Sensory Data Classification by Fuzzy Spiking Neural Network

János Botzheim

BME GPK
FACULTY OF MECHANICAL ENGINEERING

DEPARTMENT OF MECHATRONICS, OPTICS AND MECHANICAL ENGINEERING INFORMATICS

Outline

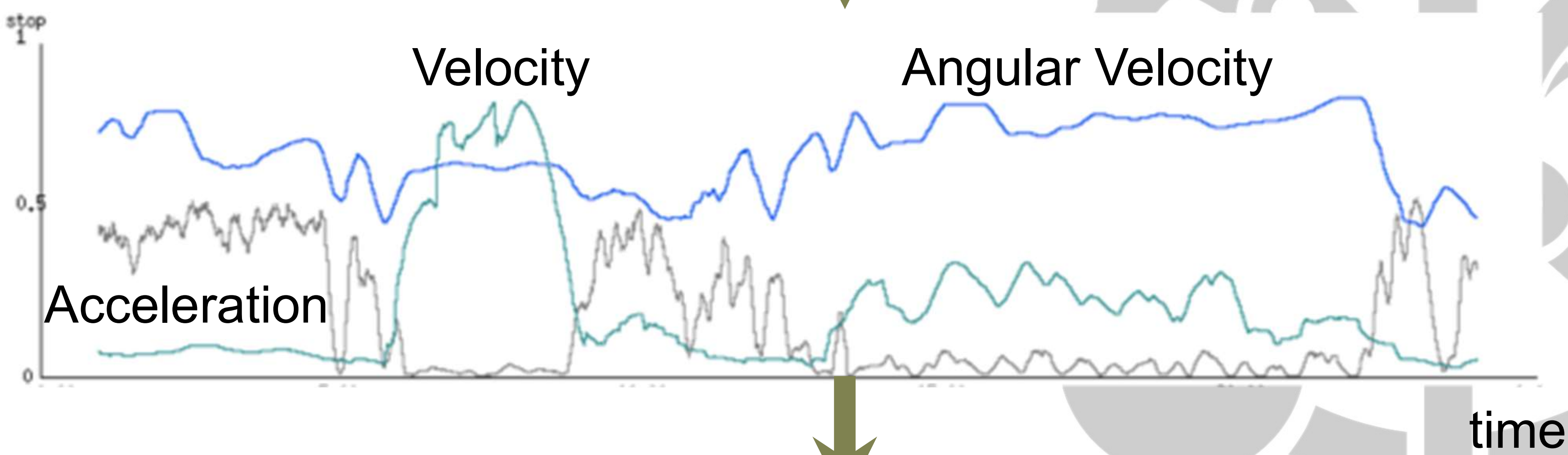
- A sensory data classification task
- Proposed architecture
- Simple Spike Response Model
- Fuzzy Spiking Neural Network
- Evolution Strategy
- Experimental results
- Conclusions

BME GPK
FACULTY OF MECHANICAL ENGINEERING

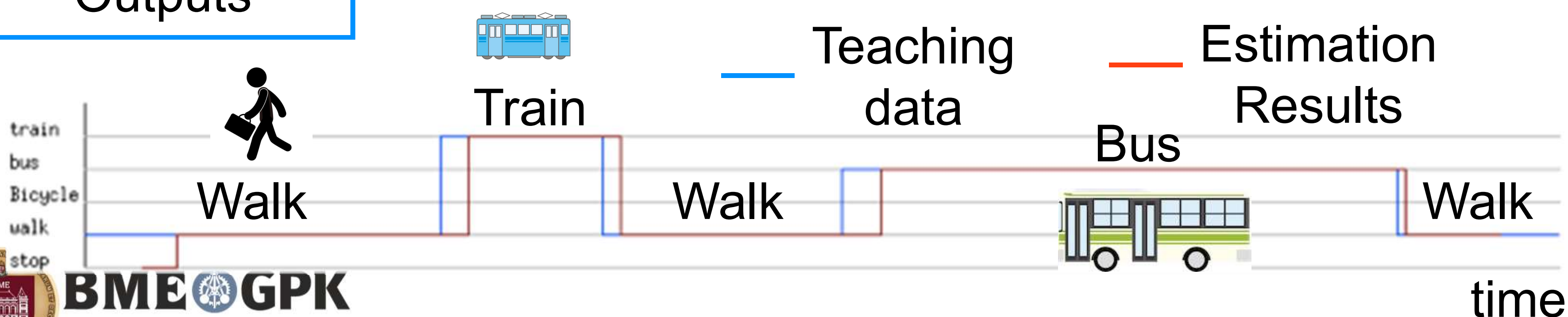
A sensory data classification task Human transport modes estimation

Smart Phone | Accelerometer | Gyro | GPS

Inputs



Outputs



BME GPK
FACULTY OF MECHANICAL ENGINEERING

Specification of sensory data

Sensor Name	Acceleration	Gyro	GPS
Acquired data	x, y, z	roll, pitch, yaw	latitude, longitude
Range of data	-/+2.3G	-/+180, -/+90, -/+180,	-/+90, -/+180
Sampling time	100ms	100ms	100ms
Recording time	500ms	500ms	500ms

The acceleration can be calculated as:

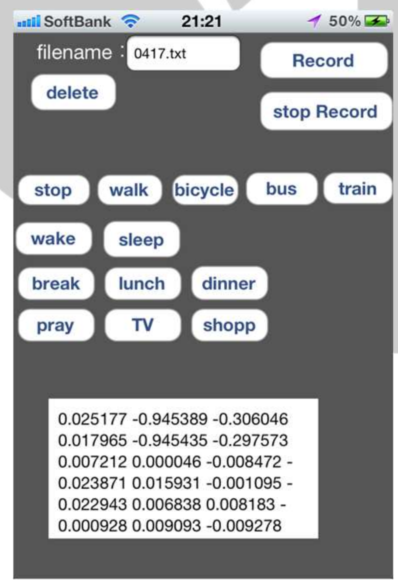
$$a(t) = \sqrt{a_x(t)^2 + a_y(t)^2 + a_z(t)^2}$$

The angular velocity is computed as:

$$v(t) = \sqrt{v_x(t)^2 + v_y(t)^2 + v_z(t)^2}$$

The movement distance by GPS is:

