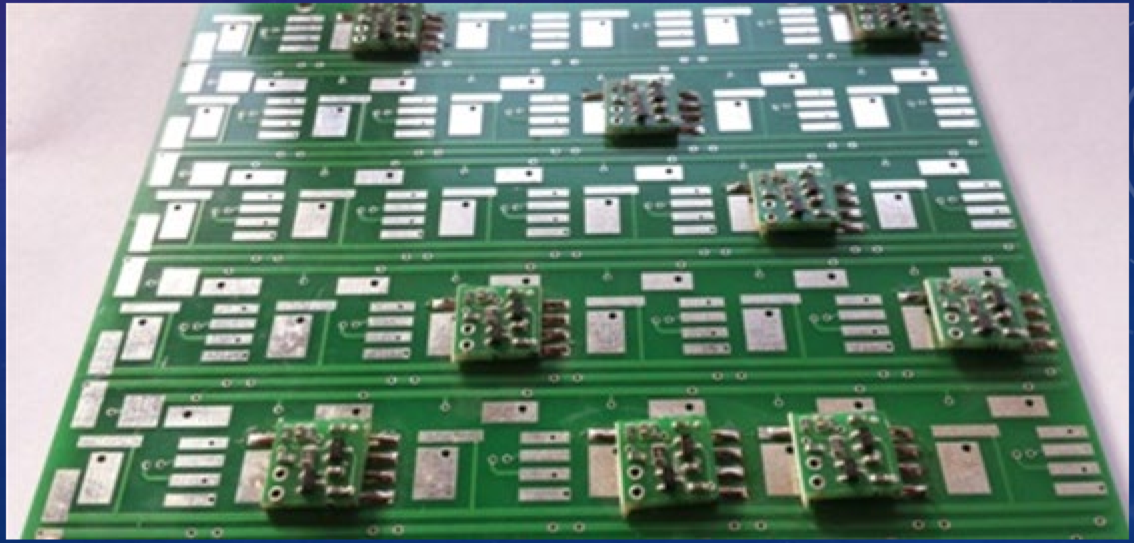


- **Robotic fingers**:
  - Flexed by SMA actuators
  - SMA contracts because of heating
  - Force sensor stops the finger motion

