Research on Intelligent Robotic Systems at Hosei University

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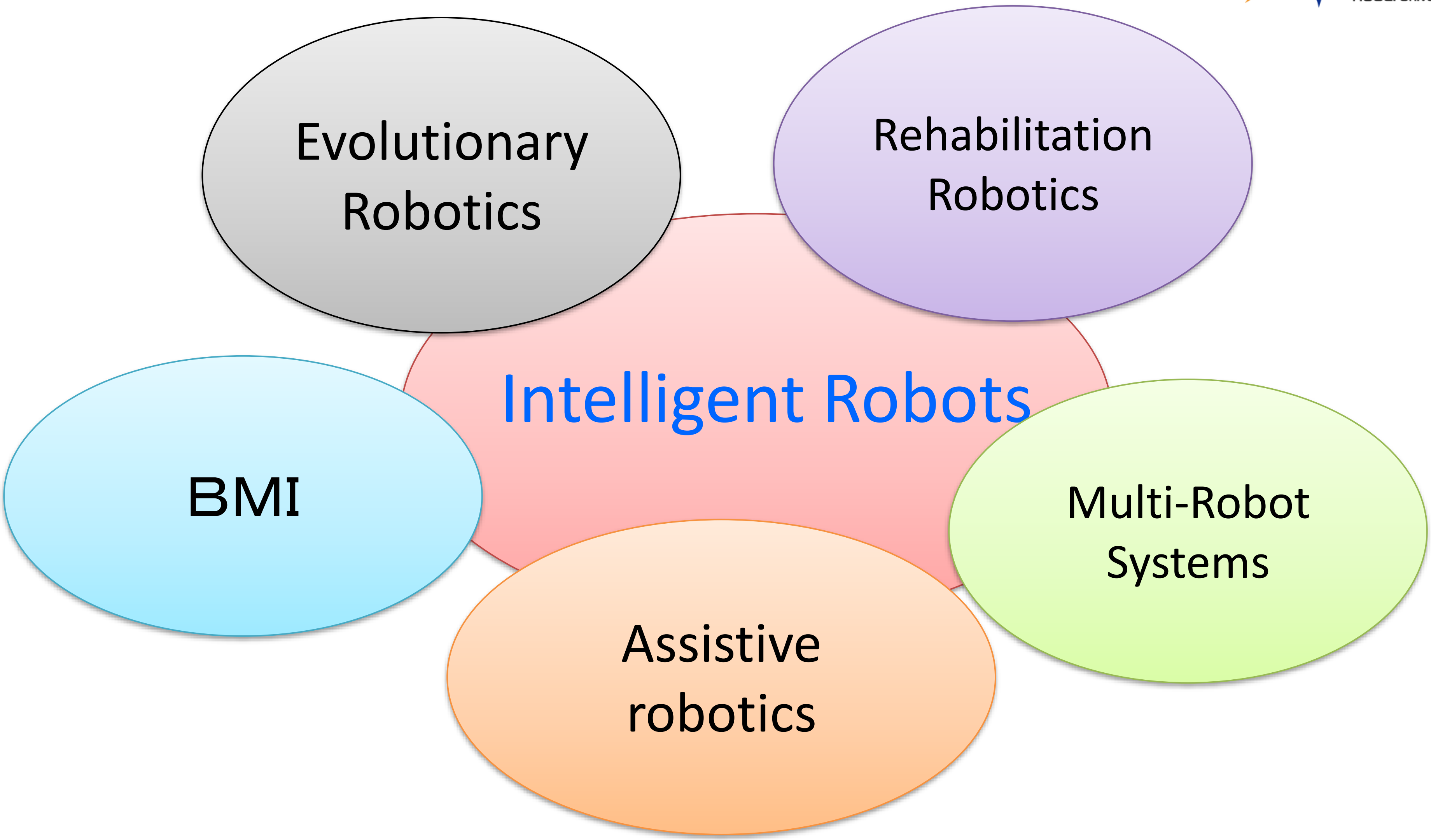
法政大学 HOSEI University



Guide robot for visually impaired people

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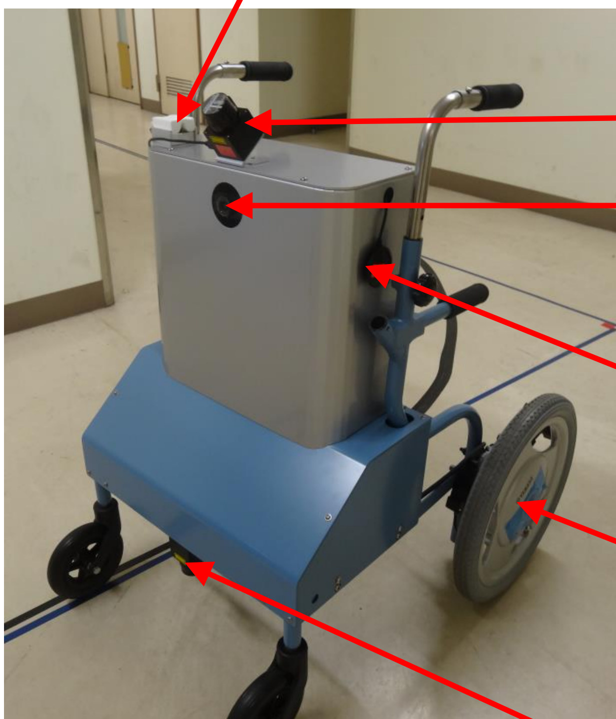
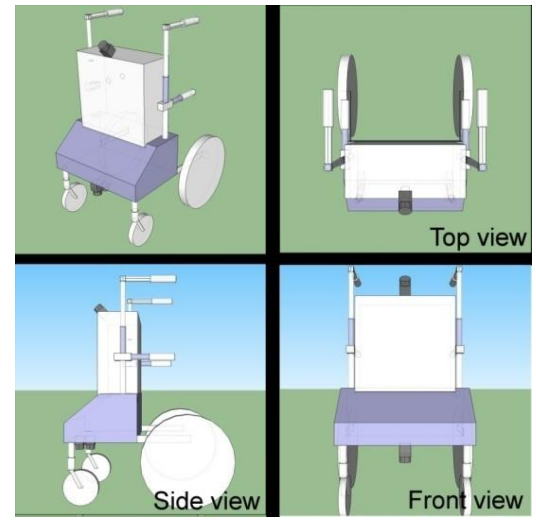
Introduction

- Most of visually impaired people lost their sight in the elderly age.
  - Difficult to learn to walk with the long cane or the guide dog
    - not so rich in the auditory and haptic sensing and have not good memory for the cognitive map.
- Development of a mobile robot that operates in
  - Assistive mode
  - Guide mode