$$s(t) = \sqrt{(g_x(t) - g_x(t-1))^2 + (g_y(t) - g_y(t-1))^2}$$

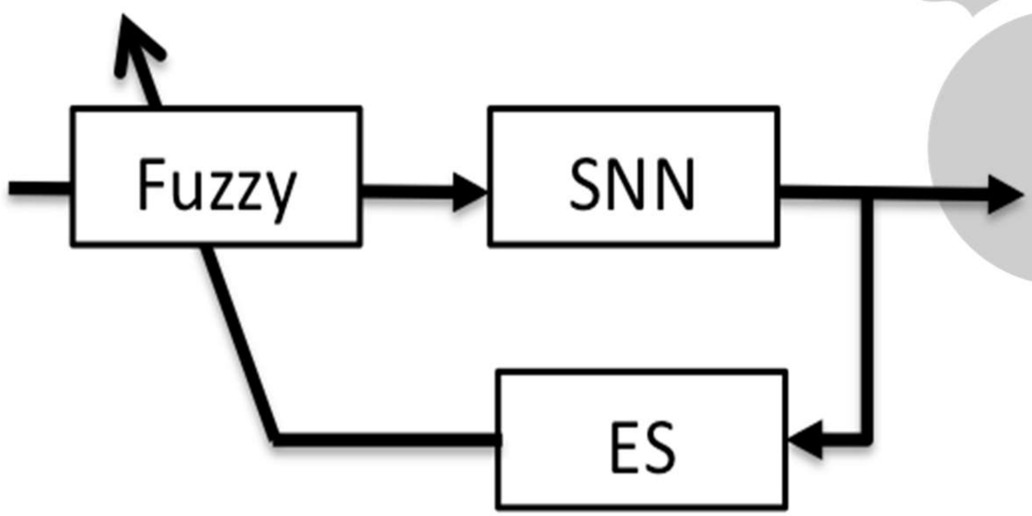


application for measurement

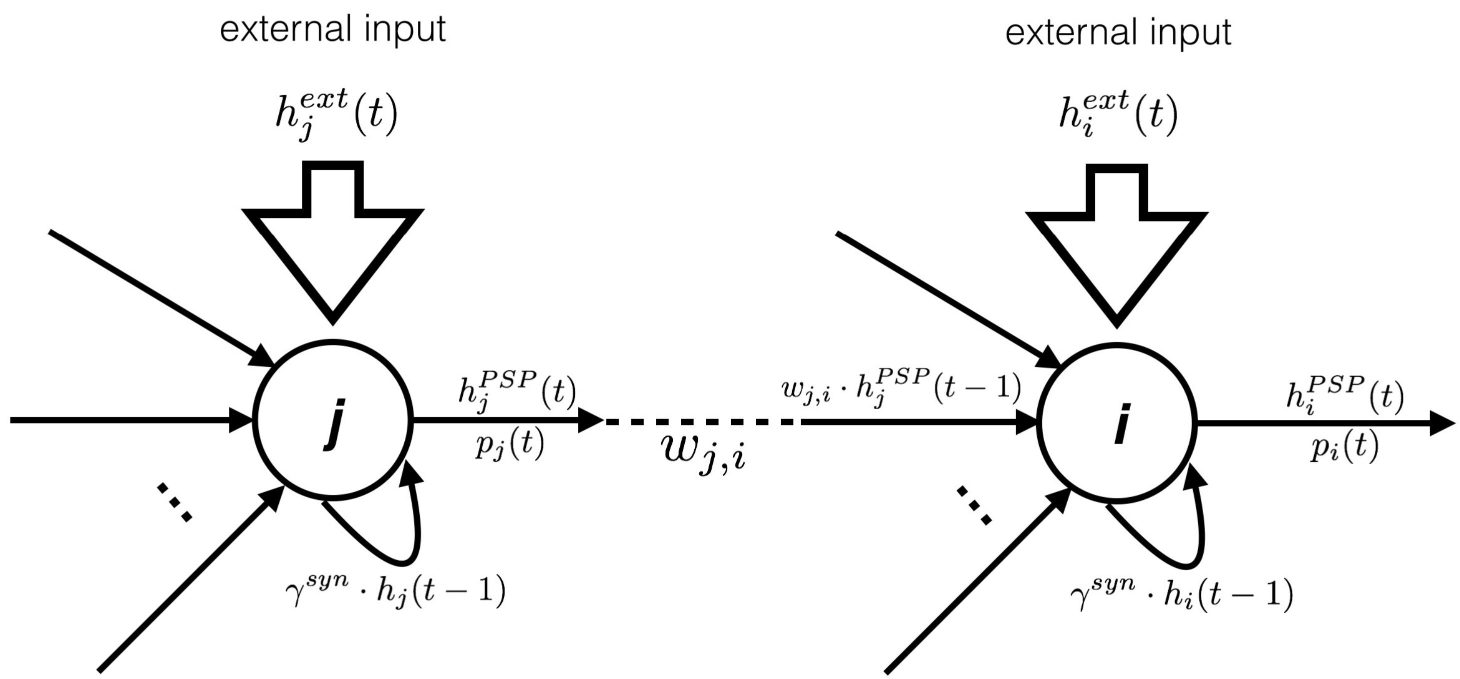
BME GPK
FACULTY OF MECHANICAL ENGINEERING

Proposed architecture

- Simple Spike Response Model
- Fuzzy Spiking Neural Network
- Evolution Strategy



Simple Spike Response Model



$$h_i(t) = \tanh(h_i^{syn}(t) + h_i^{ext}(t) + h_i^{ref}(t))$$

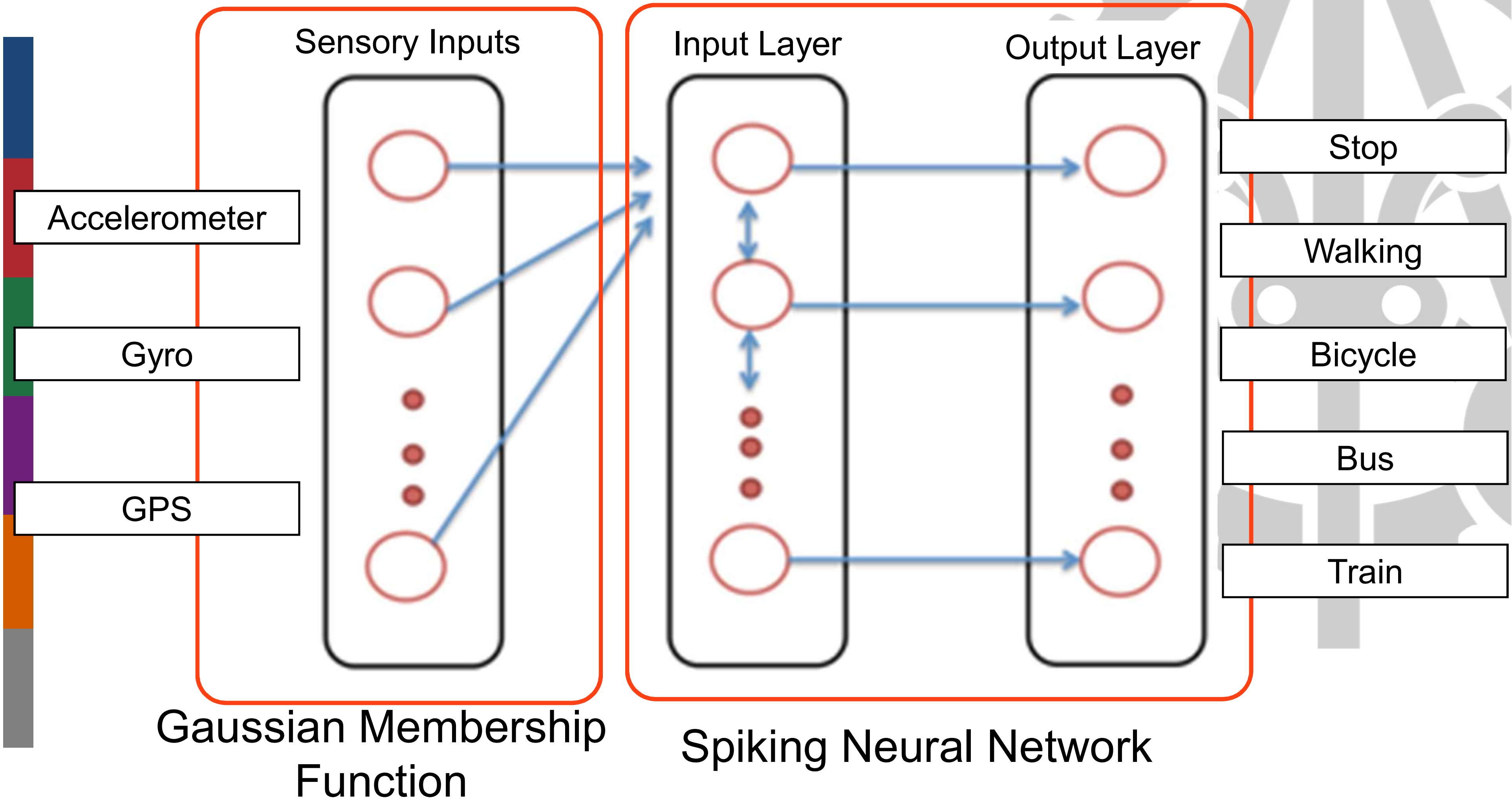
$$h_i^{syn}(t) = \gamma^{syn} \cdot h_i(t-1) + \sum_{j=1, j\neq i}^{N} w_{j,i} \cdot h_j^{PSP}(t-1)$$

$$h_i^{ref}(t) = \begin{cases} \gamma^{ref} \cdot h_i^{ref}(t-1) - R & \text{if } p_i(t-1) = 1, \\ \gamma^{ref} \cdot h_i^{ref}(t-1) & \text{otherwise,} \end{cases}$$

$$p_i(t) = \begin{cases} 1 & \text{if } h_i(t) \geq \theta, \\ 0 & \text{otherwise,} \end{cases}$$