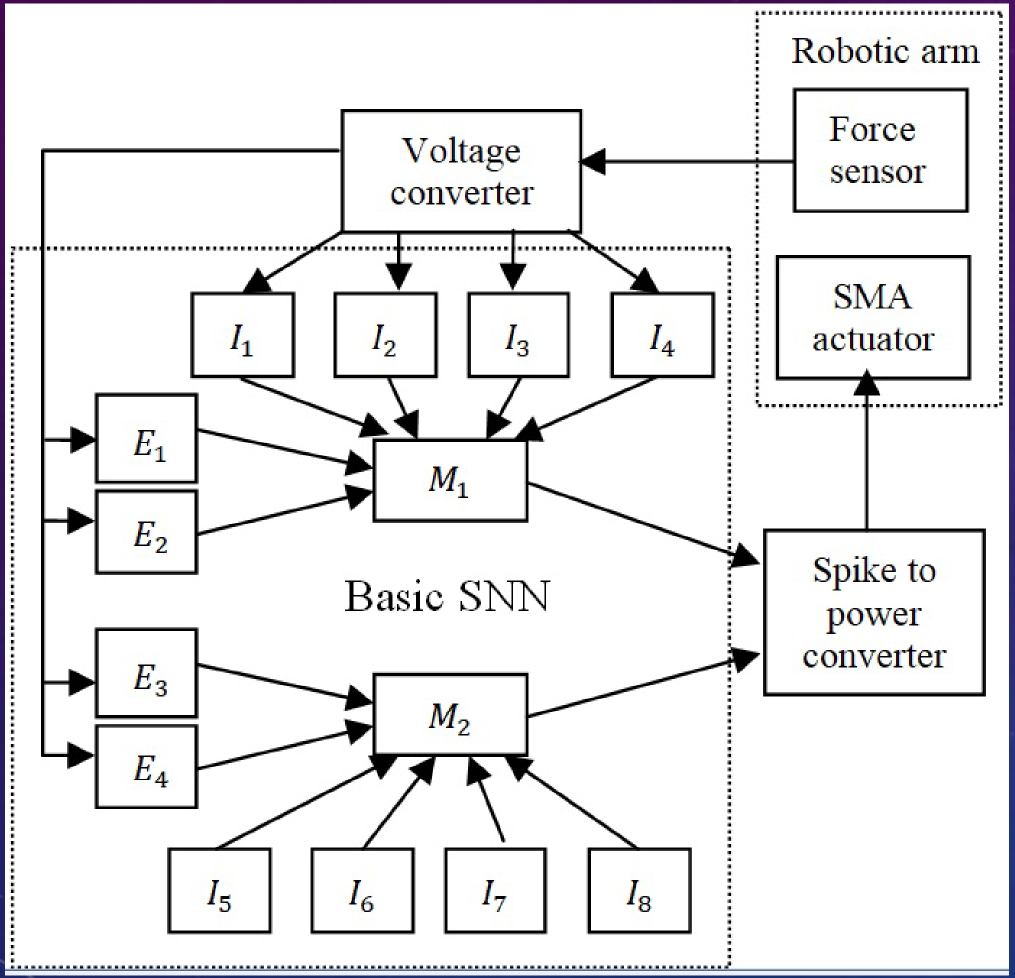
ELECTRONIC NEURON OPERATION



- PCB implementation of unconnected neurons



NEURAL NETWORK

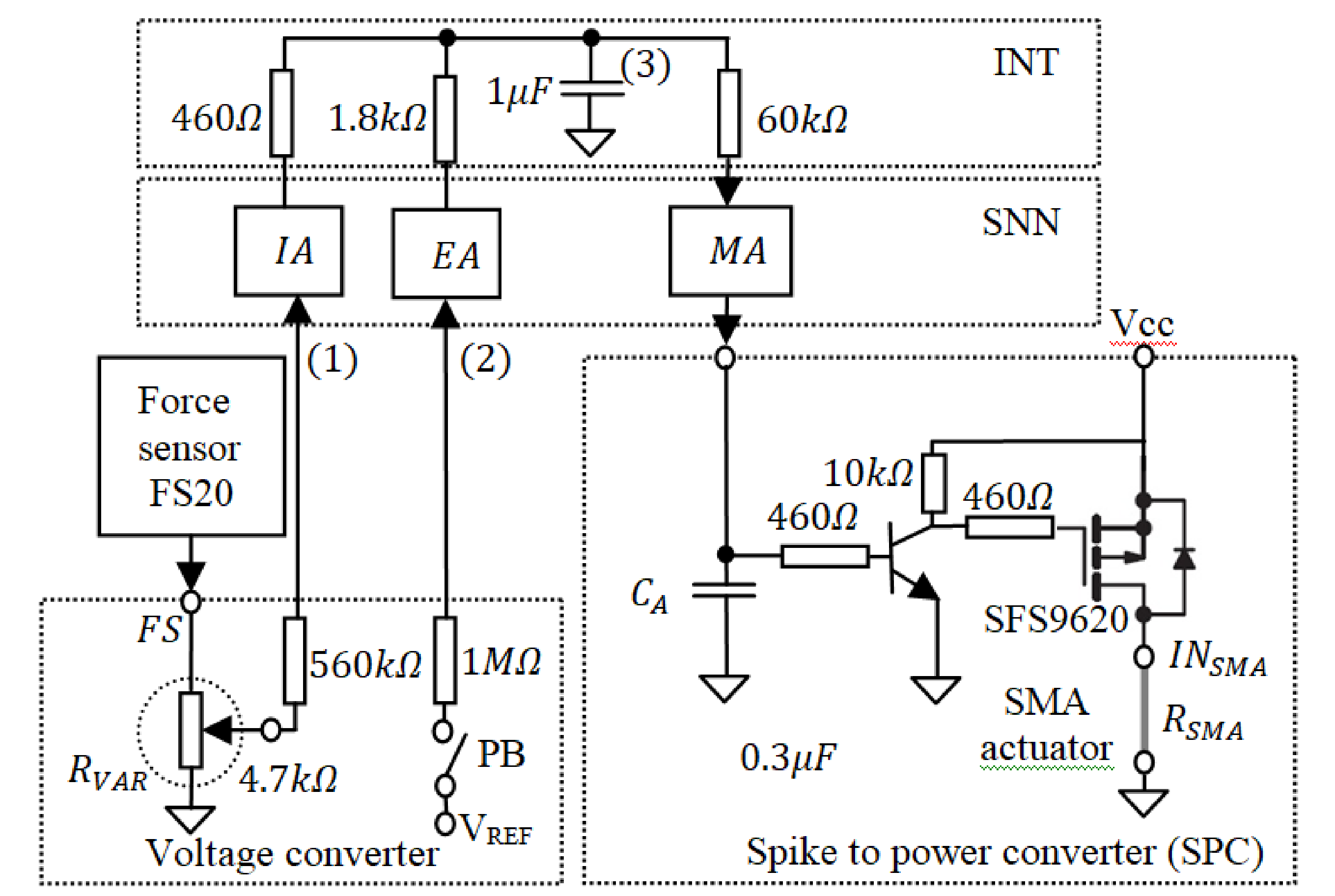


Basic SNN includes:

- two motor neurons (M)
- 4 excitatory neurons (E)
- 8 inhibitory neurons (I)

- SMA actuator is driven by the SPC
- Integrated excitatory output of M
- Inhibitory neurons stimulated by FS
- SNN controls the contraction force

STRUCTURE OF THE BIOINSPIRED SYSTEM



ANALOGUE ELECTRONICS

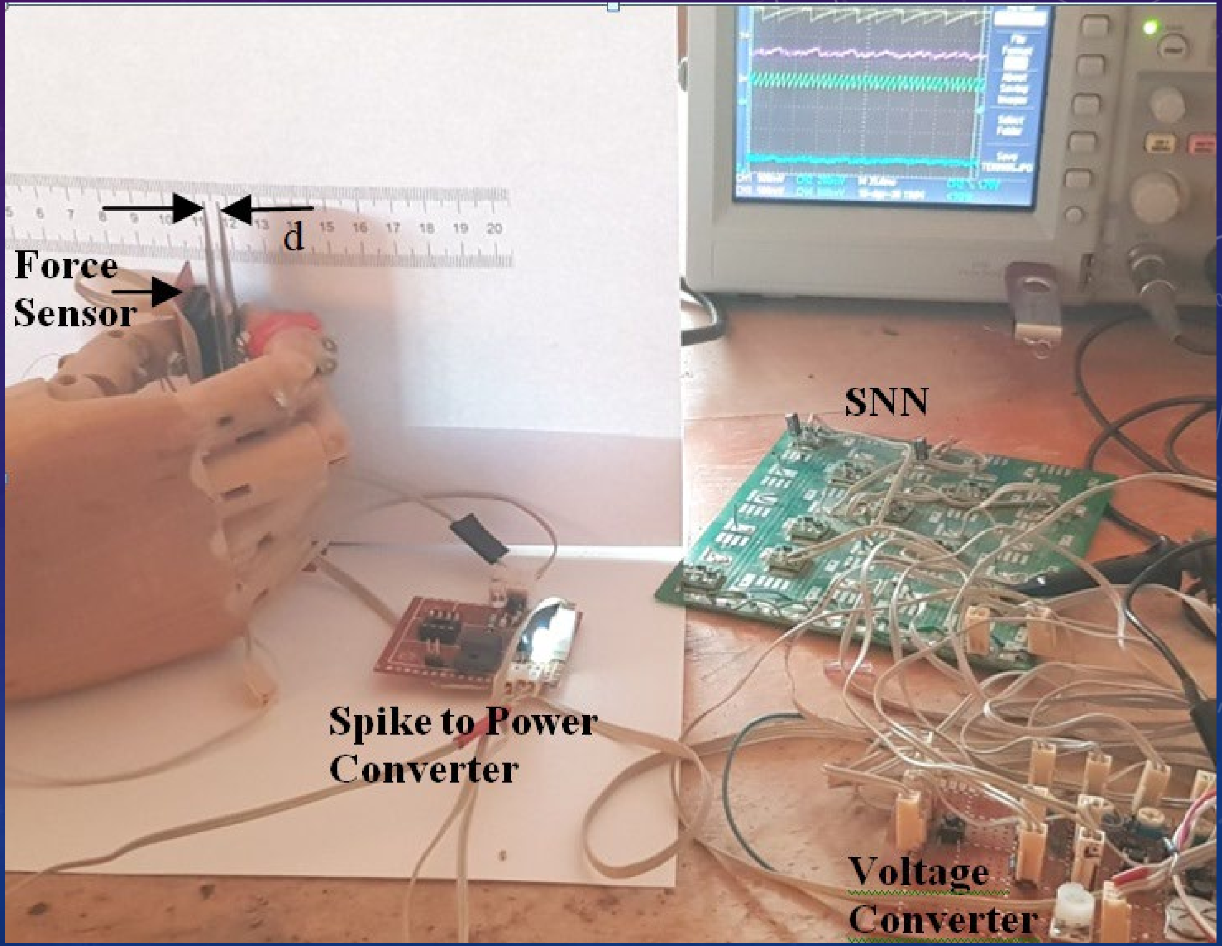
- Voltage converter
- Spike to power converter
- Integrator (INT)

- SMA converts current into force
- Force sensor (FS) converts force into voltage