Robot hardware





Compass

LRF

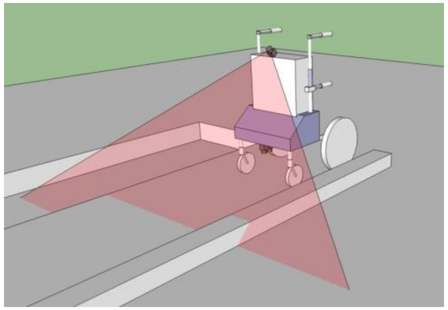
Camera

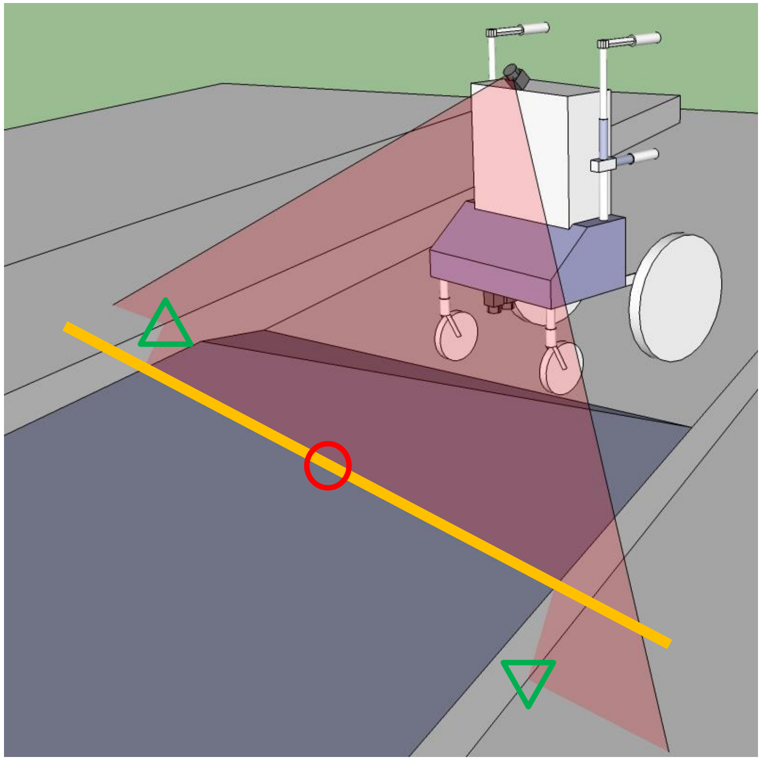
GPS

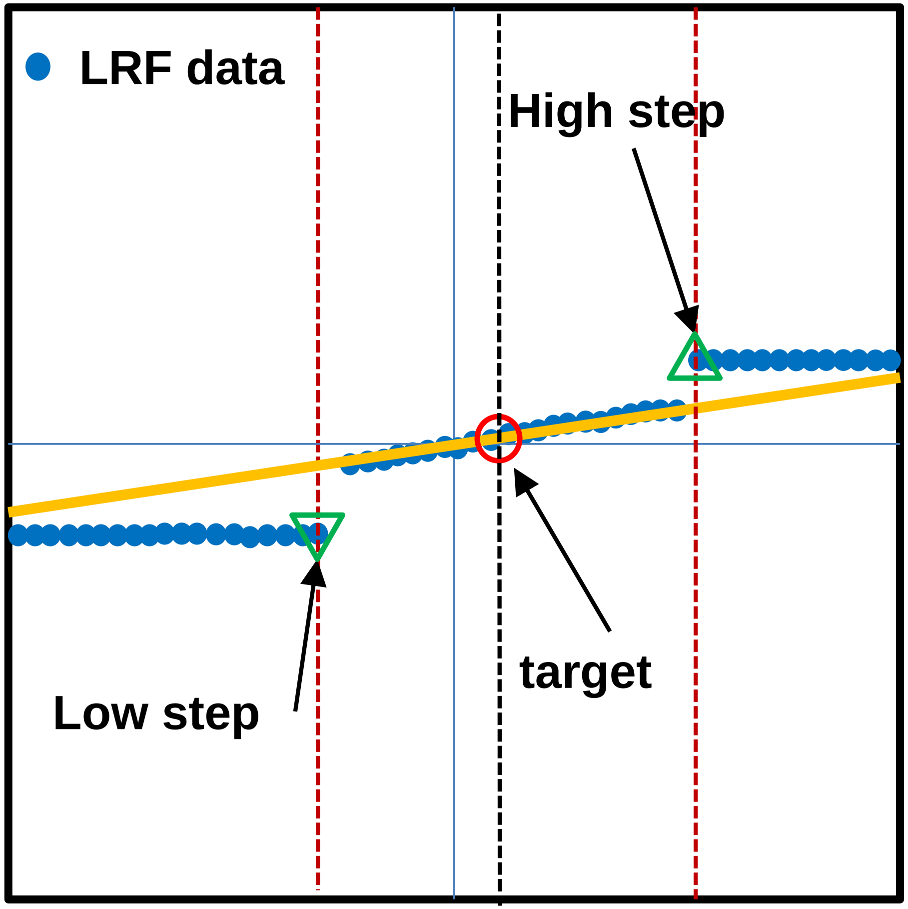
AC motor

LRF

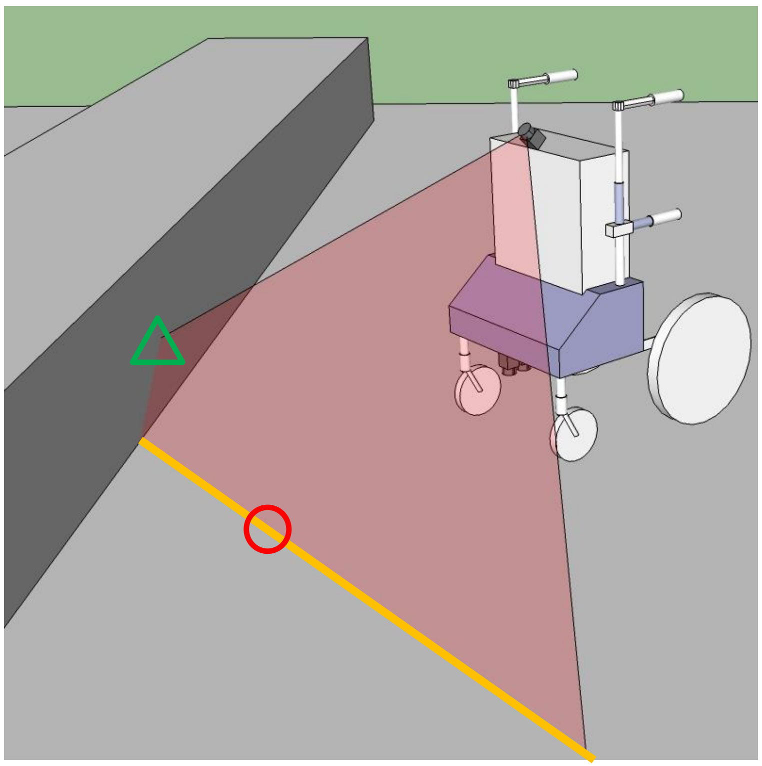
Navigation in pedestrians

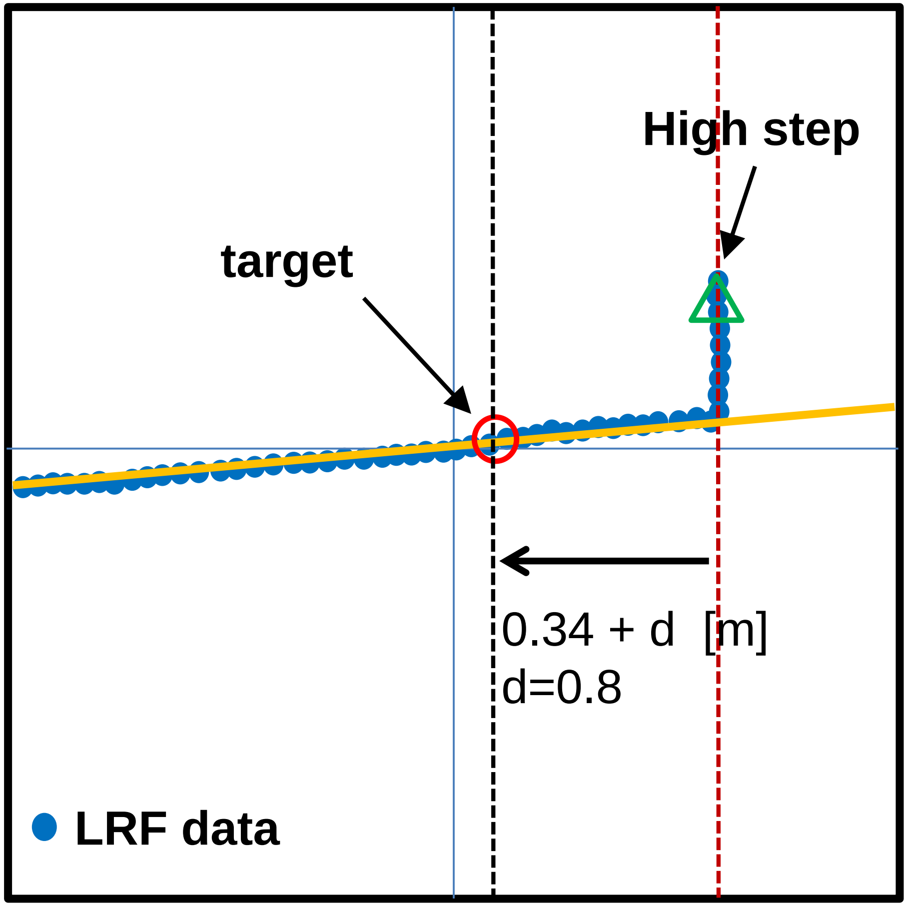




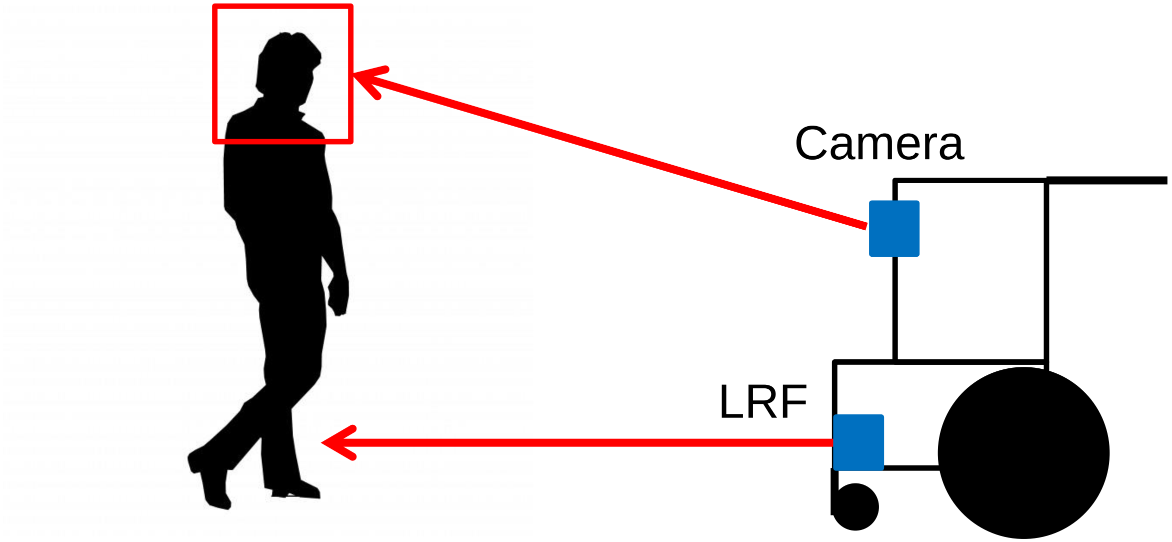


One side step recognition

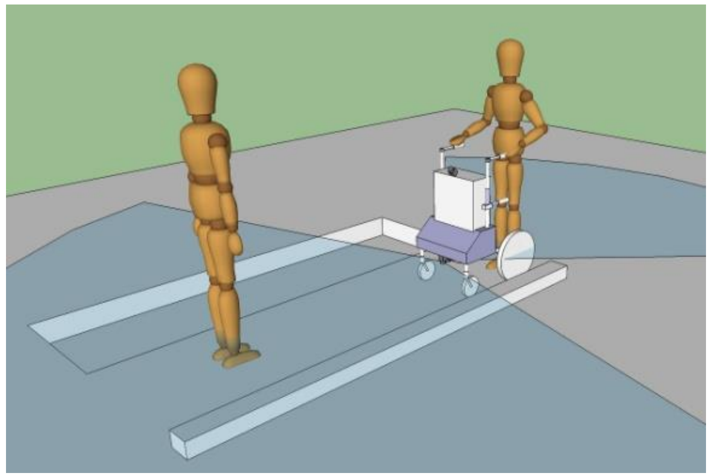


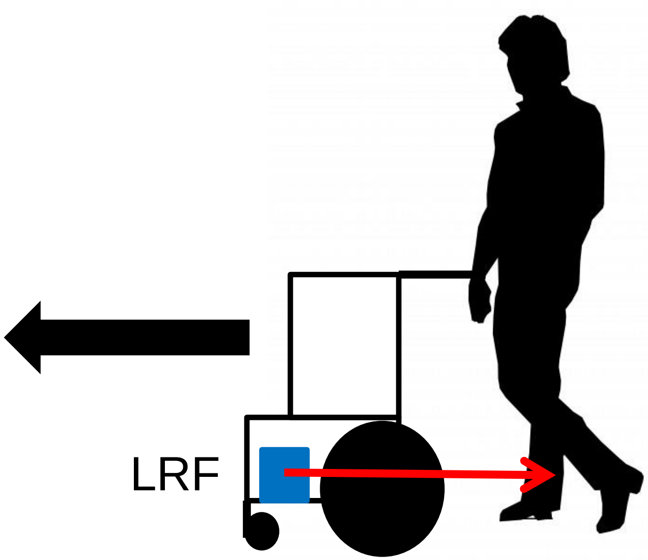


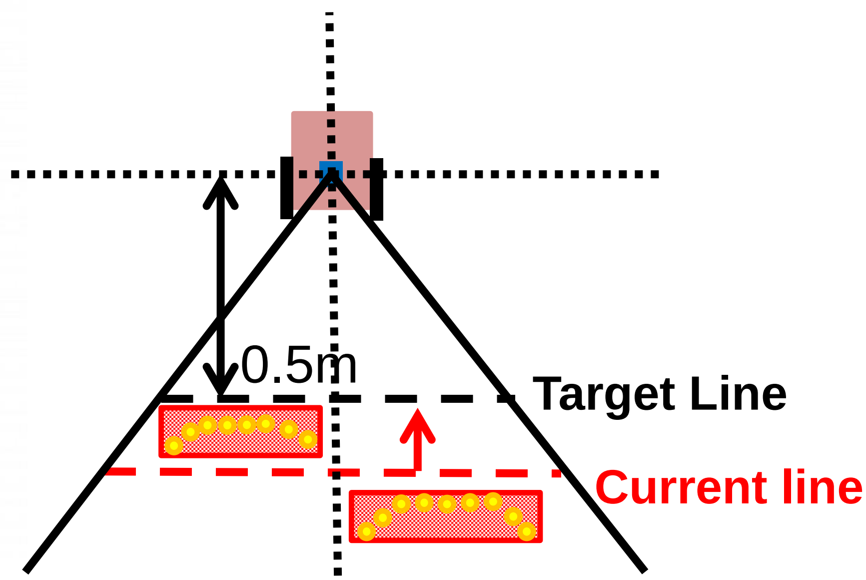
Pedestrian recognition