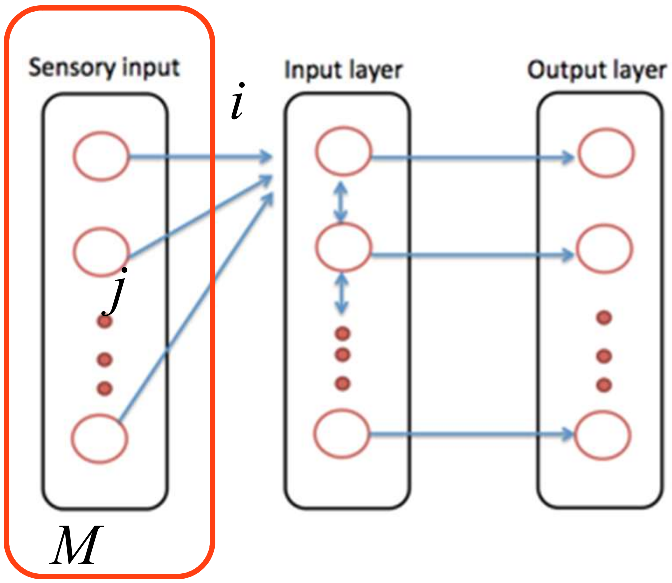
$$h_i^{PSP}(t) = \begin{cases} 1 & \text{if } p_i(t) = 1, \\ \gamma^{PSP} \cdot h_i^{PSP}(t-1) & \text{otherwise,} \end{cases}$$

Fuzzy Spiking Neural Networks



BME GPK
FACULTY OF MECHANICAL ENGINEERING

Fuzzy Spiking Neural Networks



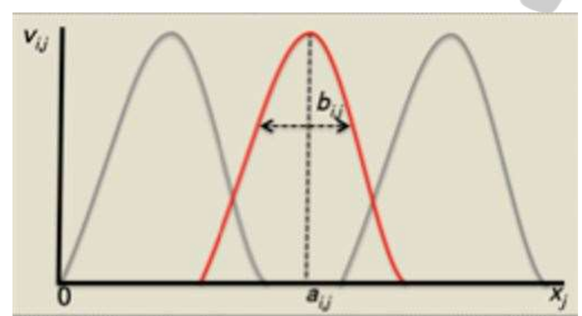
Gaussian Membership Function

The input to the FSNN is calculated by Gaussian membership functions

$$\mu_{A_{i,j}}(x_j) = \exp\left(-\frac{\left(x_j - a_{i,j}\right)^2}{b_{i,j}} \right)$$

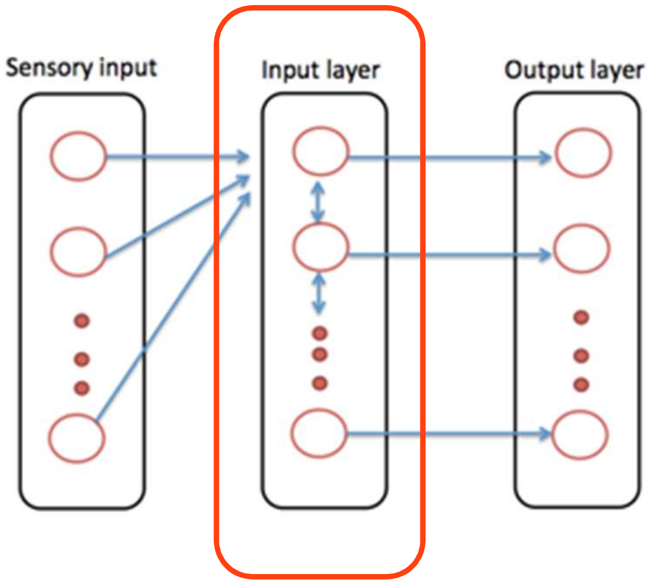
$$y_i = \prod_{j=1}^{m} v_{i,j} \cdot \mu_{A_{i,j}}(x_j)$$

where $a_{i,j}$ and $b_{i,j}$ are the central value and the width of the membership function $A_{i,j}$; $v_{i,j}$ is the contribution of the jth input to the estimation of the ith human transport mode.



$a_{i,j}$, $b_{i,j}$, $v_{i,j}$

Fuzzy Spiking Neural Networks



Interconnected Spiking Neurons

The membrane potential, or internal state $h_i(t)$ of the ith spiking neuron at the discrete time t is given by:

$$h_i(t) = \tanh(\underline{h_i^{syn}(t)} + \underline{h_i^{ext}(t)} + h_i^{ref}(t))$$

$h_i^{syn}(t)$ indicates the output pulses from other neurons:

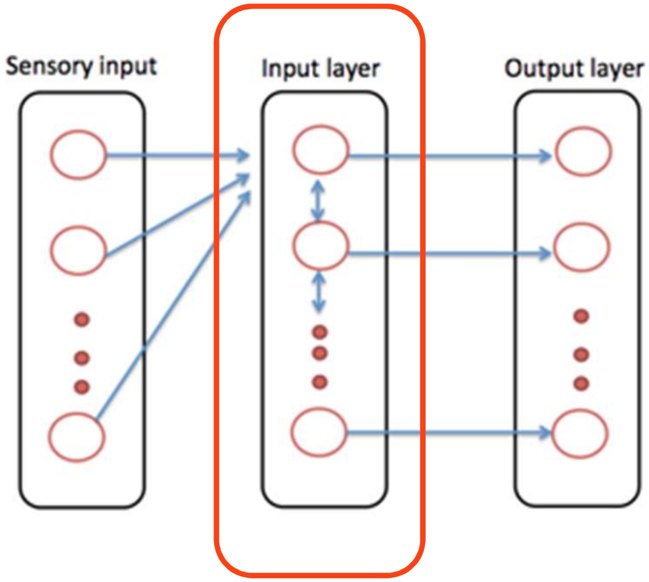
$$h_i^{syn}(t) = \sum_{j=1, j\neq i}^{N} w_{j,i} \cdot h_j^{PSP}(t-1),$$

The external input, $h_i^{ext}(t)$ is calculated based on the fuzzy inference

$$h_i^{ext}(t) = \prod_{j=1}^{M} v_{i,j} \cdot \exp\left(-\frac{(x_j - a_{i,j})^2}{b_{i,j}}\right)$$

BME GPK
FACULTY OF MECHANICAL ENGINEERING

Fuzzy Spiking Neural Networks



Interconnected Spiking Neurons

The membrane potential, or internal state $h_i(t)$ of the ith spiking neuron at the discrete time t is given by:

$$h_i(t) = \tanh(h_i^{syn}(t) + h_i^{ext}(t) + h_i^{ref}(t))$$

When the internal action potential of the ith neuron is larger than the predefined threshold, a pulse is outputted as follows:

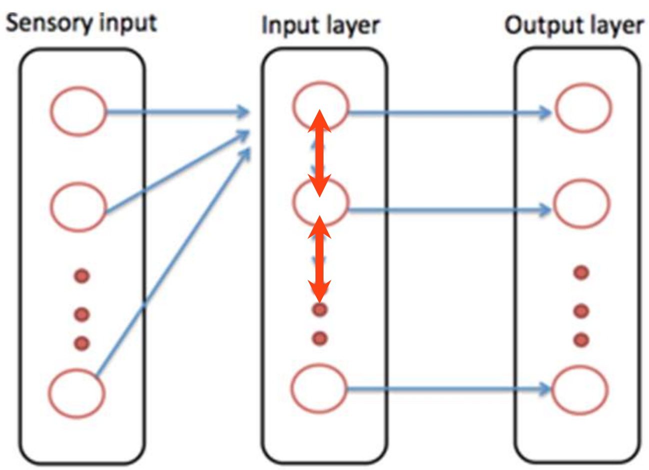
$$p_i(t) = \begin{cases} 1 & \text{if } h_i(t) \geq \theta, \\ 0 & \text{otherwise,} \end{cases}$$

R is subtracted from the refractoriness value in the following:

$$h_i^{ref}(t) = \begin{cases} \gamma^{ref} \cdot h_i^{ref}(t-1) - R & \text{if } p_i(t-1) = 1, \\ \gamma^{ref} \cdot h_i^{ref}(t-1) & \text{otherwise,} \end{cases}$$

BME GPK
FACULTY OF MECHANICAL ENGINEERING

Fuzzy Spiking Neural Networks



Presynaptic Potential (PSP)

The membrane potential, or internal state $h_i(t)$ of the ith spiking neuron at the discrete time t is given by:

$$h_i(t) = \tanh(h_i^{syn}(t) + h_i^{ext}(t) + h_i^{ref}(t))$$

When the internal action potential of the ith neuron is larger than the predefined threshold, a pulse is outputted as follows:

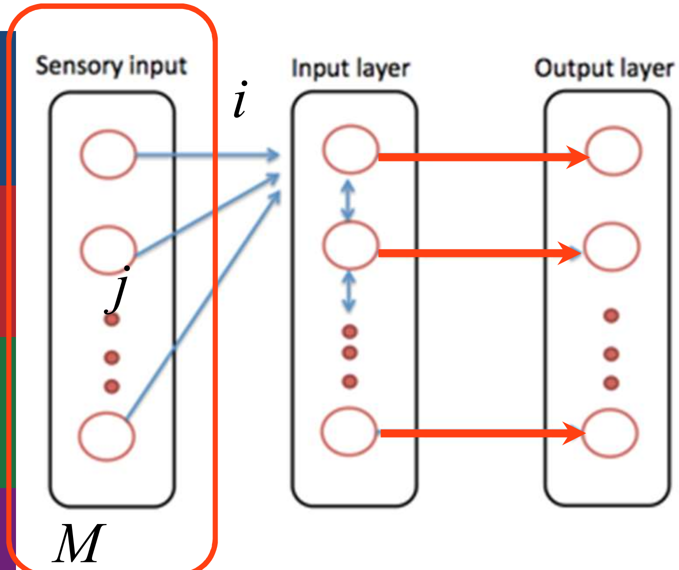
$$p_i(t) = \begin{cases} 1 & \text{if } h_i(t) \geq \theta, \\ 0 & \text{otherwise,} \end{cases}$$

The presynaptic spike output is transmitted to the connected neuron according to the PSP with the weight connection. The PSP is calculated as follows:

$$h_i^{PSP}(t) = \begin{cases} 1 & \text{if } p_i(t) = 1, \\ \gamma^{PSP} \cdot h_i^{PSP}(t-1) & \text{otherwise,} \end{cases}$$

BME GPK
FACULTY OF MECHANICAL ENGINEERING

Fuzzy Spiking Neural Networks



Gaussian Membership Function

The membrane potential, or internal state $h_i(t)$ of the ith spiking neuron at the discrete time t is given by:

$$h_i(t) = \tanh(h_i^{syn}(t) + \underline{h_i^{ext}(t)} + h_i^{ref}(t))$$

The external input, $h_i^{ext}(t)$ is calculated based on the fuzzy inference

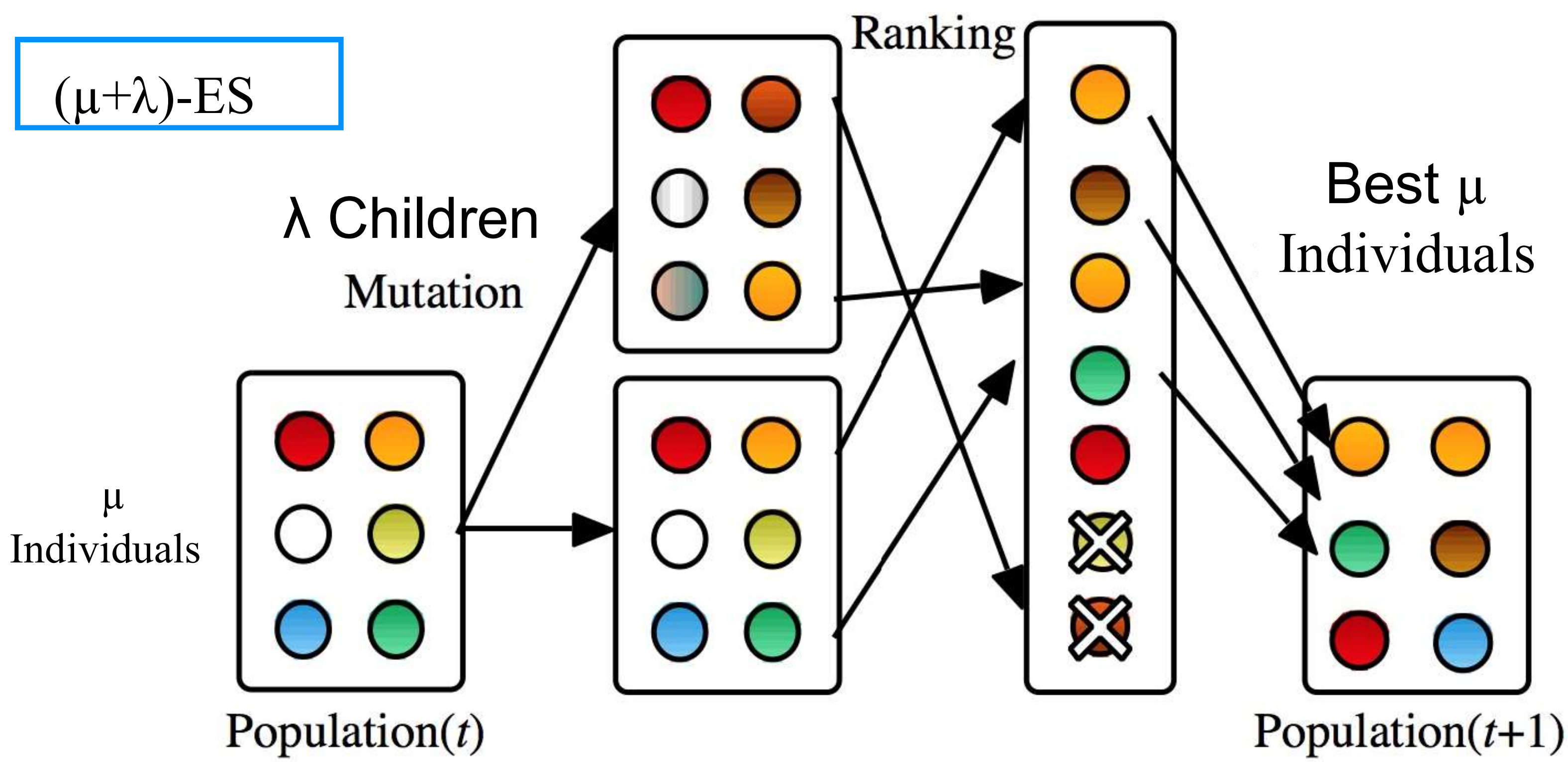
$$h_i^{ext}(t) = \prod_{j=1}^{M} \underline{v_{i,j}} \cdot \exp\left(-\frac{(x_j - \underline{a_{i,j}})^2}{\underline{b_{i,j}}}\right)$$