PROTOTYPE OF BIOINSPIRED SYSTEM

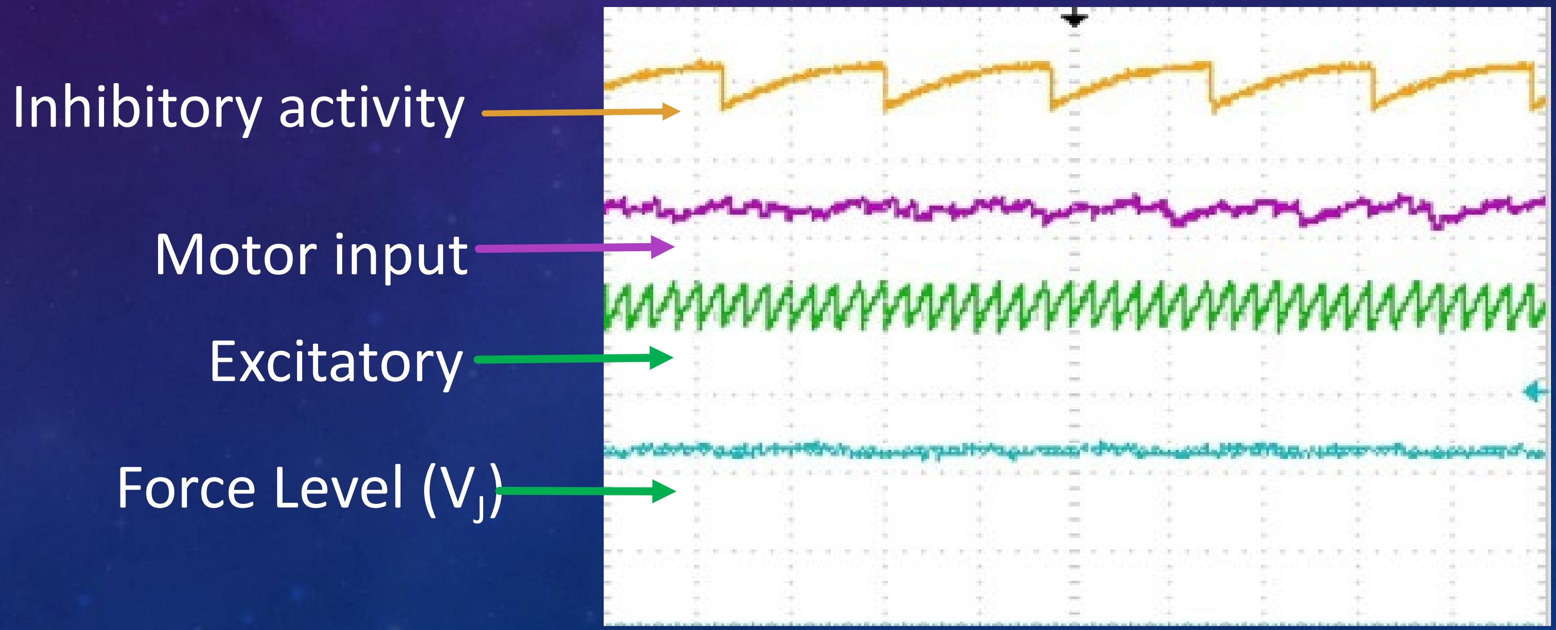
Experimental setup:

- Robotic hand holding a tweeters
  - Distance between heads (d)
- Spiking neural network
- Auxiliary electronics
  - Spike to power converter
  - Voltage converter

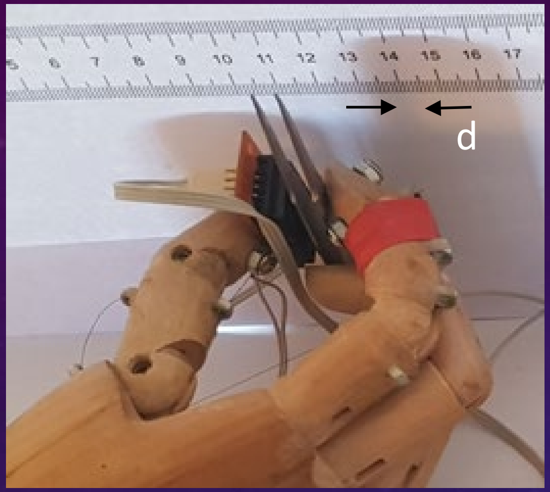


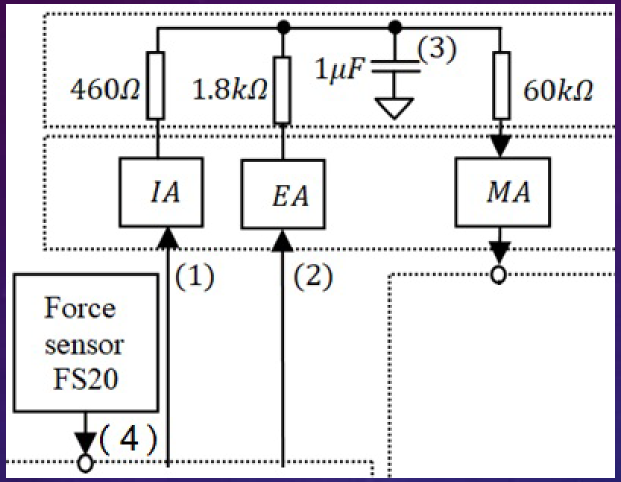
RESULTS

- **The following tests were performed:**
  - Force sensor response
  - Possibility to adjust force strength by adjusting system parameters
  - Regulatory performance of the neural network