Speed adaptation based on LRF data







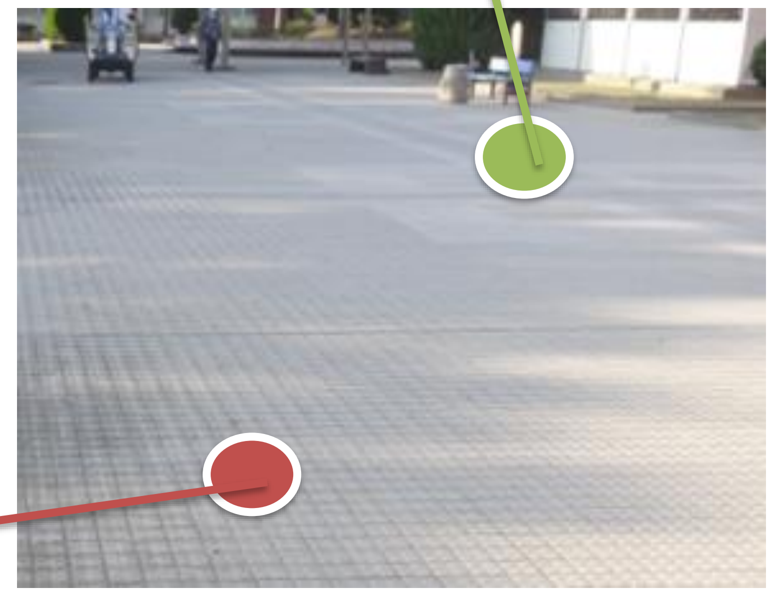
Open squares

$\Delta Longitude = G_{Lon} - R_{Lon}$

$\Delta Latitude = G_{Lat} - R_{Lat}$

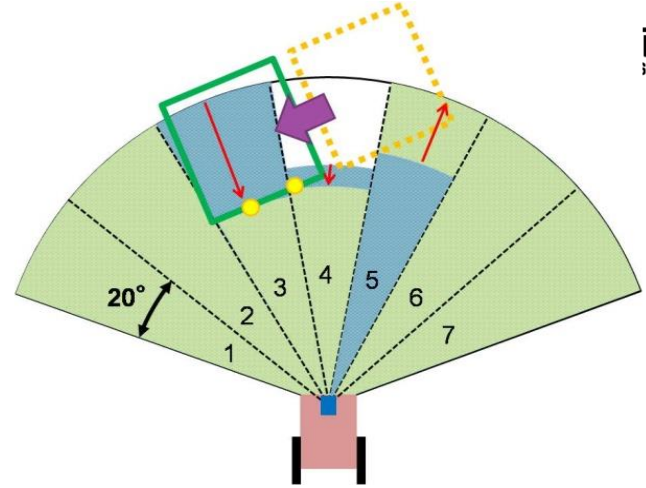
R:Guide Robot
G:Goal Location

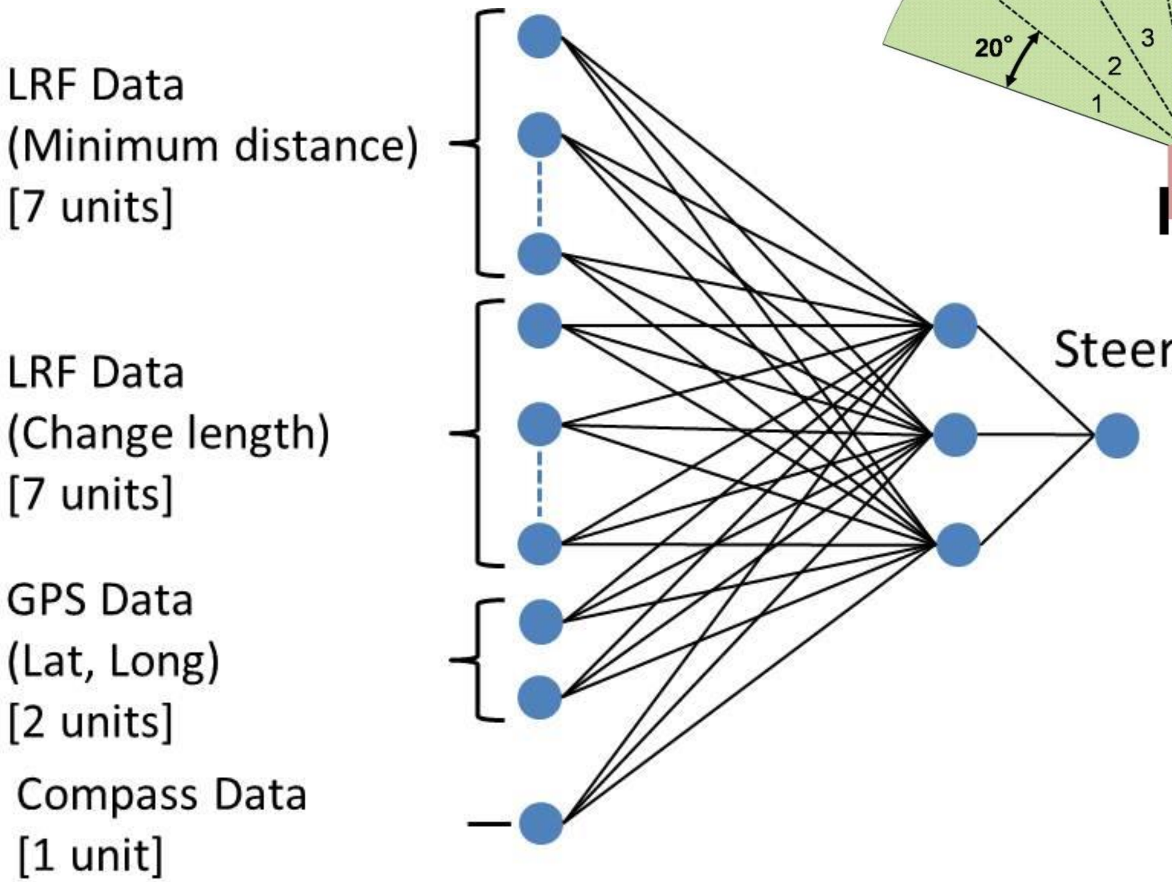
Goal



Robot location

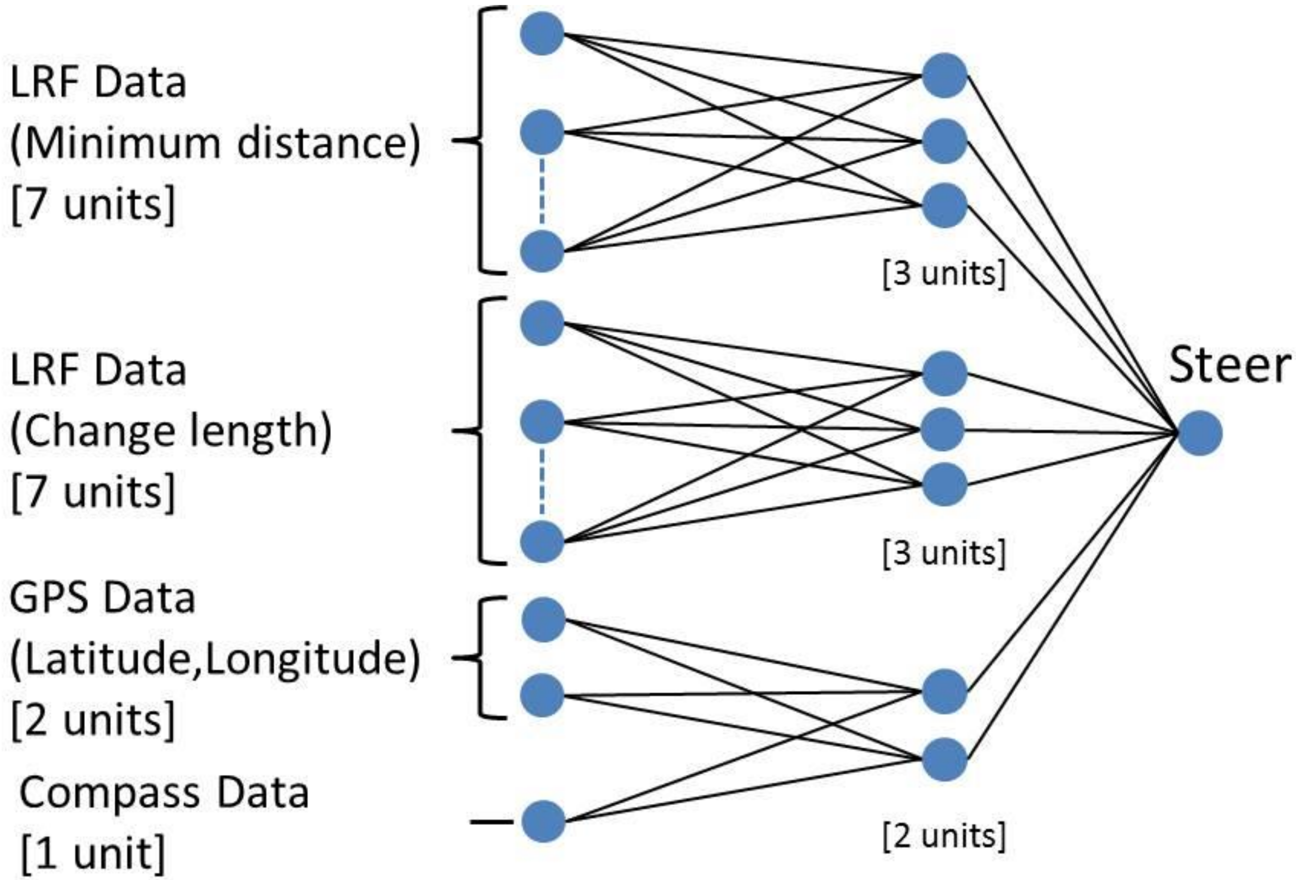
NN1





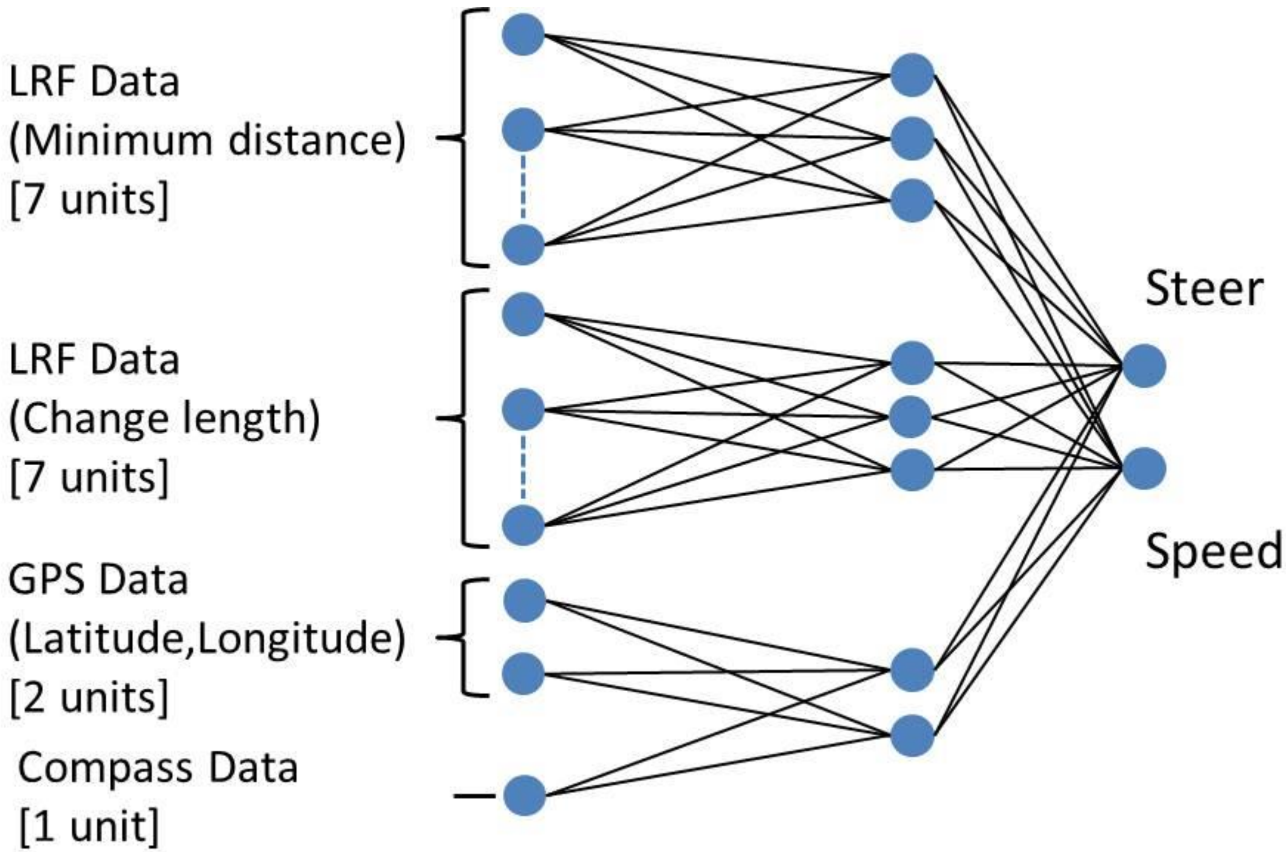
Genome length:54

NN2



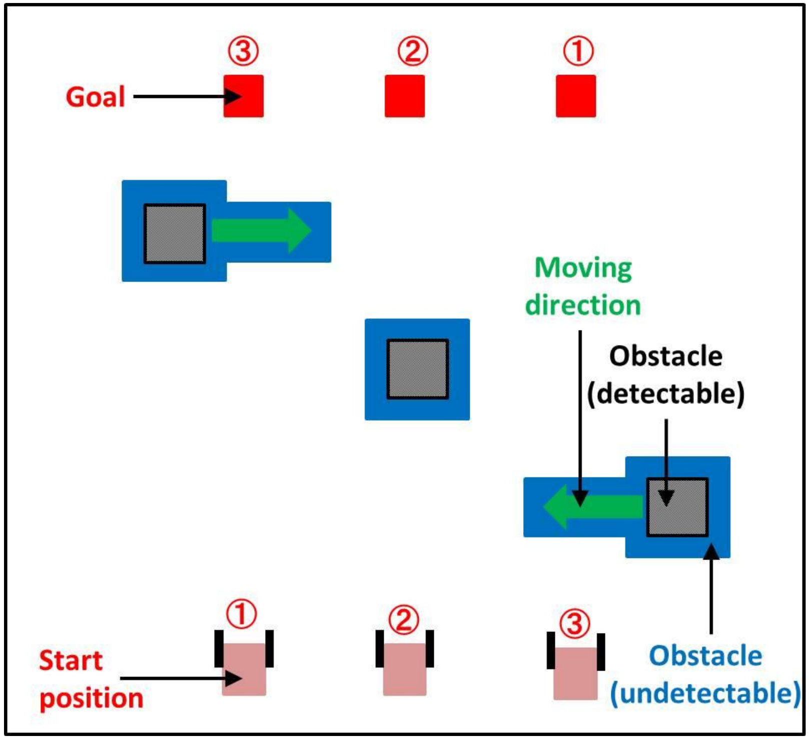
Genome length 56