Evolution Strategy for optimization of parameters of Gaussian membership functions

Evolution Strategy

- Coding: Phenotype (real number, integer etc.)
- Selection: Elitist
- Mutation: Gaussian random variable with zero mean
  - $x_{i+\lambda}(t+1) = x_i(t) + N(0,\sigma^2)$
- μ: Population size
- λ: Offspring size
- (μ,λ)-ES: discrete model
- (μ+λ)-ES: continuous model

(μ+λ)-ES



Various Evolution Strategies

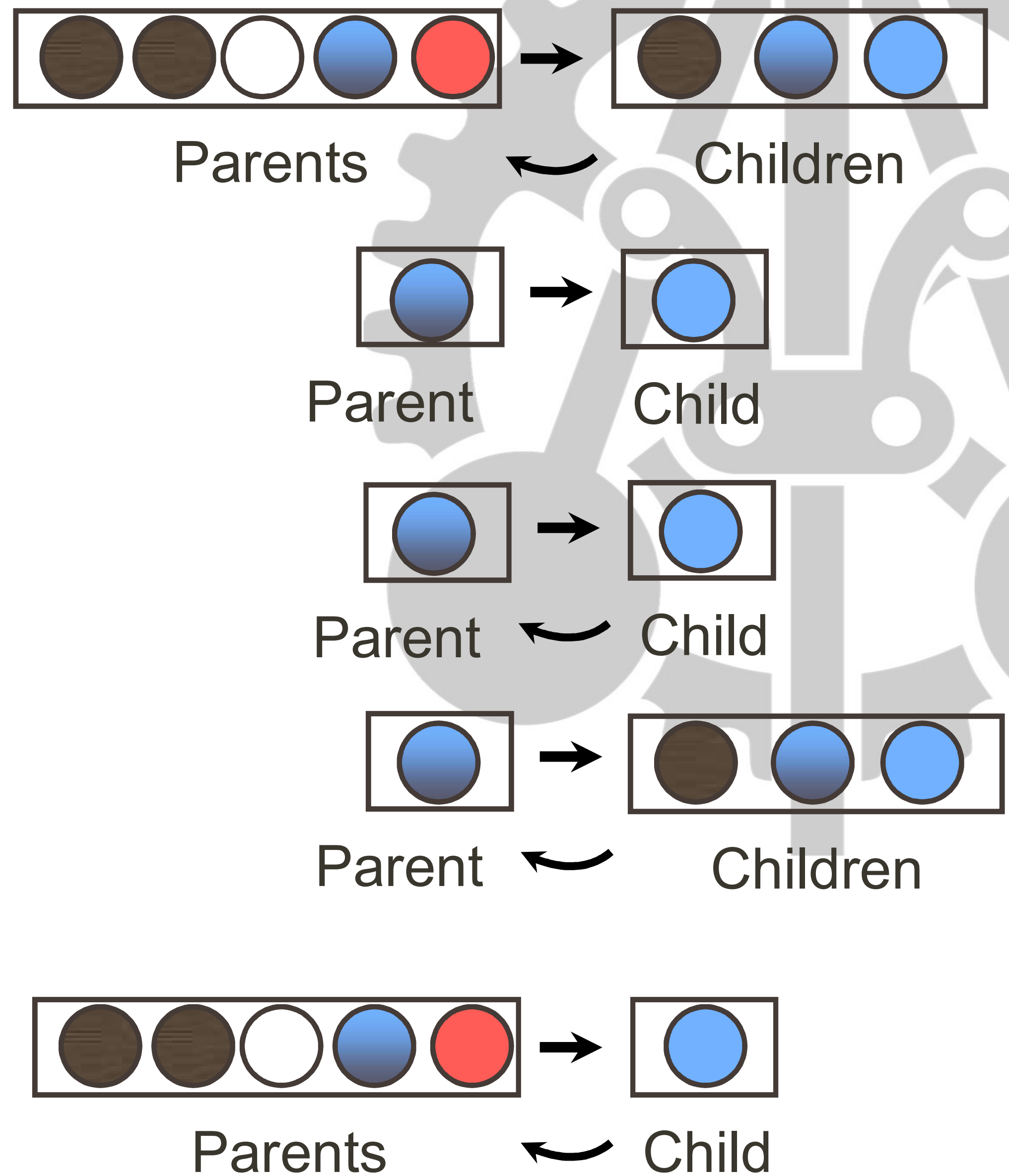
(μ+λ)-ES

(1,1)-ES: Random Search

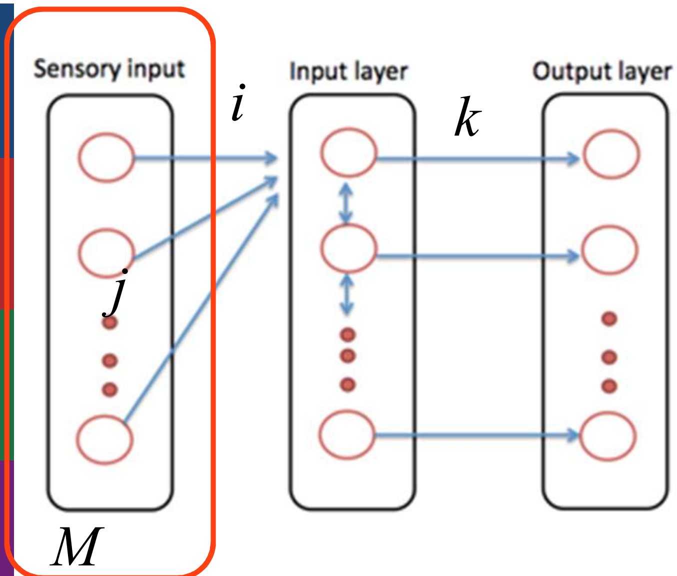
(1+1)-ES: Hill-climbing

(1+λ)-ES: Multipoint Neighboring Search

(μ+1)-ES: Steady-state GA



ES for FSNN - Genotype



Gaussian Membership Function

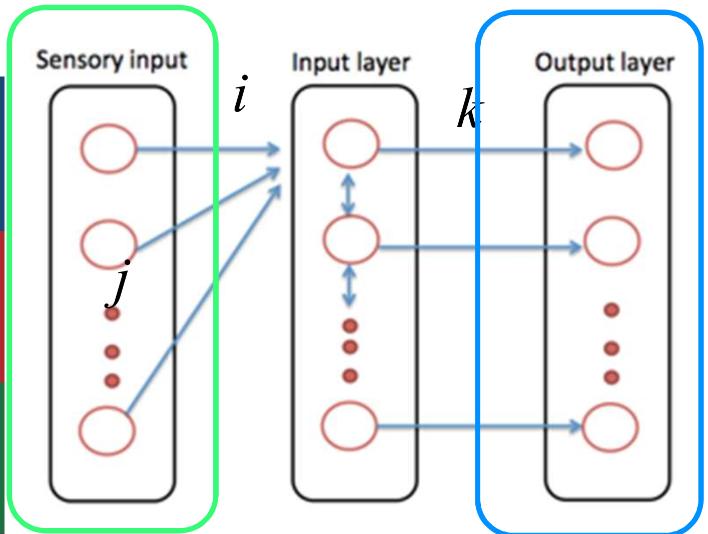
$$h_i^{ext}(t) = \prod_{j=1}^{M} \underline{v_{i,j}} \cdot \exp\left(- \frac{(x_j - \underline{a_{i,j}})^2}{\underline{b_{i,j}}} \right)$$