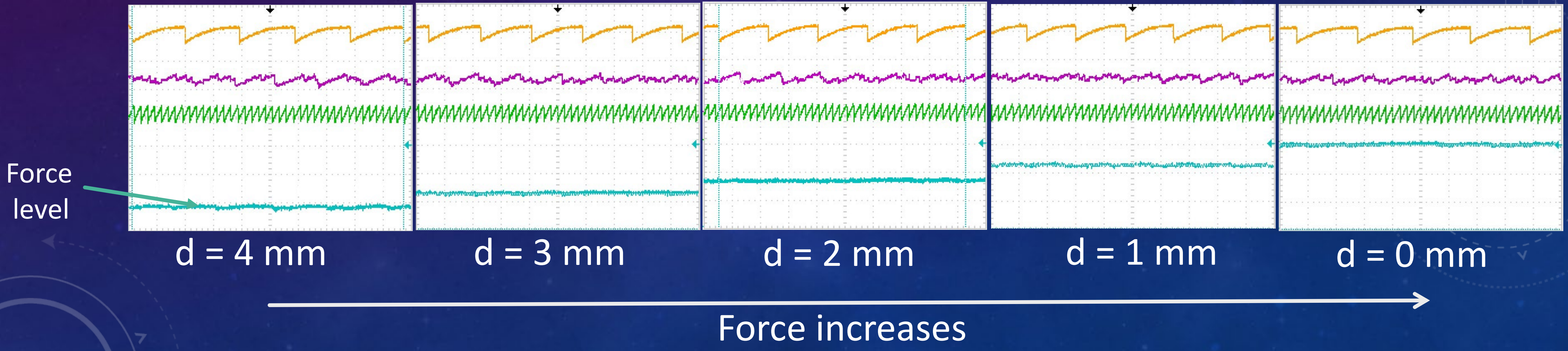


RESULTS





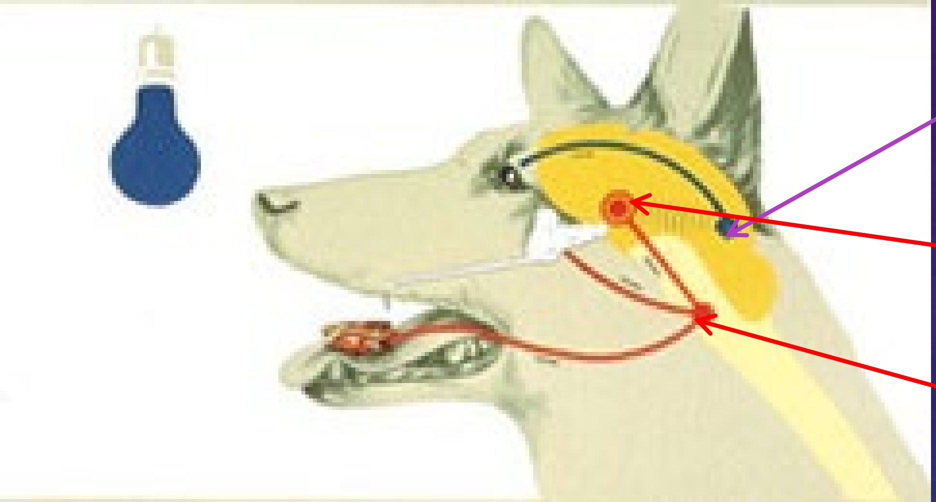
- Observations:
  - Higher motor frequency generates more force
  - Frequency of the inhibitory neurons oscillates



THUS … THE SNN IS SMALL

- The SNN includes a **few excitatory neurons** that determine SMA **actuator contraction**
- And a few **inhibitory neurons** that are driven by a **force sensor**
- With a few neurons **SNN** is able to control the force applied on an object by the two opposing fingers
- SNN is a good regulator for the contraction force of SMA actuators

HEBBIAN LEARNING

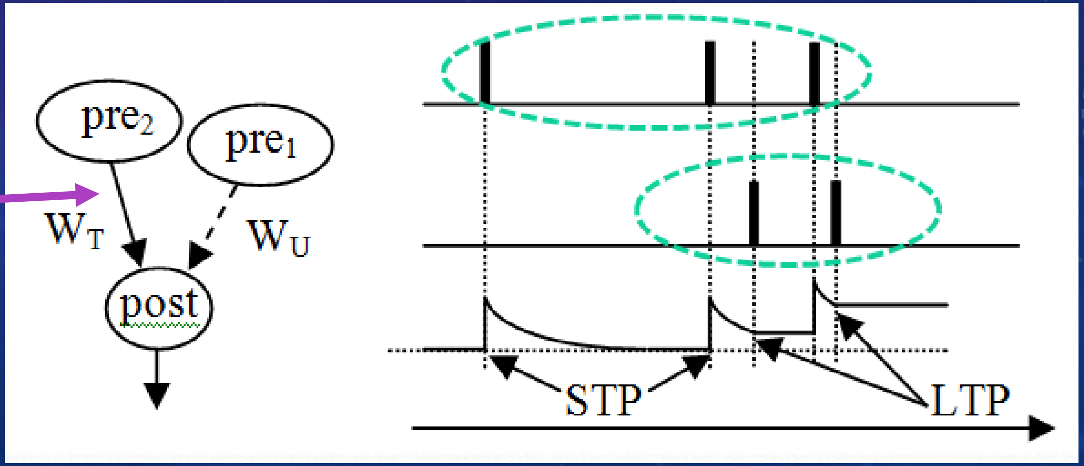


Occipital lobe *Image processing*

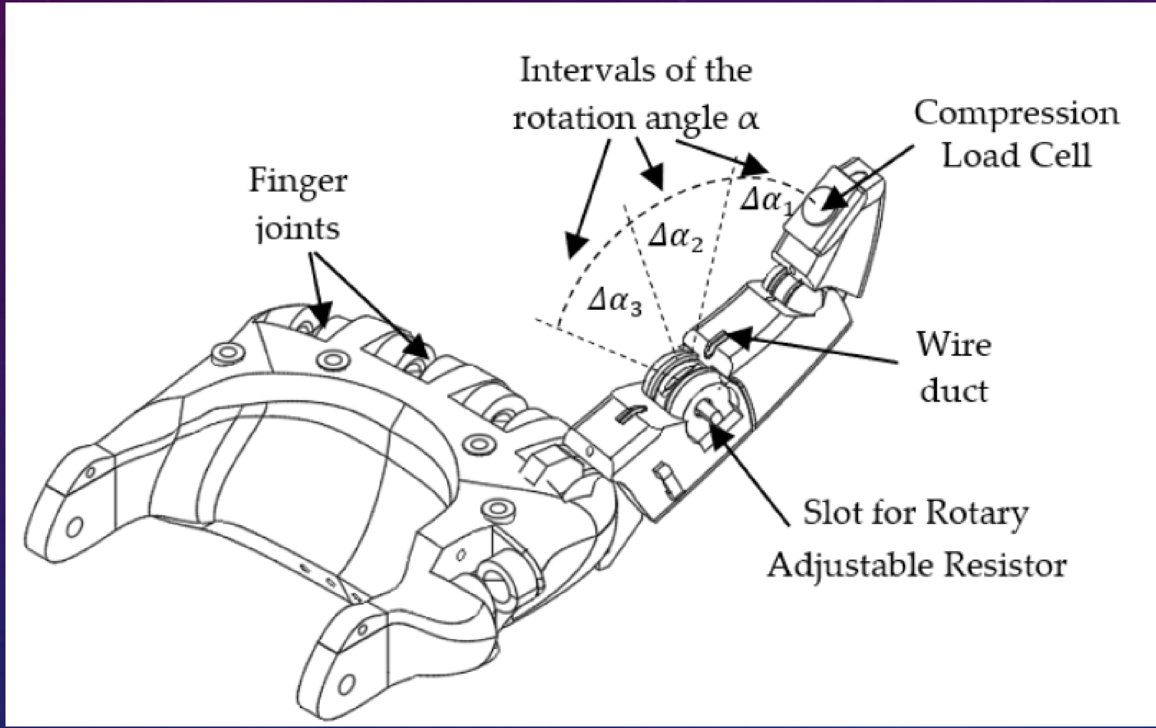
Salivary nucleus: *Activation of glands*