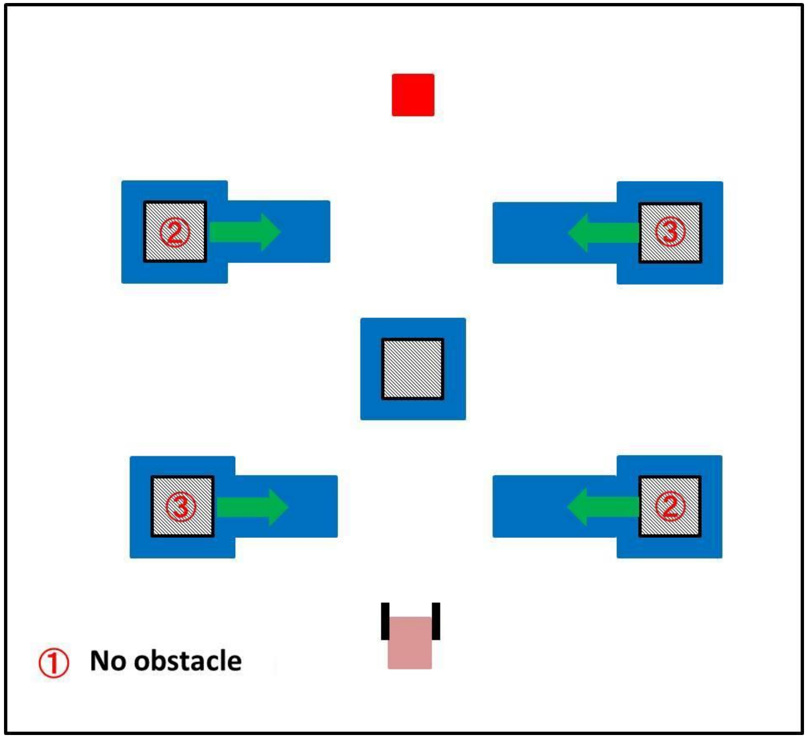
NN3



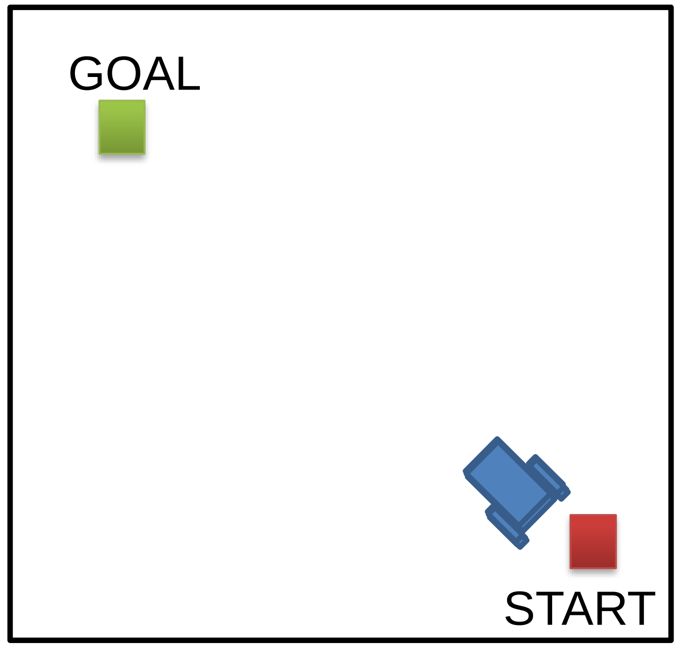
Genome length 64

Environments

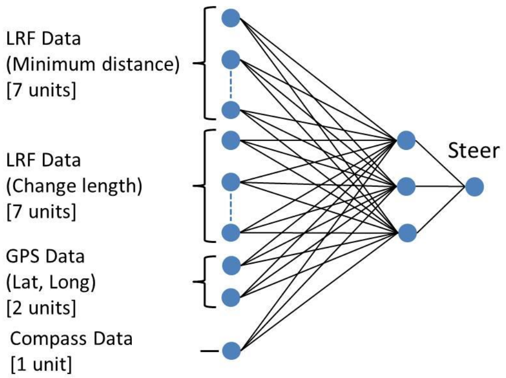




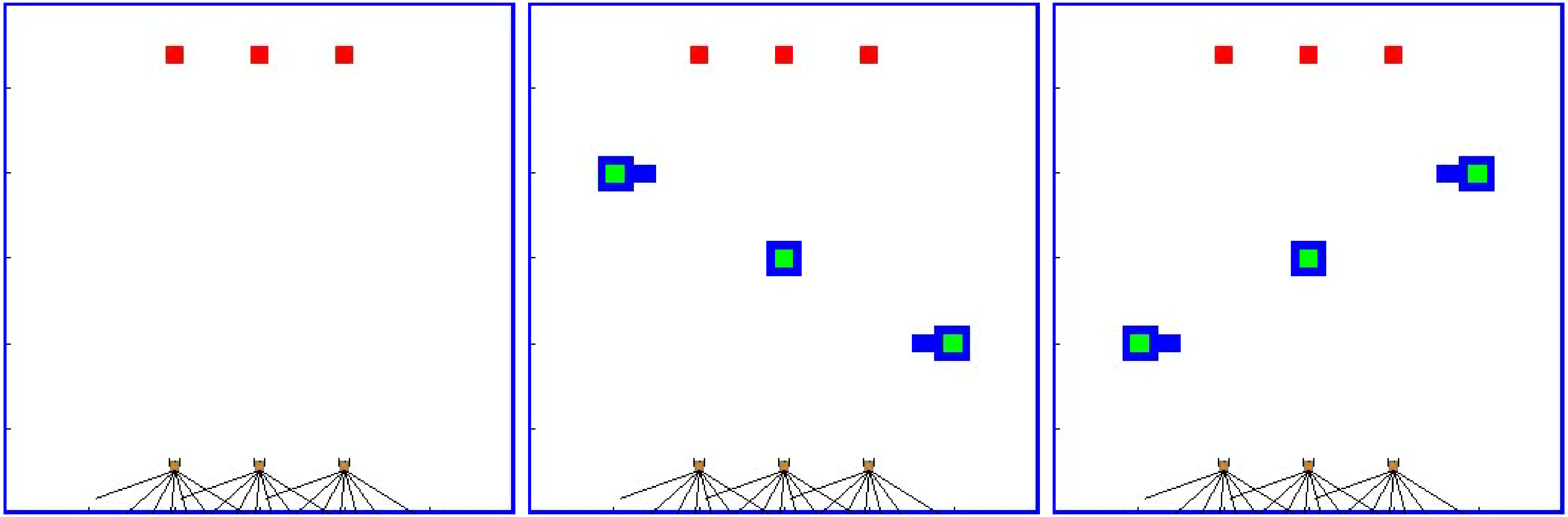
Evolution of NN



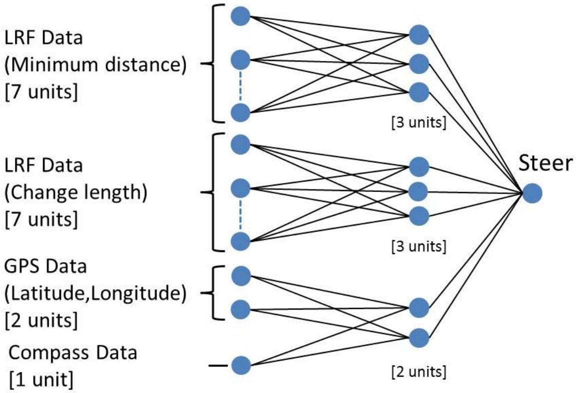
$$f = \sqrt{(goal\_x - robot\_x) + (goal\_y - robot\_y)} + \text{number\_of\_steps}$$

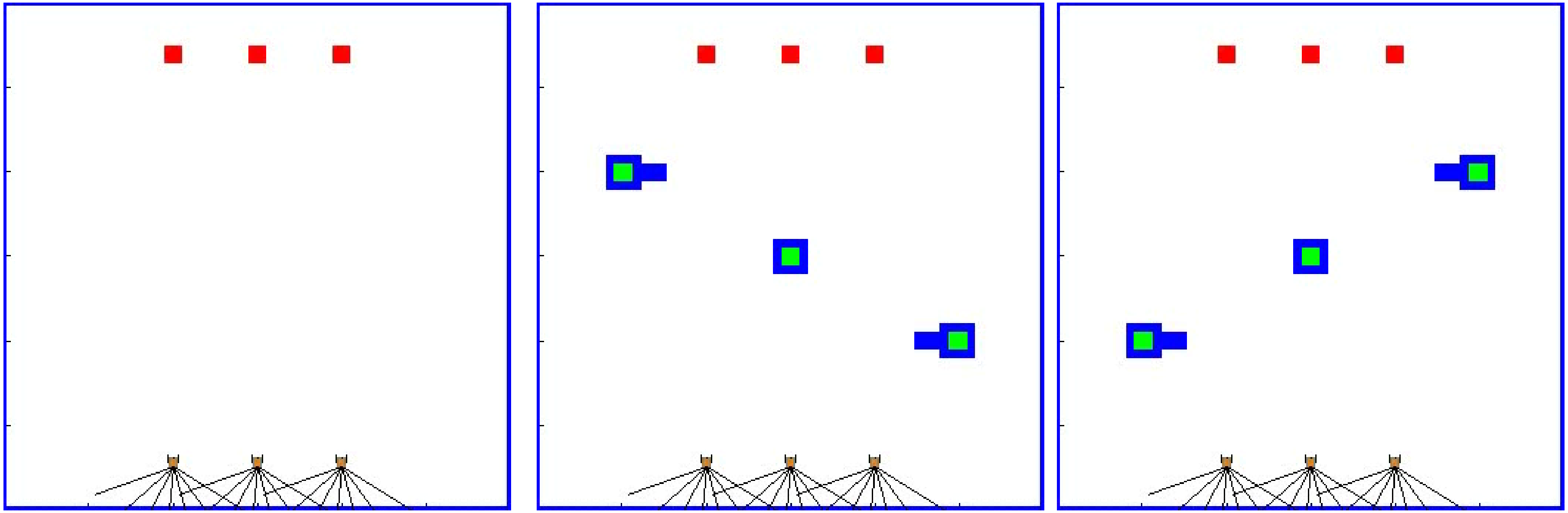

LRF Data
(Minimum distance)
[7 units]
LRF Data
(Change length)
[7 units]
GPS Data
(Lat, Long)
[2 units]
Compass Data
[1 unit]
Steer