Genotype

$$\mathbf{g}_k = \left[g_{k,1} \;\; g_{k,2} \;\; g_{k,3} \cdots g_{k,l} \right]$$
$$= \left[a_{k,1,1} \;\; b_{k,1,1} \;\; v_{k,1,1} \ldots \; v_{k,n,m} \right]$$

$g_{k,1}$	$g_{k,2}$	$g_{k,3}$	$\cdots$	$g_{k,l}$

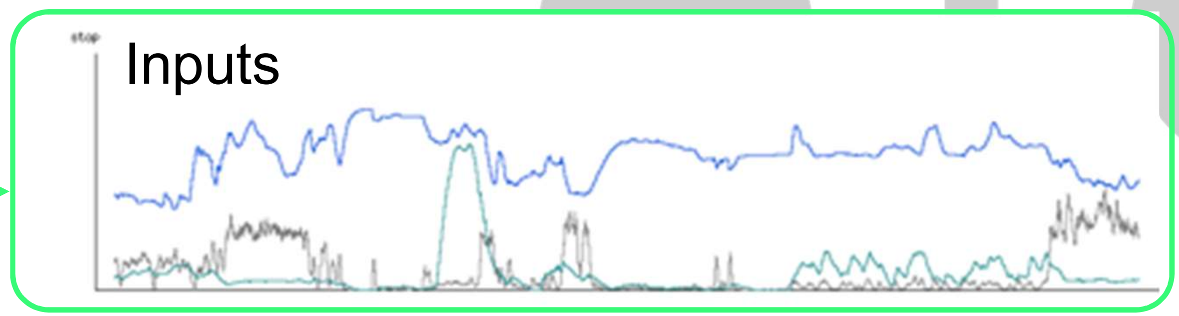
ES for FSNN - Fitness

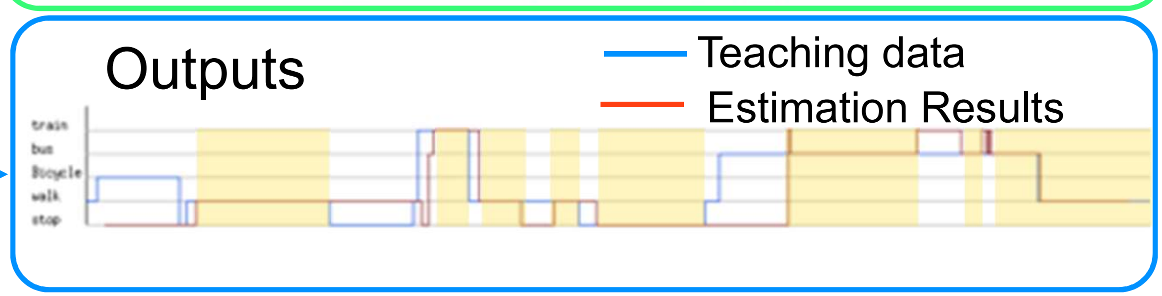


Fitness Function

$$f_k = \sum_{i=1}^{n} f_{k,i}$$

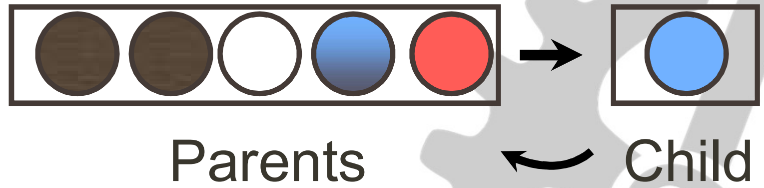
The number of correct estimation rates of the *i*th human transport mode.





ES for FSNN - Operators

(μ+1)-ES: Steady-state GA



Elitist Crossover

$$p_i = \frac{1}{2} \cdot (1 + f_{best,i} - f_{k,i})$$

$f_{best,i}$: the ith rule of the best individuals
$f_{k,i}$:the ith rule of kth individuals