Parietal lobe: *Taste detection*

Trained



MORE COMPLEX CONTROL OF FINGER'S MOTION

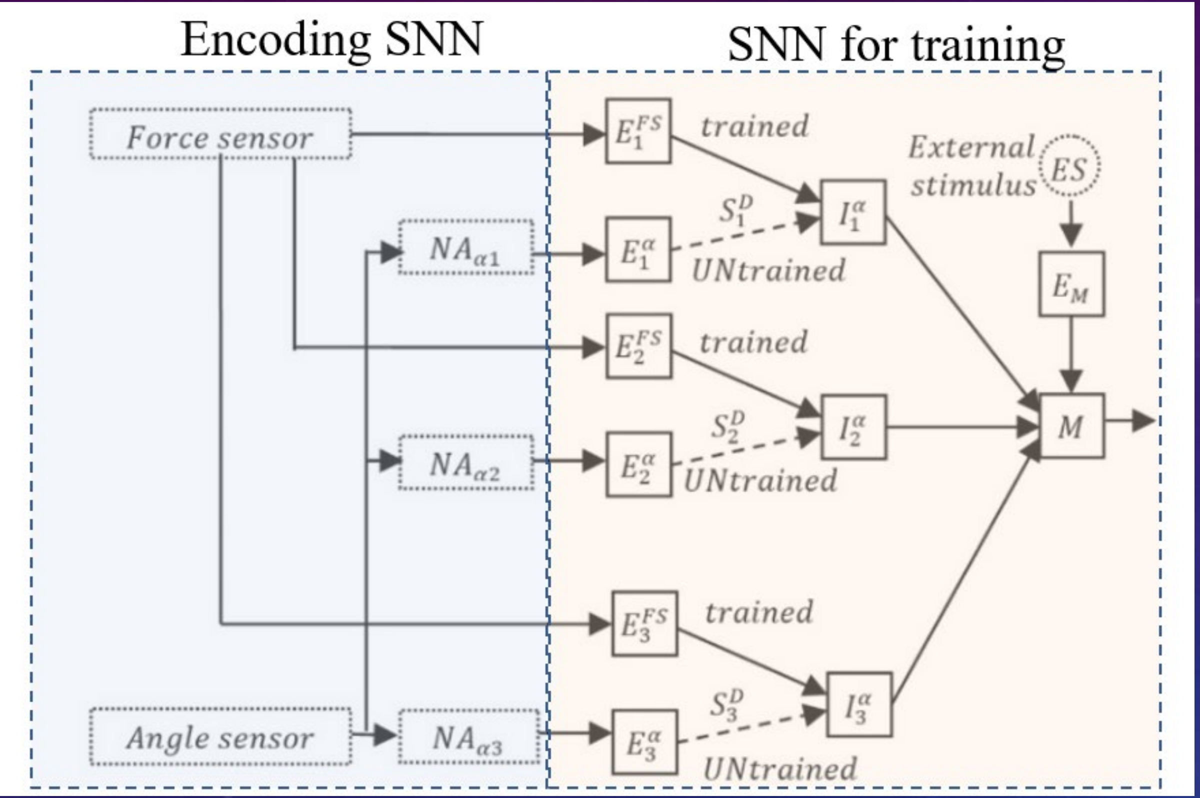


The finger can be stopped in target angles of rotation

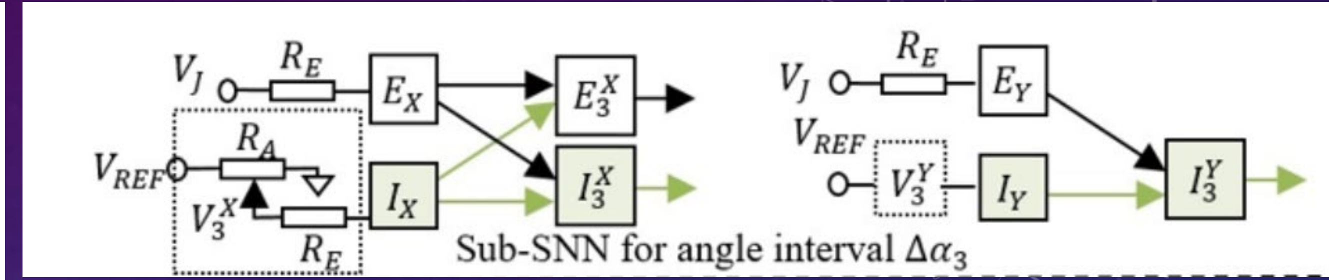
The finger motion is stopped where the finger tip is blocked

- Anthropomorphic finger which is actuated by SMA and have two force sensors on the tip and rotary sensor in the junction.