NN1 results

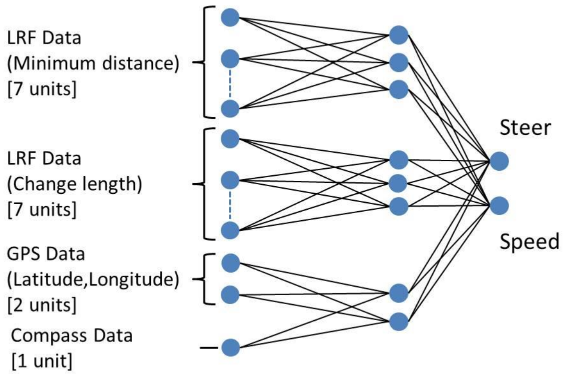


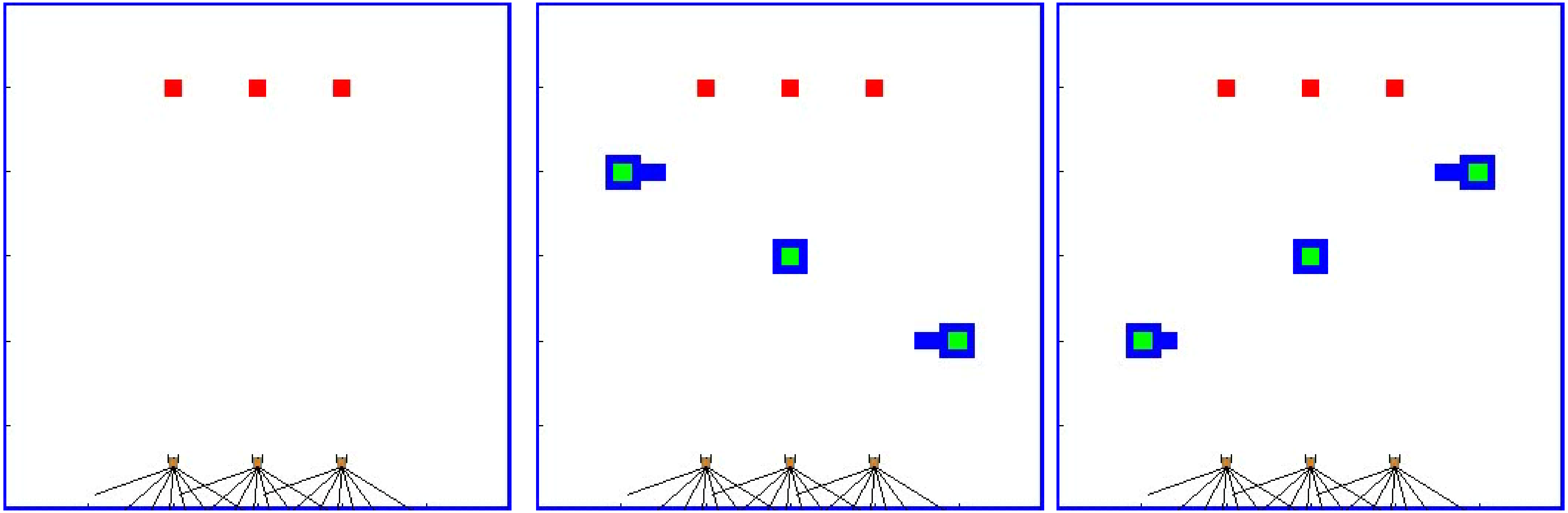
NN2 results


LRF Data
(Minimum distance)
[7 units]
[3 units]
LRF Data
(Change length)
[7 units]
[3 units]
GPS Data
(Latitude,Longitude)
[2 units]
Compass Data
[1 unit]
[2 units]
Steer

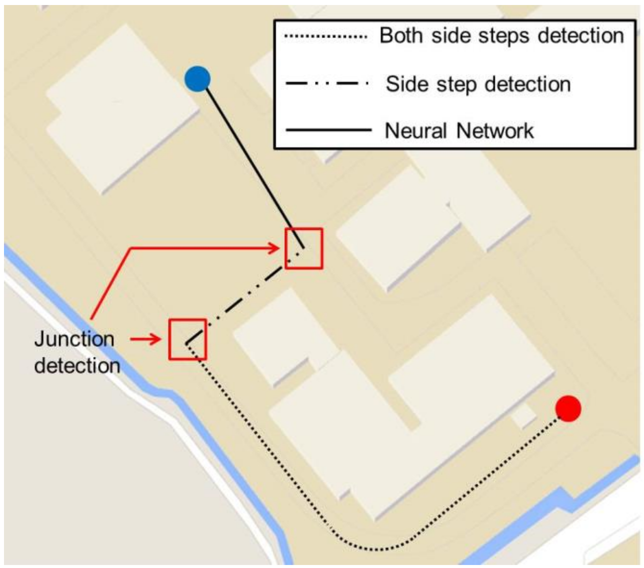


NN3 results

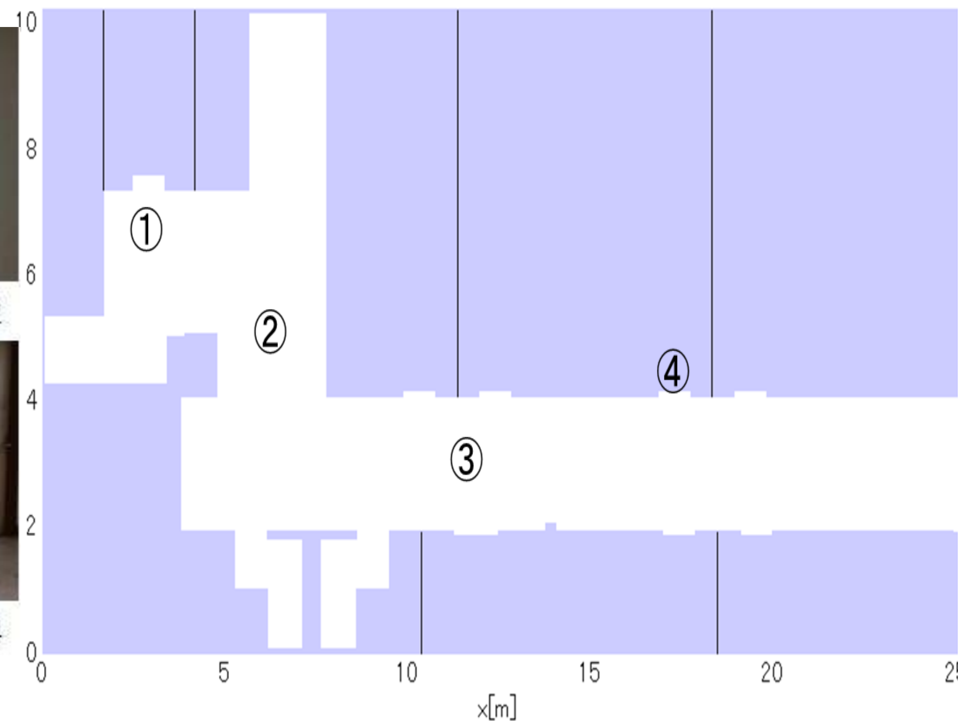

LRF Data
(Minimum distance)
[7 units]
LRF Data
(Change length)
[7 units]
GPS Data
(Latitude,Longitude)
[2 units]
Compass Data
[1 unit]
Steer
Speed



Experimental results



Indoor navigation



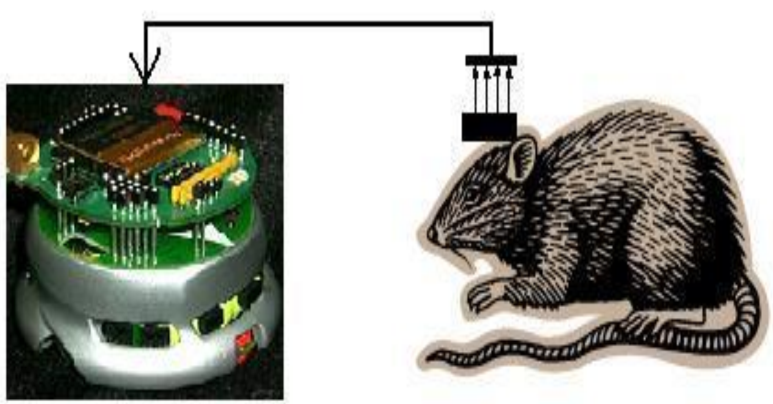
Experimental results

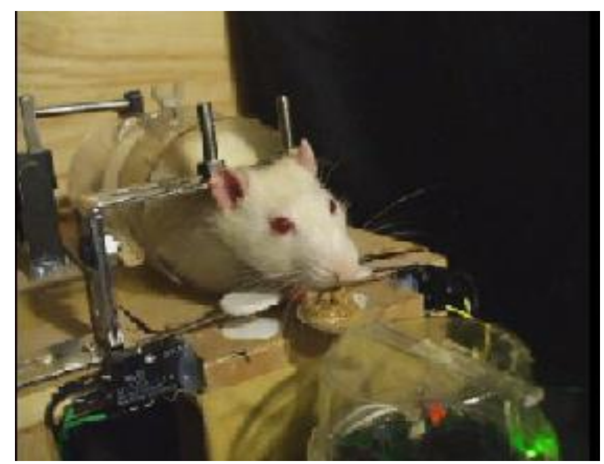

6:26

BMI

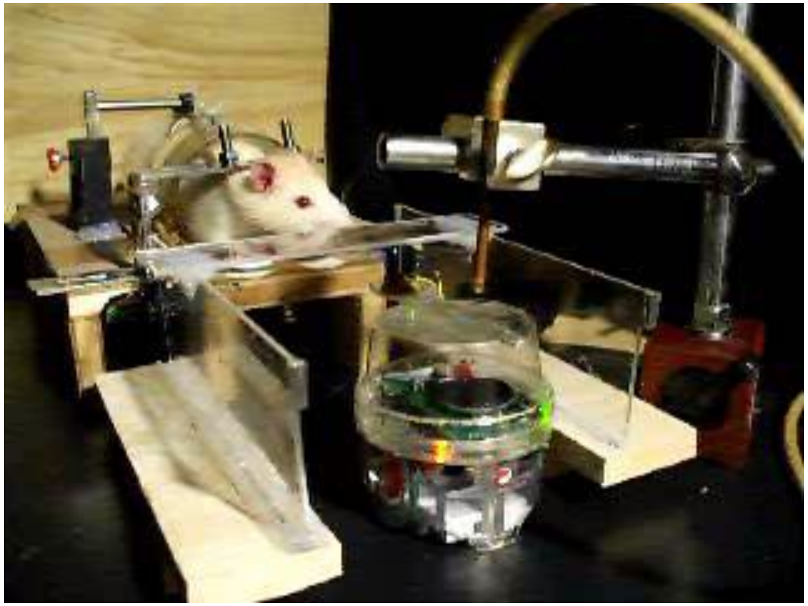
Goal

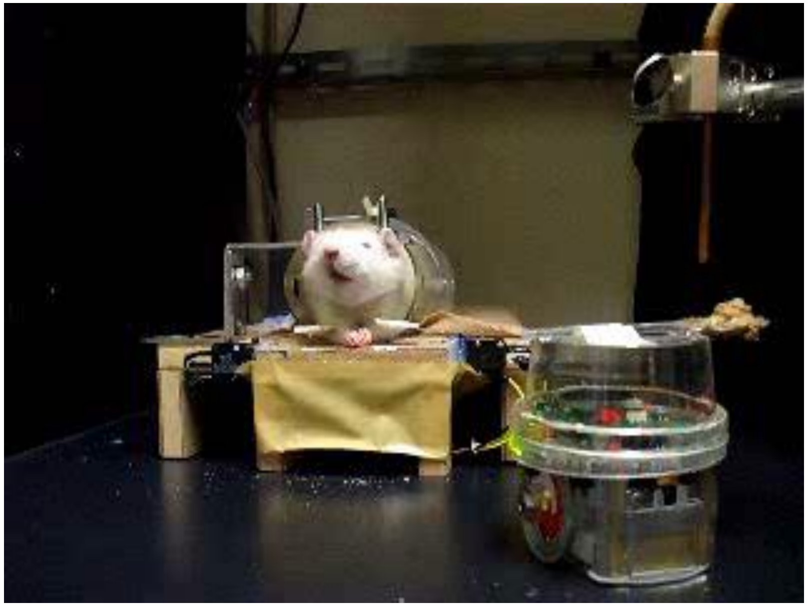
- Using brain signals to control the robot
- Building biologically motivated neural controllers