$g_{k,1}$	$g_{k,2}$	$g_{k,3}$	$\cdots$	$g_{k,l}$

$g_{k,1}$	$g_{h,2}$	$g_{k,3}$	$\cdots$	$g_{h,l}$

$g_{h,1}$	$g_{h,2}$	$g_{h,3}$	$\cdots$	$g_{h,l}$

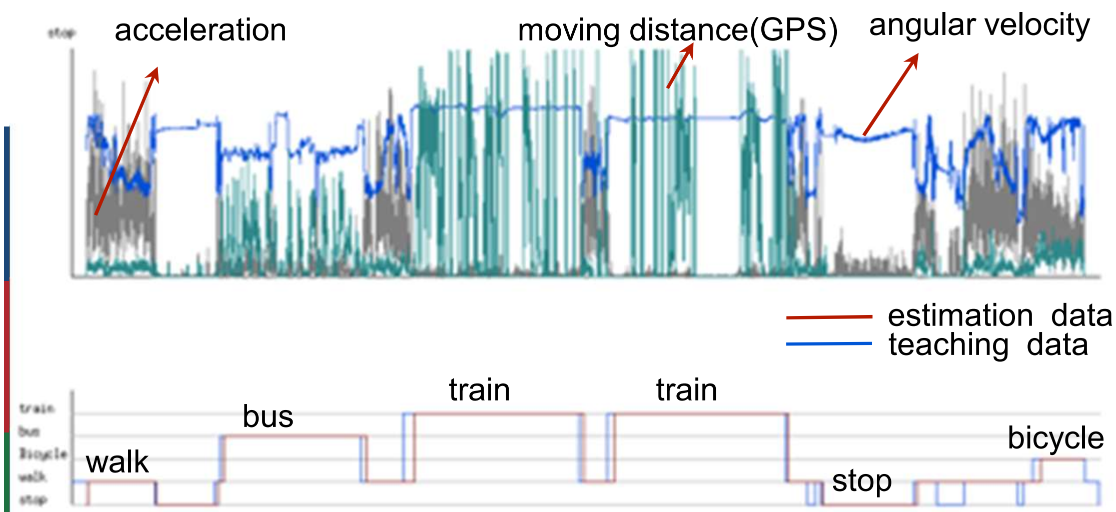
Adaptive Mutation

$$g_{k,h} \leftarrow g_{k,h} + \alpha_h \cdot (1 - t / T) \cdot N(0,1)$$

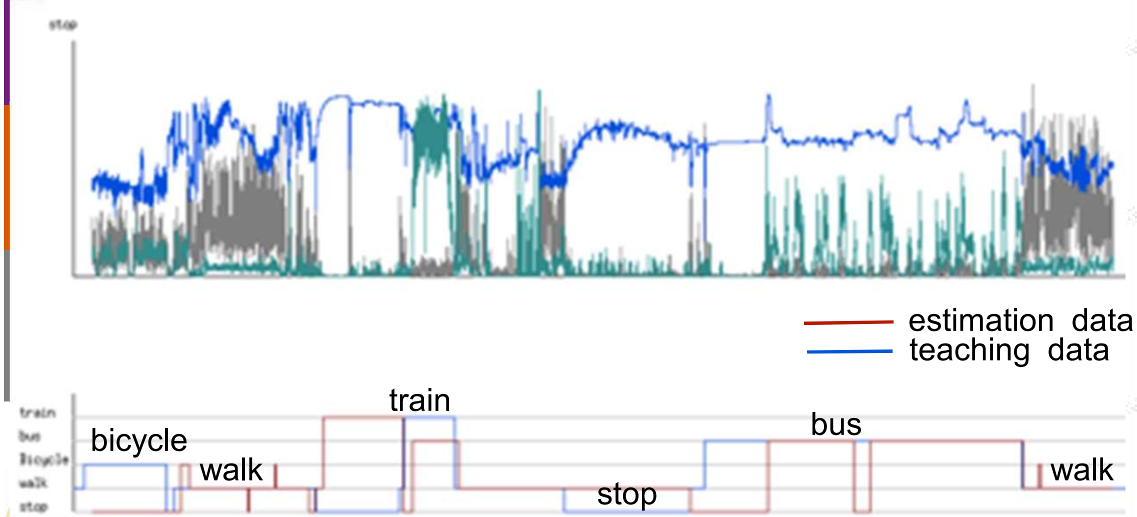
$N(0,1)$: indicates a normal random value,
t : the current generation,
T : the maximum number of generations.

$g_{k,1}$	$g_{h,2}$	$g_{k,3}$	$\cdots$	$g_{h,l}$

Experimental results



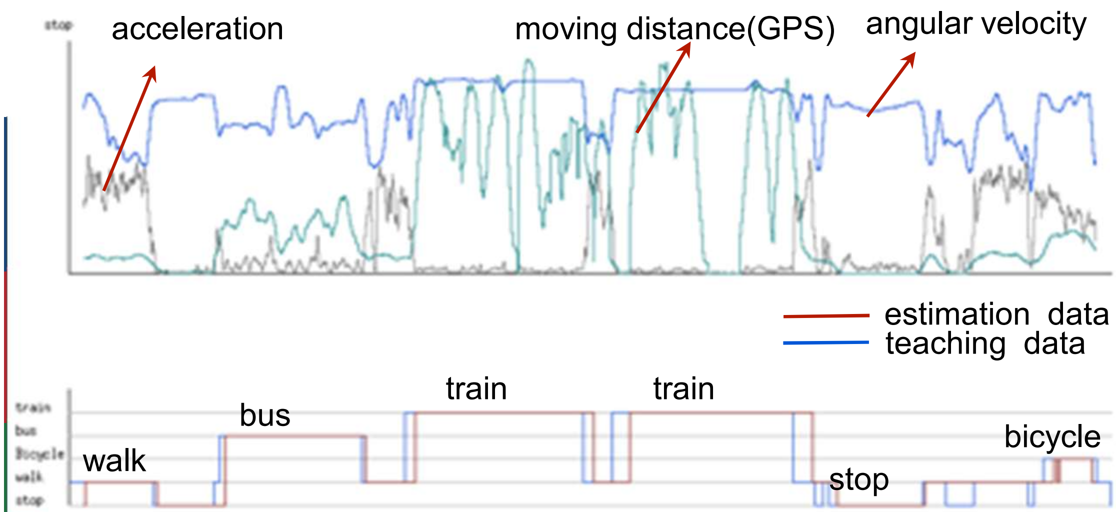
Experimental results by using the raw data for training dataset



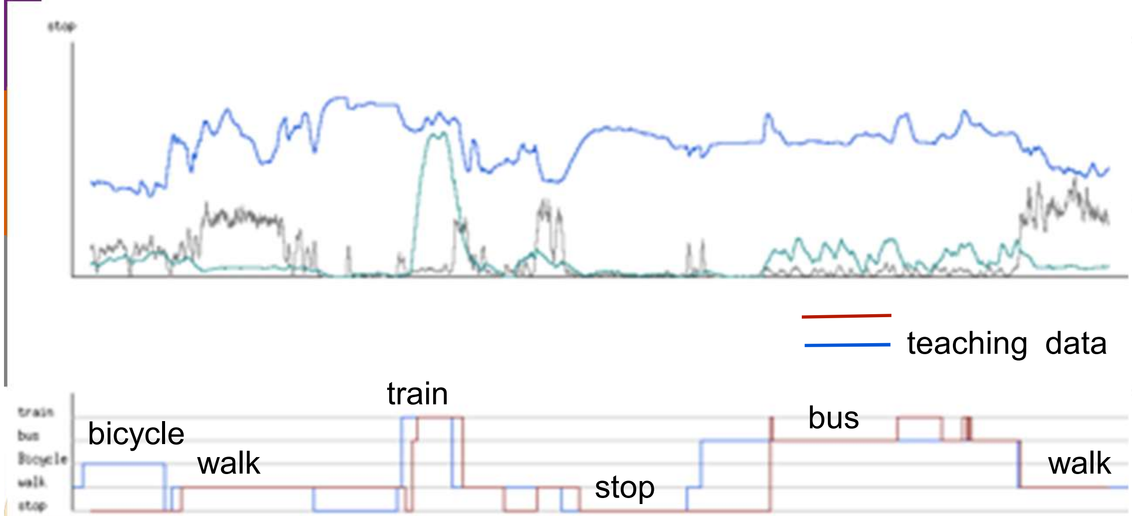
Experimental results by using the raw data for test

	Experiment	Number of data	Number of fitting data	Fitting rate	Running time (ms)
Raw data	traning	18923	13362	70.6%	56
	test	11251	5658	50.2 %	33
Smoothing function Eq.(4)	traning	18923	13632	72.0%	53
	test	11251	6792	60.3%	31
Smoothing function Eq.(5)	traning	18923	14574	77.0%	56
	test	11251	8292	73.7%	31
ES for row data	traning	18923	15936	84.2%	182149
	test	11251	9407	83.6%	191762
ES for Smoothing function Eq.(4)	traning	18923	16631	87.8%	186698
	test	11251	9872	87.7%	193606
ES for Smoothing function Eq.(5)	traning	18923	16925	89.4%	186362
	test	11251	10054	89.3%	190135

Experimental results



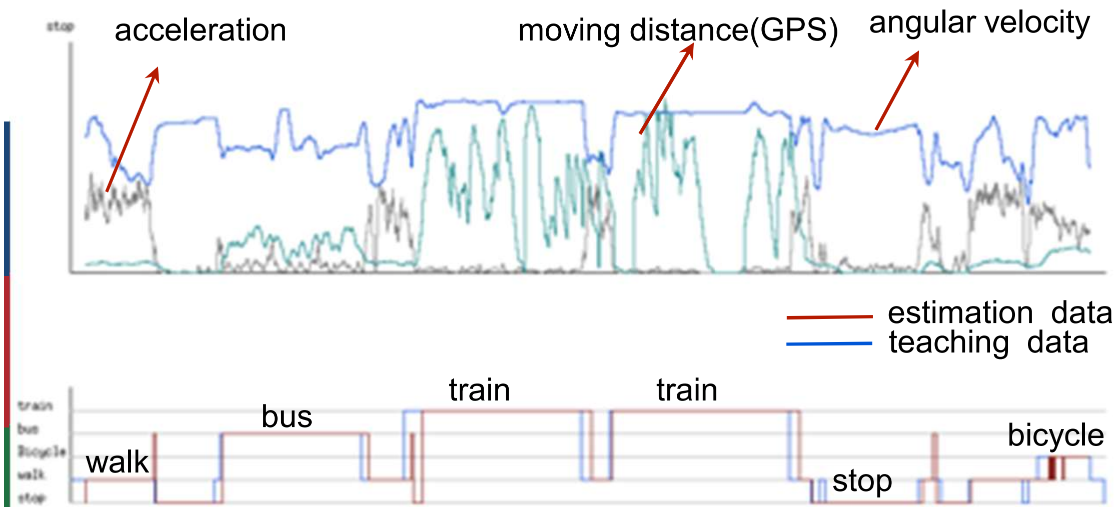
Experimental results by using the smoothing functions (5) for training dataset