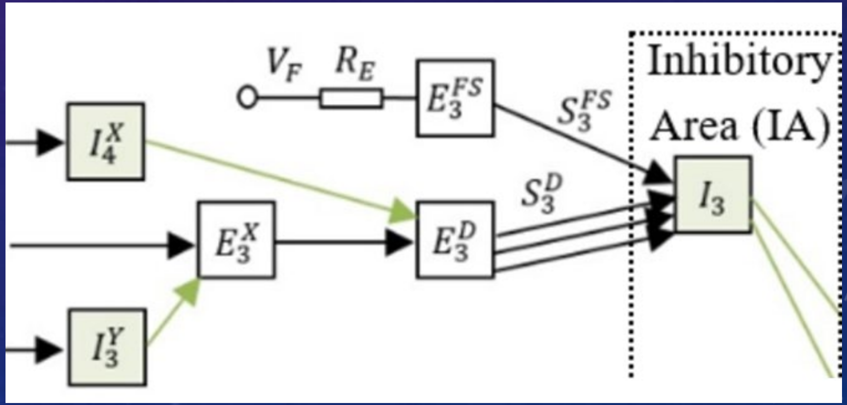
SNN STRUCTURE – HIGHER COMPLEXITY



Encoding SNN for a single α



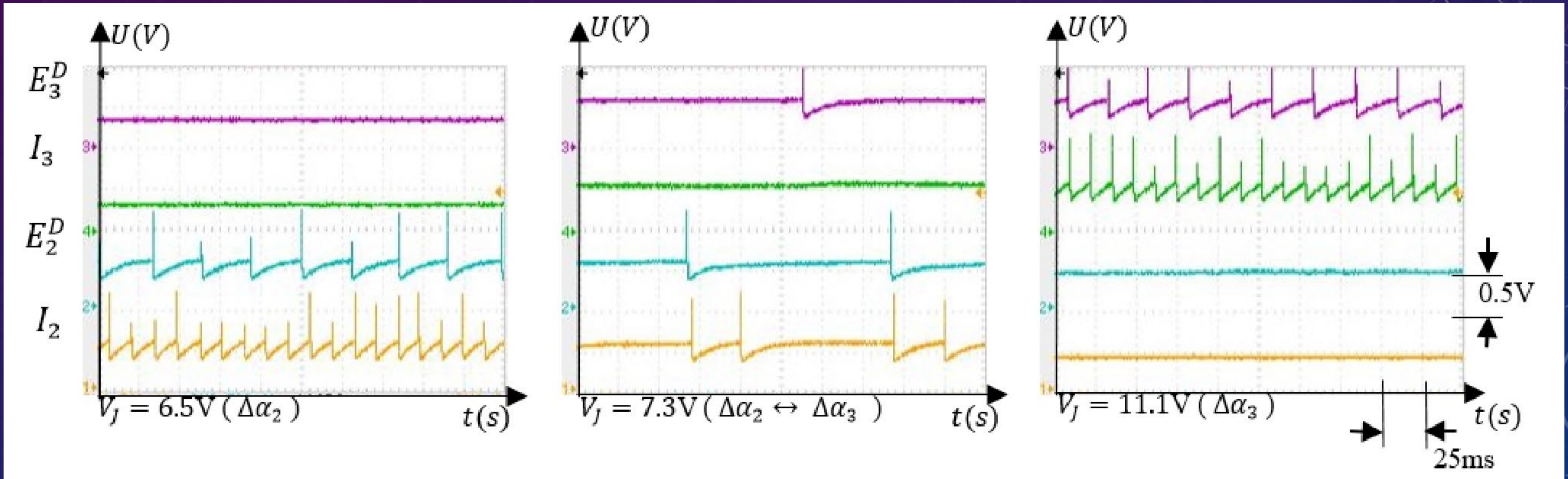
Inhibitory motor neuron for one α



- The **Spiking Neural Network** includes an:
  - Encoding SNN module for the angle of rotation.
  - A decoding SNN that can be trained.

RESULTS – ENCODING LAYER

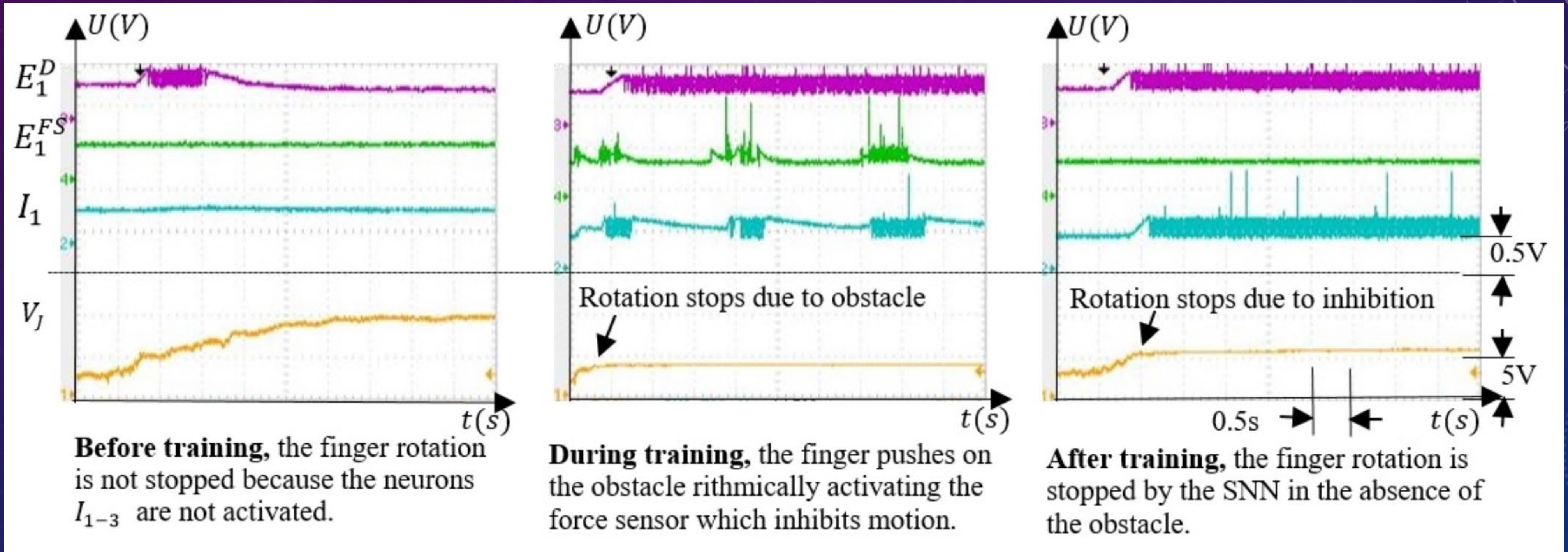
First interval | Between the angle intervals | Second interval



The activity of the inhibitory neurons when the finger crosses between two angle intervals.