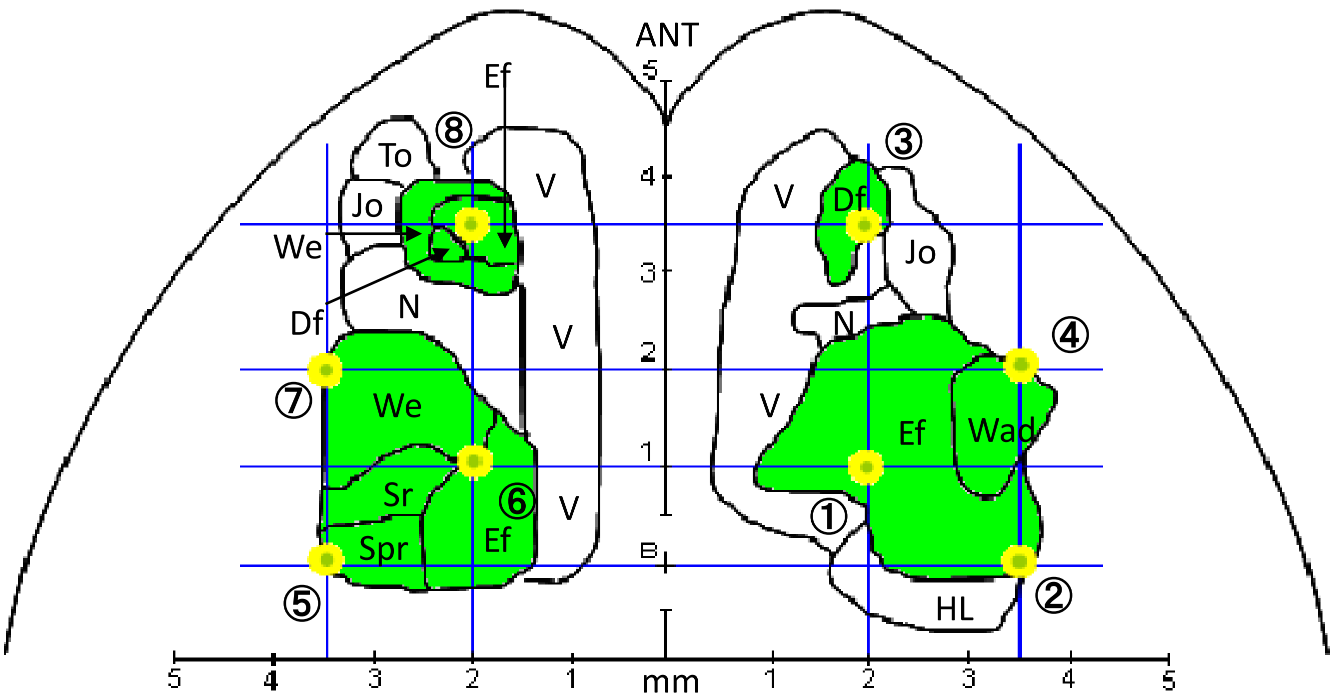


Rat learn to press the appropriate lever to get food



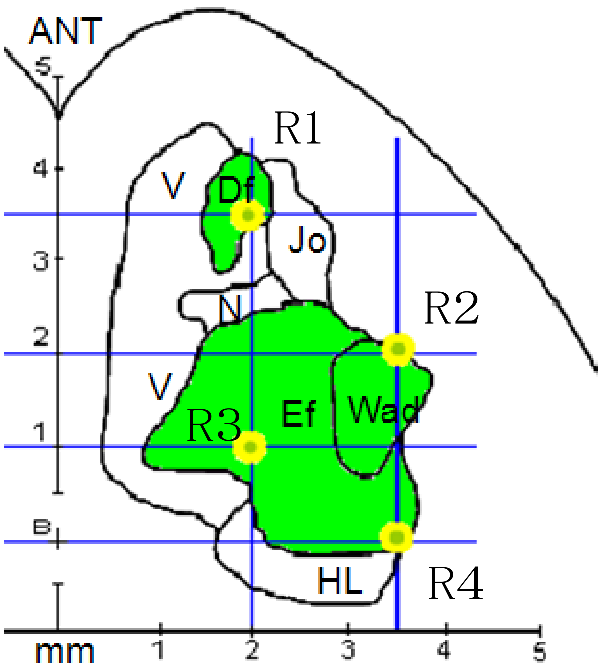


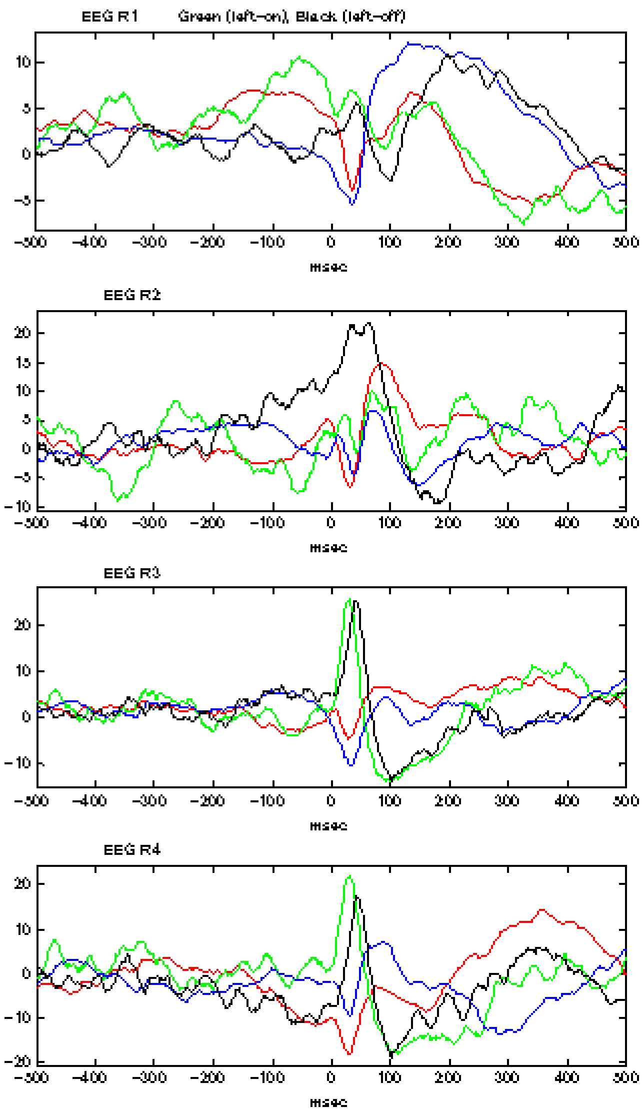
Electode position in rats brain



①	R1
②	R2
③	R3
④	R4
⑤	L1
⑥	L2
⑦	L3
⑧	L4

Brain signals





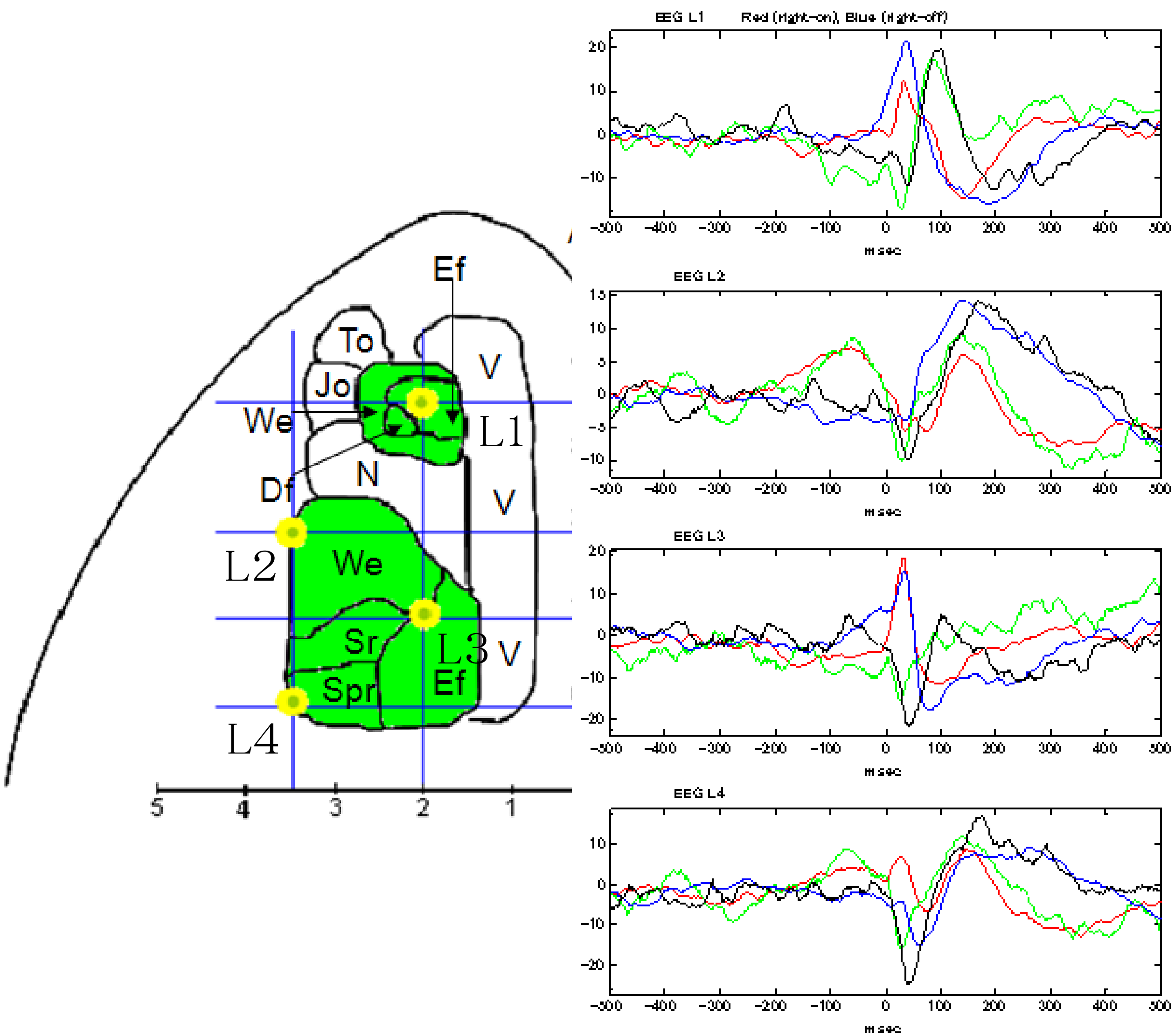
Left lever pressed

Left lever released

Right lever pressed

Right lever released

Brain activity



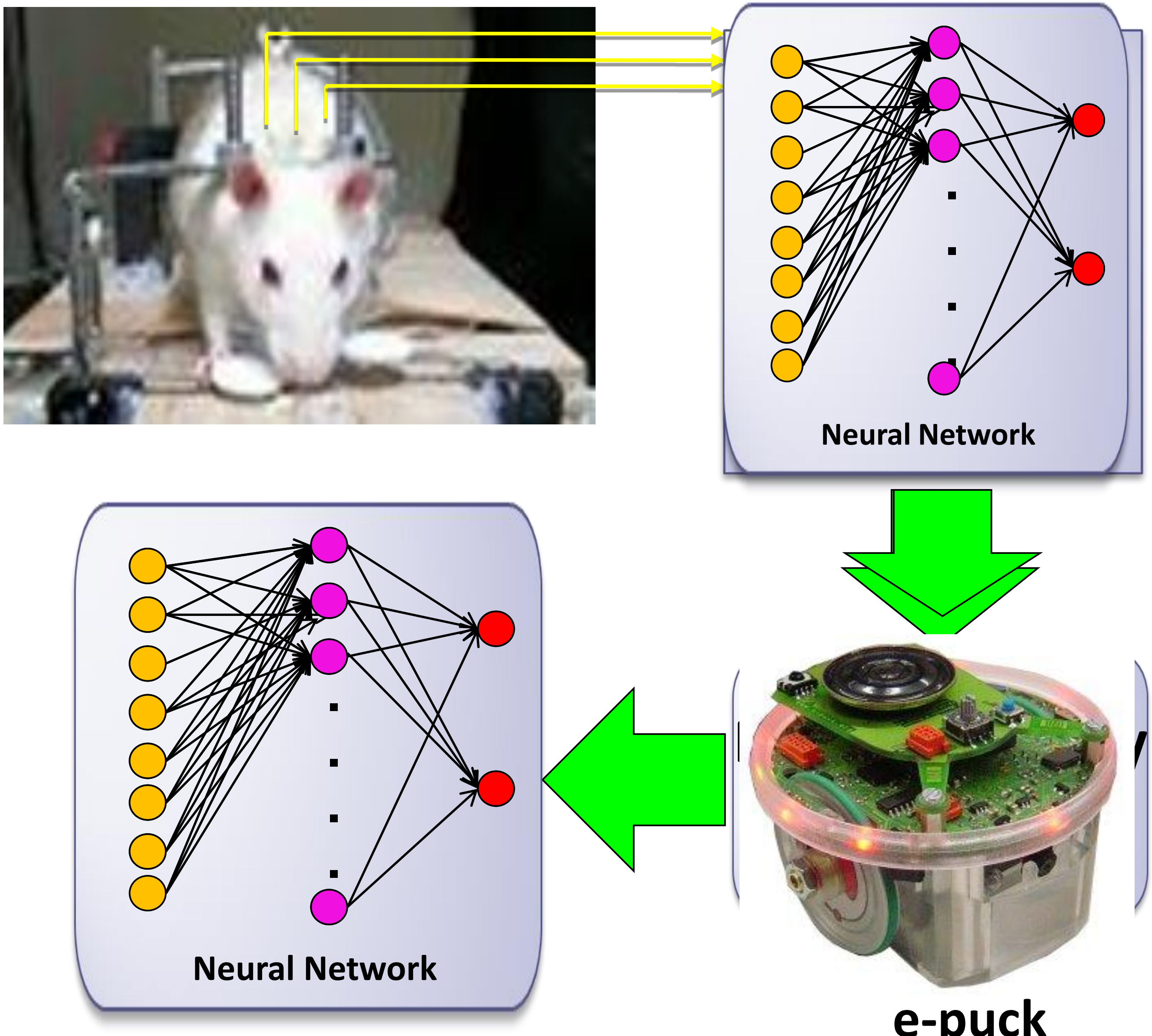
Left lever pressed

Left lever released

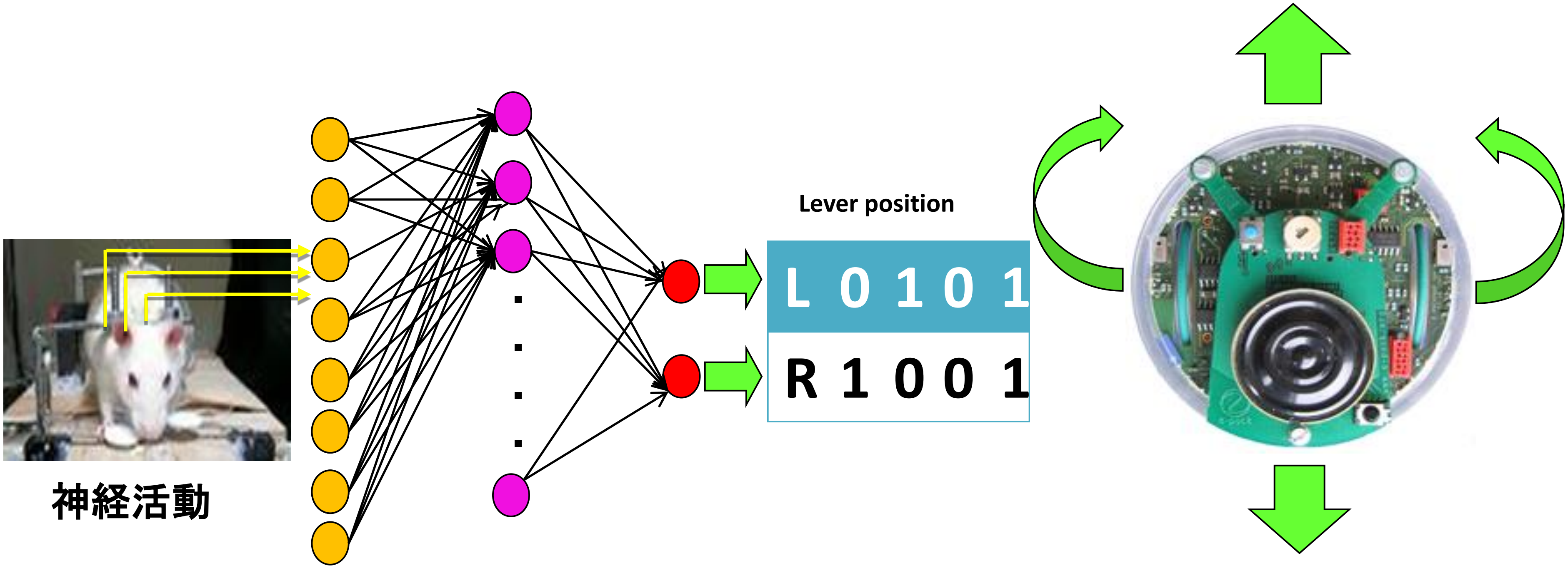
Right lever pressed

Right lever released