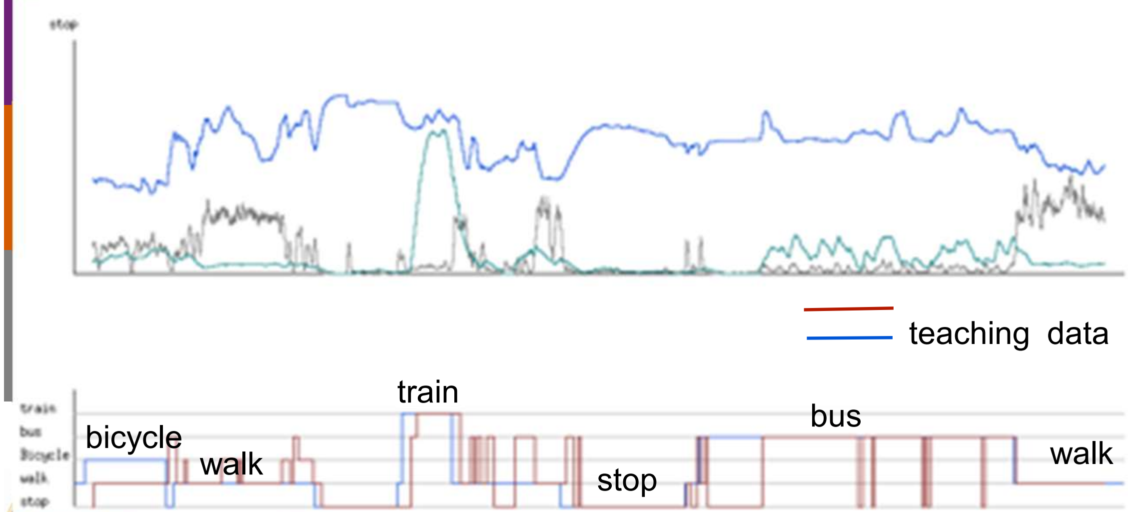
Experimental results by using the smoothing functions (5) for test

	Experiment	Number of data	Number of fitting data	Fitting rate	Running time (ms)
Raw data	traning	18923	13362	70.6%	56
	test	11251	5658	50.2 %	33
Smoothing function Eq.(4)	traning	18923	13632	72.0%	53
	test	11251	6792	60.3%	31
Smoothing function Eq.(5)	traning	18923	14574	77.0%	56
	test	11251	8292	73.7%	31
ES for row data	traning	18923	15936	84.2%	182149
	test	11251	9407	83.6%	191762
ES for Smoothing function Eq.(4)	traning	18923	16631	87.8%	186698
	test	11251	9872	87.7%	193606
ES for Smoothing function Eq.(5)	traning	18923	16925	89.4%	186362
	test	11251	10054	89.3%	190135

Experimental results



Experimental results by the smoothing functions (5) and Evolution Strategy for parameter optimization for training dataset



Experimental results by the smoothing functions (5) and Evolution Strategy for parameter optimization for test

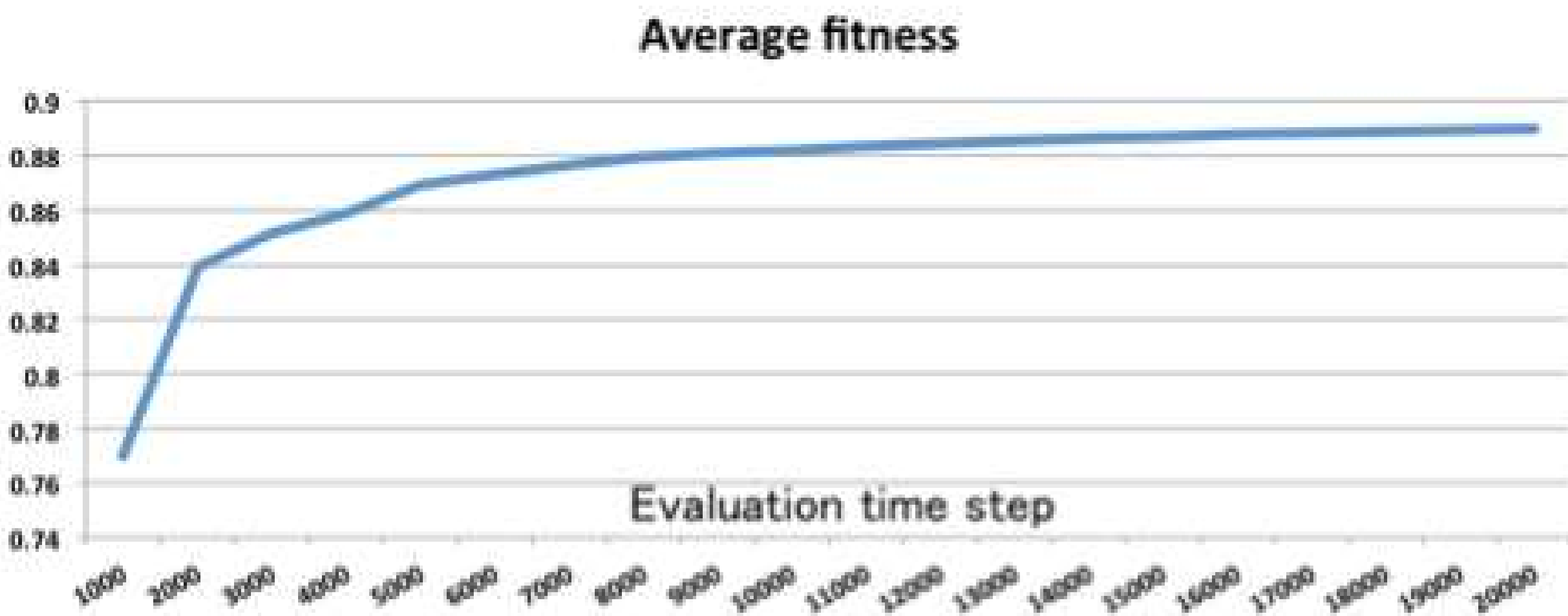
	Experiment	Number of data	Number of fitting data	Fitting rate	Running time (ms)
Raw data	traning	18923	13362	70.6%	56
	test	11251	5658	50.2 %	33
Smoothing function Eq.(4)	traning	18923	13632	72.0%	53
	test	11251	6792	60.3%	31
Smoothing function Eq.(5)	traning	18923	14574	77.0%	56
	test	11251	8292	73.7%	31
ES for row data	traning	18923	15936	84.2%	182149
	test	11251	9407	83.6%	191762
ES for Smoothing function Eq.(4)	traning	18923	16631	87.8%	186698
	test	11251	9872	87.7%	193606
ES for Smoothing function Eq.(5)	traning	18923	16925	89.4%	186362
	test	11251	10054	89.3%	190135

FACULTY OF MECHANICAL ENGINEERING

Experimental results

SNN:
the temporal discount rate for refractoriness is 0.68,
the temporal discount rate for EPSP is 0.72,
the threshold for firing is 1.0, and R is 1.0.

Best fitness values based on ten simulations



Conclusions

- A Fuzzy Spiking Neural Network is applied to solve a sensory data classification task
- A Simple Spike Response Model is used in order to reduce the computational cost
- Evolution Strategy is applied to optimize the parameters of the fuzzy membership functions
- Experimental results showed the effectiveness of the proposed method