LEARNING TO STOP THE FINGER

Rhythmic actuation – The finger tries to push on the obstacle

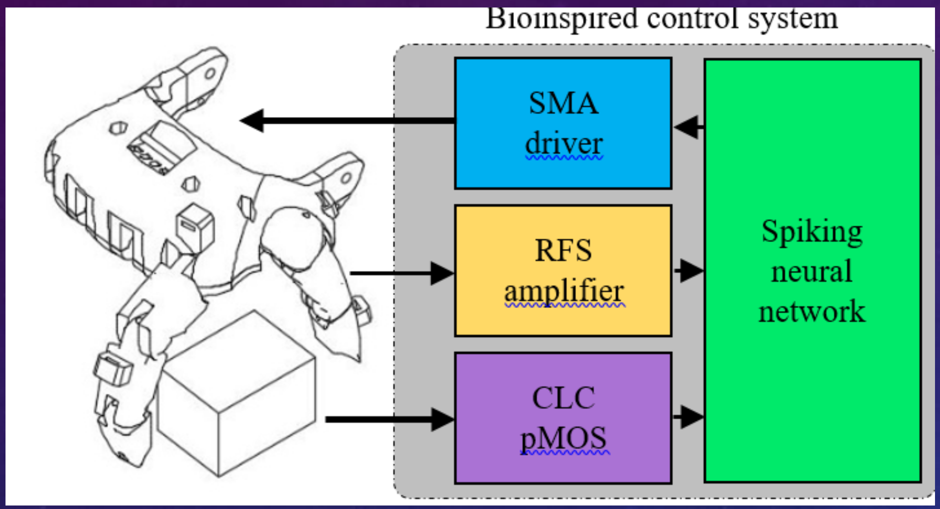


Initial state: With no obstacle the finger does not stop

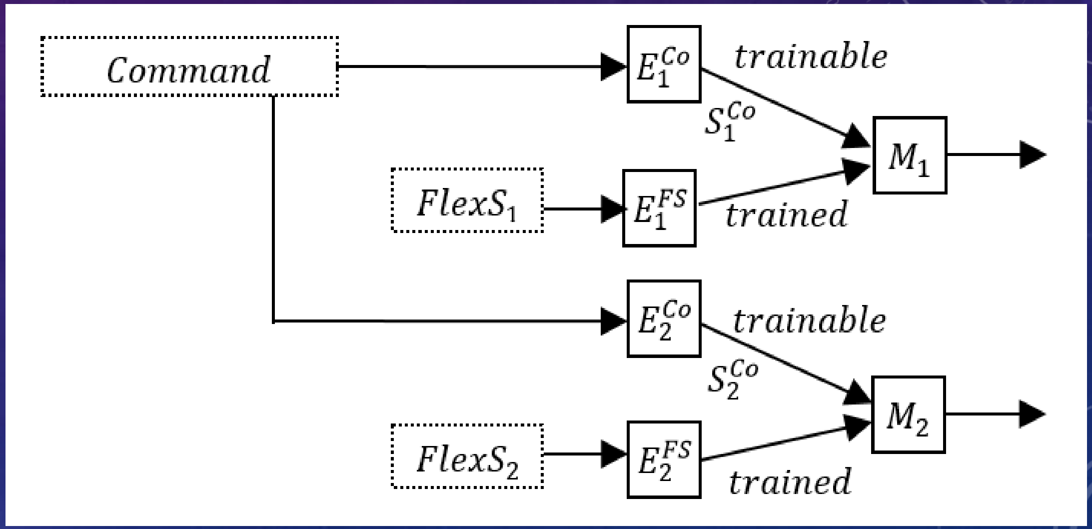
After learning: The finger stops without the obstacle

LEARNING WHICH MOTION TO INITIATE

Robotic hand with flex and force sensors

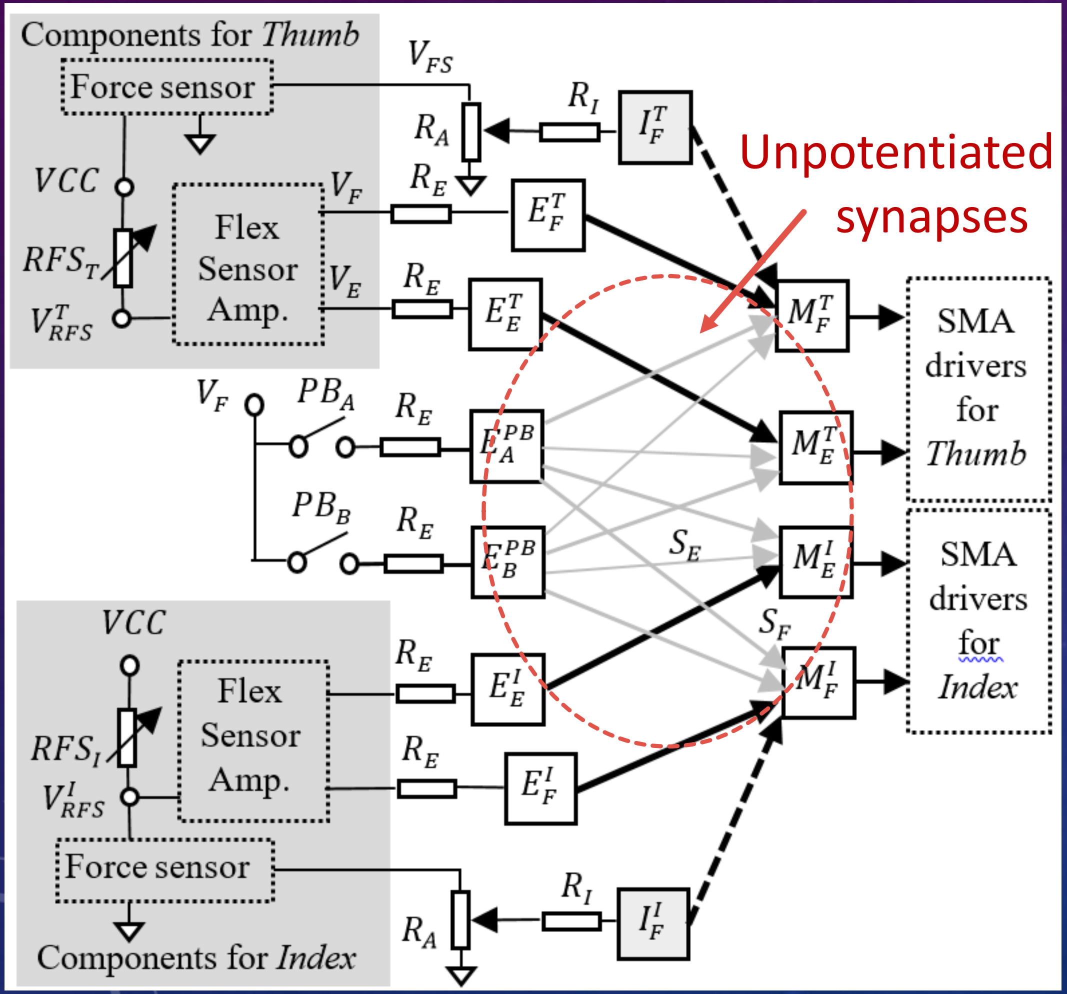


The general structure of the SNN

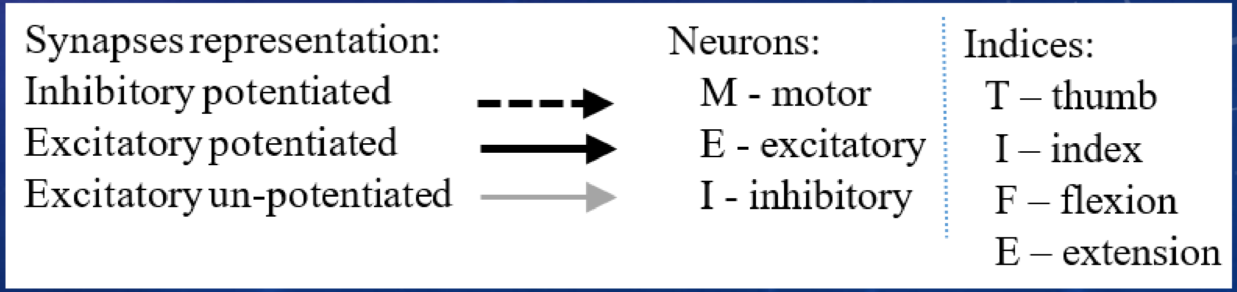


- Flex sensors detect which finger is moved and in which direction
- Force sensors detect if the finger touches an object