Training NN based on brain signals



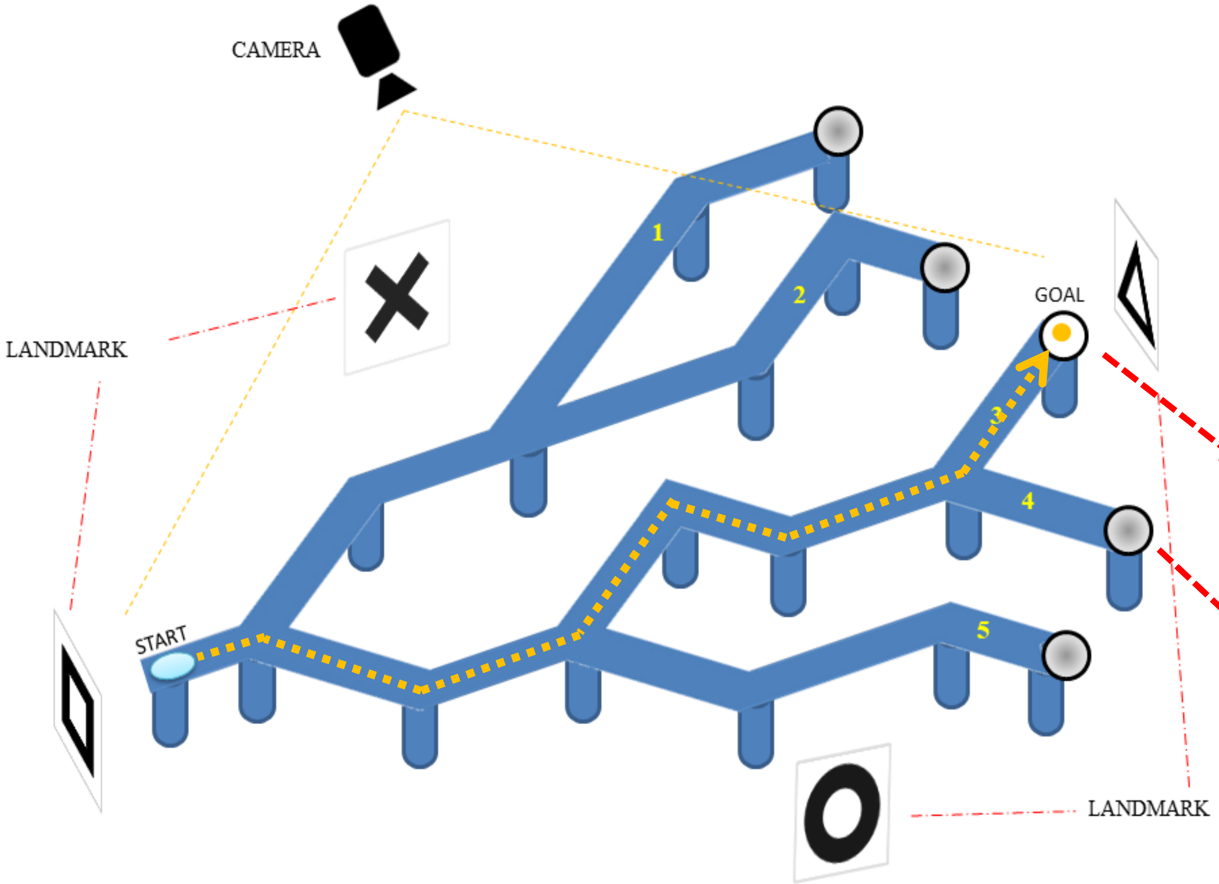
Robot motion generated by NN



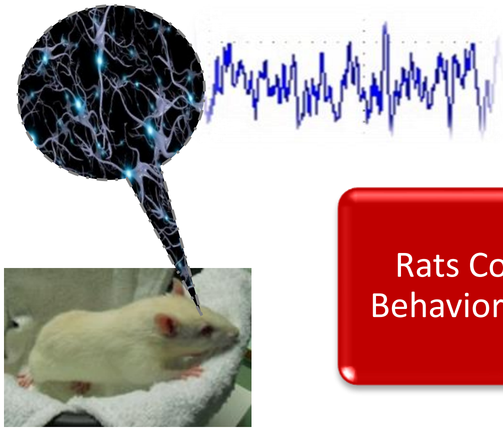
Right [0 1]	Left [1 0]	No [0 0]	Both [1 1]
Right turn	Left turn	Backward	Forward

Training environment

- <u>Novel multiple Y-maze</u>



METHODOLOGY



Witsar/ST Rat

Rats Cognitive Behavior Analysis

Local Field Potentials (LFPs) Recordings

LFPs Pre-processing and Analysis

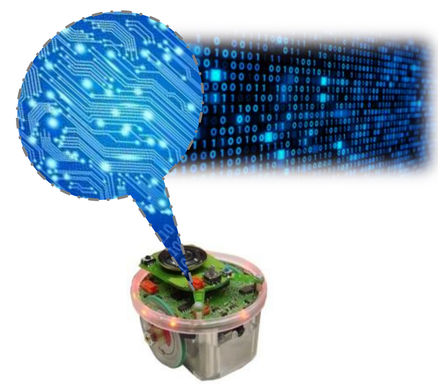
Detection of Intervals of Interest

Feature Extraction

Evolutionary Computation (Genetic Algorithm)