SNN STRUCTURE

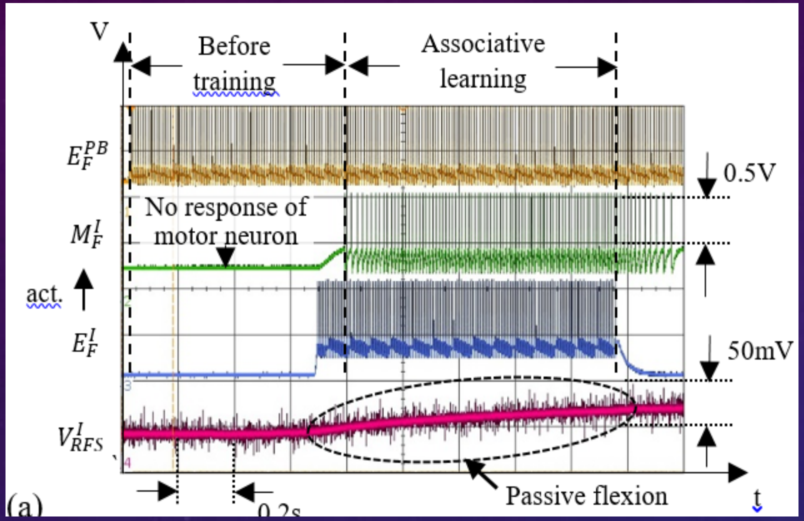


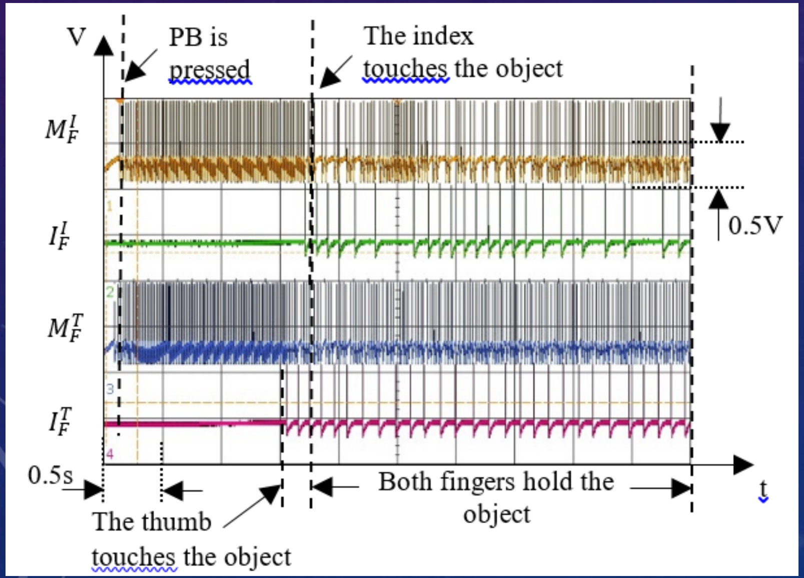
- The SNN includes excitatory, inhibitory and motor neurons
- The neurons with potentiated synapses are connected to the sensors that detect motion.
- The un-potentiated synapses are connected command
- Concurrent activation of potentiated and un-potentiated synapses determine learning



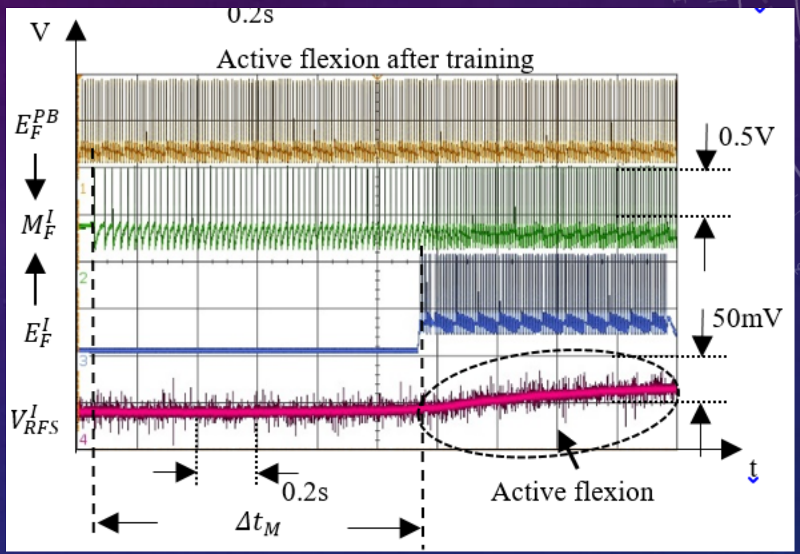
RESULTS

During training





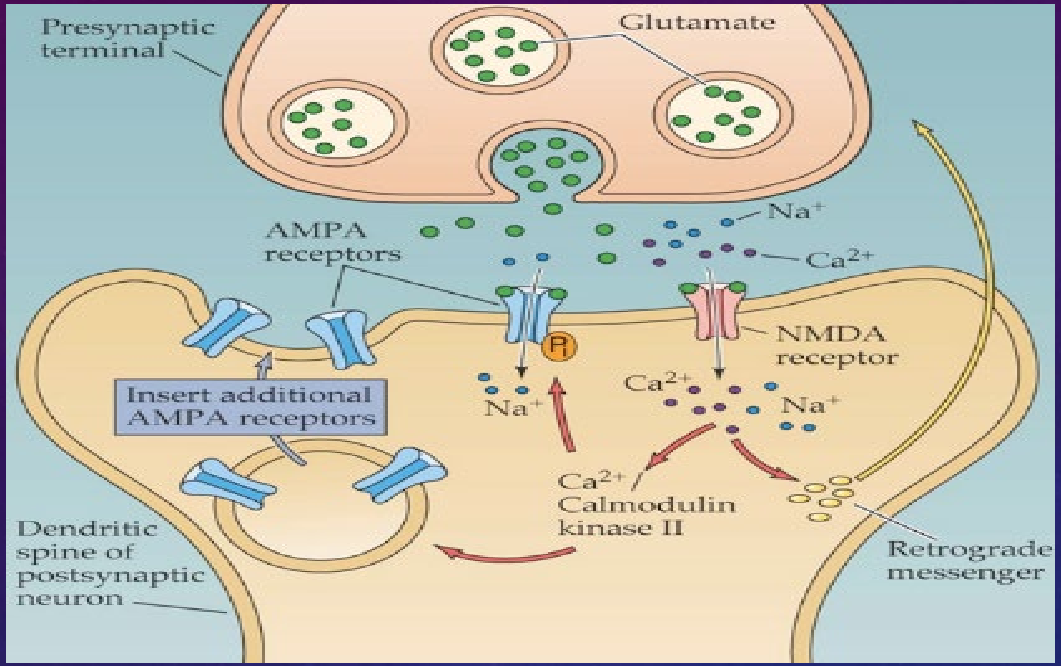
After training



- During training the finger is moved by hand
- After training the same motion is controlled by the SNN
- The finger is stopped when it touches an object

REMARKS

- The SNN can be trained by **physical guidance**
  - Good to teach the children handwriting (for biological networks)
  - Special skills such as walking on a rope
- SNN learns to:
  - Start motion of the fingers – that were executed passively
  - Stop motion in the target intervals
- The synapses are potentiated by the mechanisms of Hebbian learning
- SNN is simple with just a few neurons



THANKS FOR YOUR ATTENTION