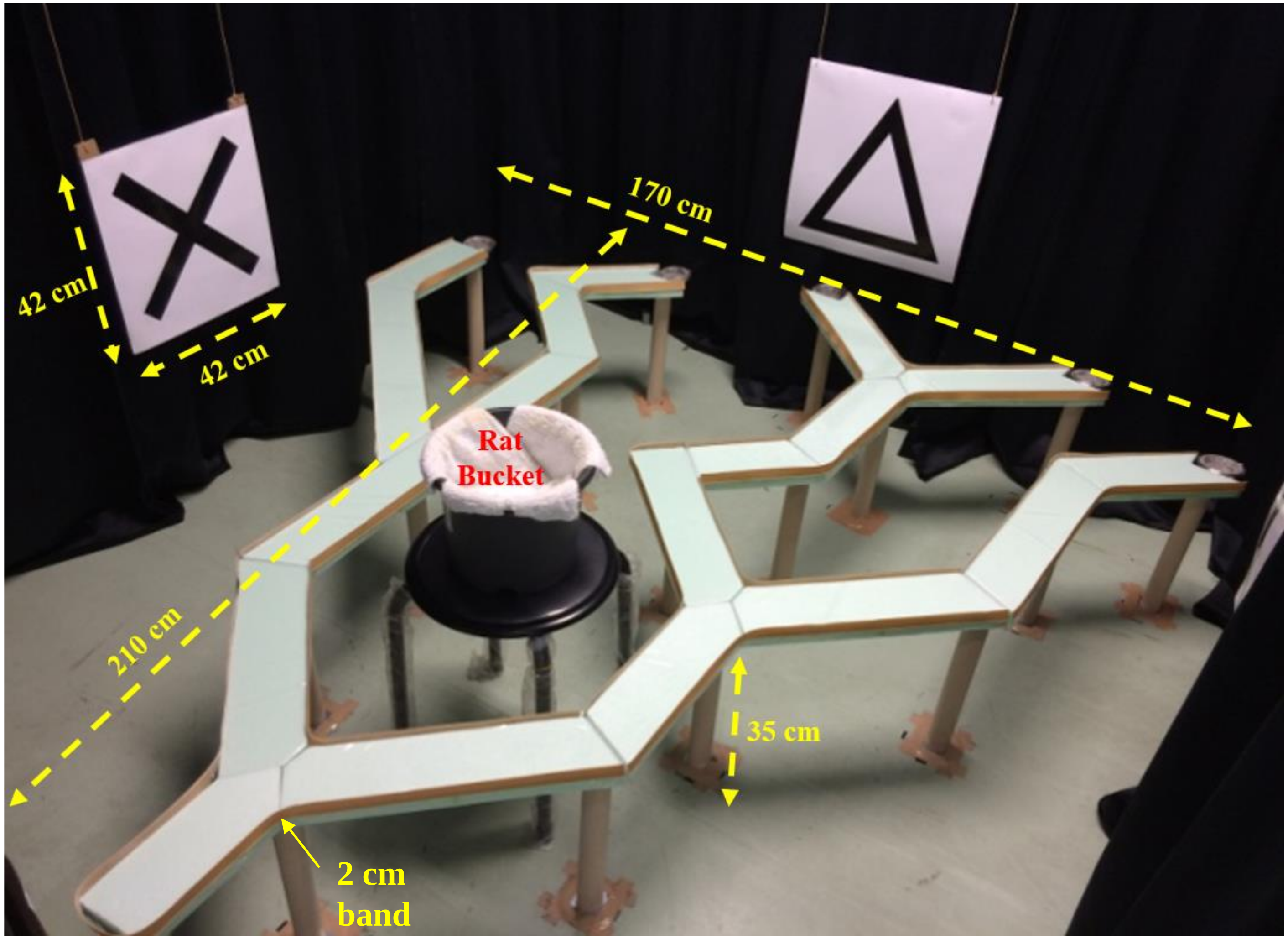
Direction Prediction (decision-making)

Real Robot Navigation



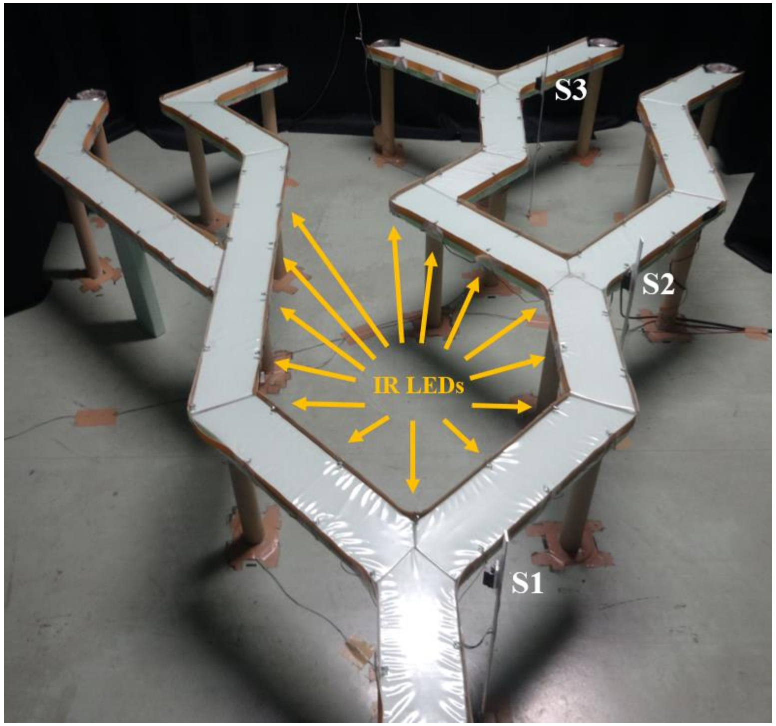
e-Puck Robot

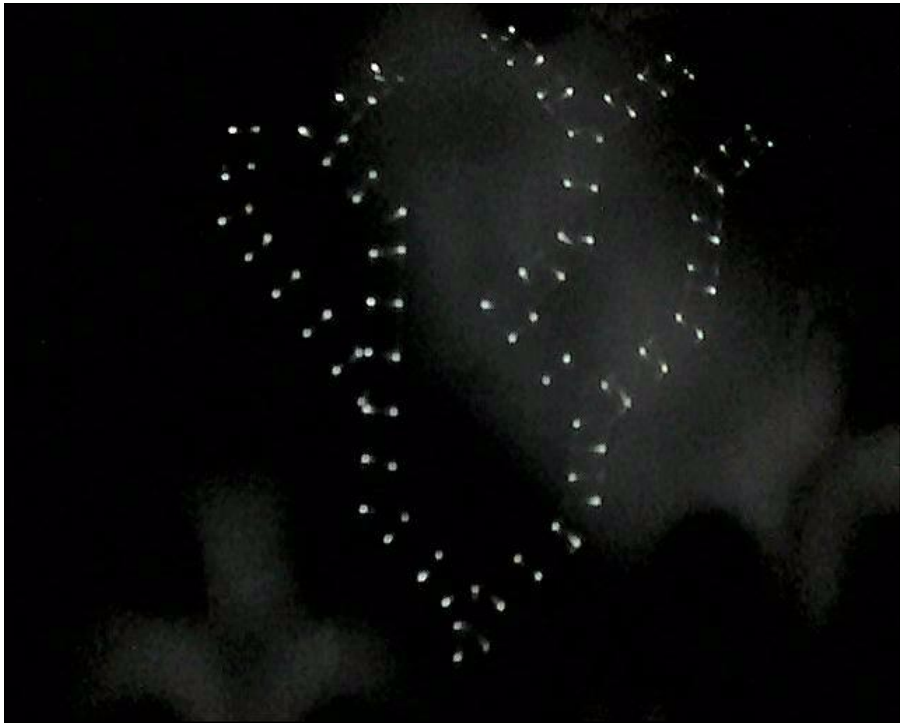
Rat training environment



Rat training environment

- 96 Infrared Light Emitting Diodes





- 3 distance sensors S1, S2, S3, in each Y- junction of the maze.
- Distance sensor model GP2Y0A21YK0F

Rat training flowchart

All the procedures were approved by the University of Toyama Committee on the Animal Care and were in accordance with the National Institutes of Health guidelines for the Care and Use of Laboratory Animals.

STEP 1

- Handling (~10 minutes)
- 4 days familiarization with the housing cage

STEP 2

- Environment Habituation
- 3 days (~20minutes)

Total subjects: 6 rats
Procedures: 2 rats per day

STEP 3

- Training Sessions
- 1 session per day (20 trials)
- ~18 days for each rat

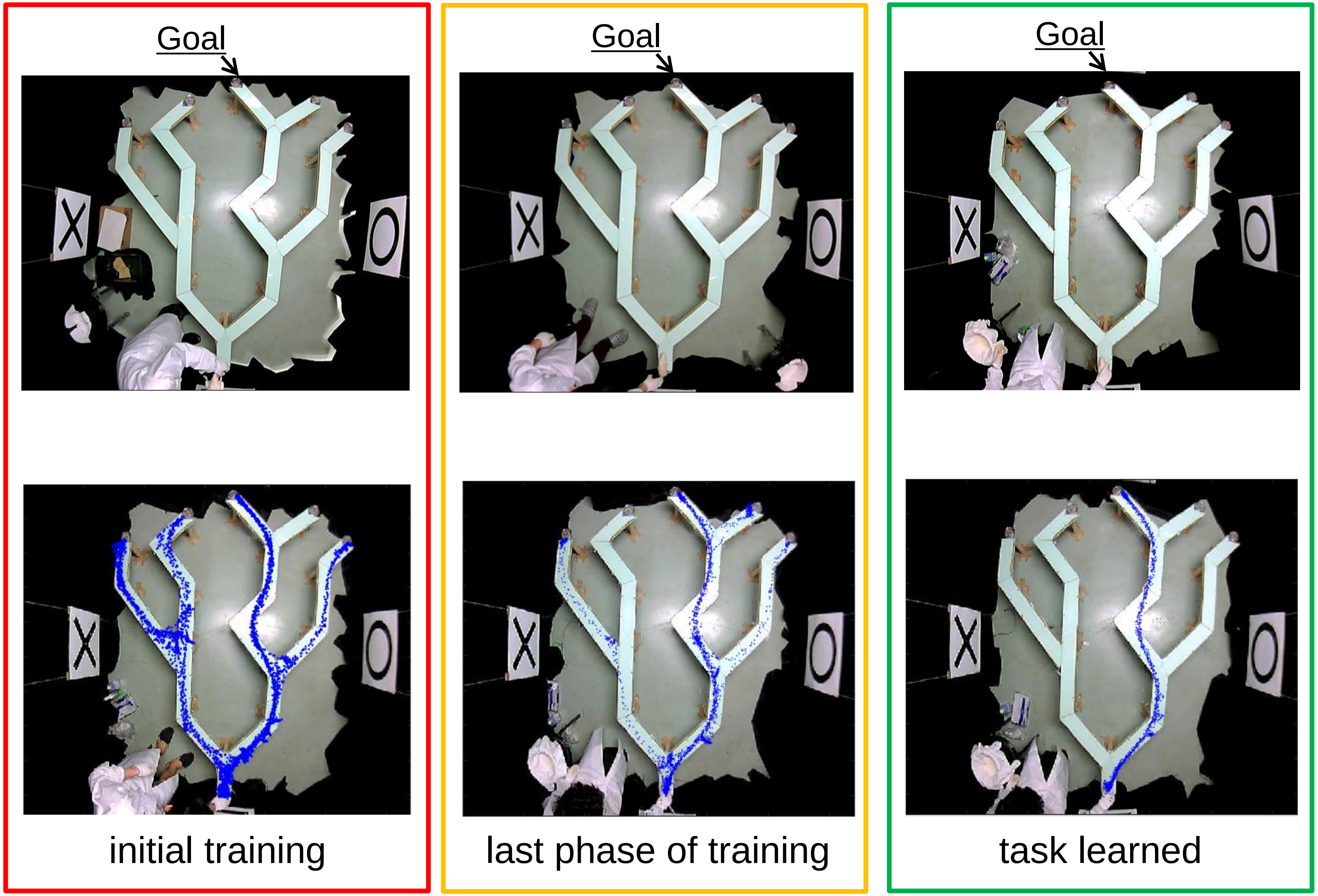
STEP 4

- Experiments sessions
- 3~5 days per experiment

STEP 5

- Electrode implantation

Rat learning progress



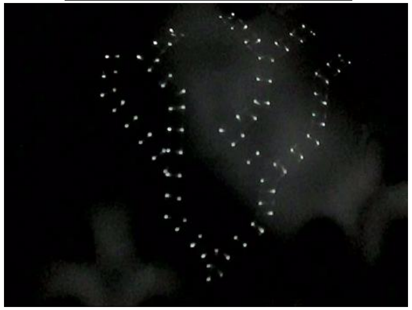
Training criterion & Performance evaluation

- Rats are trained in a lighted environment until they reached an asymptotic level of learning with a criterion above 85% correct choices.
- Learned behavior is tested in different experiments, under different changes of the environment settings.
- Analyzed the rats' behavior and strategies while it navigates in a multiple Y-maze.

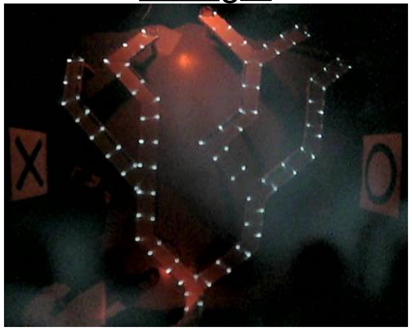
Rat's learning performance:

- percentage of success rate
- time to reach the target food location.

dark environment

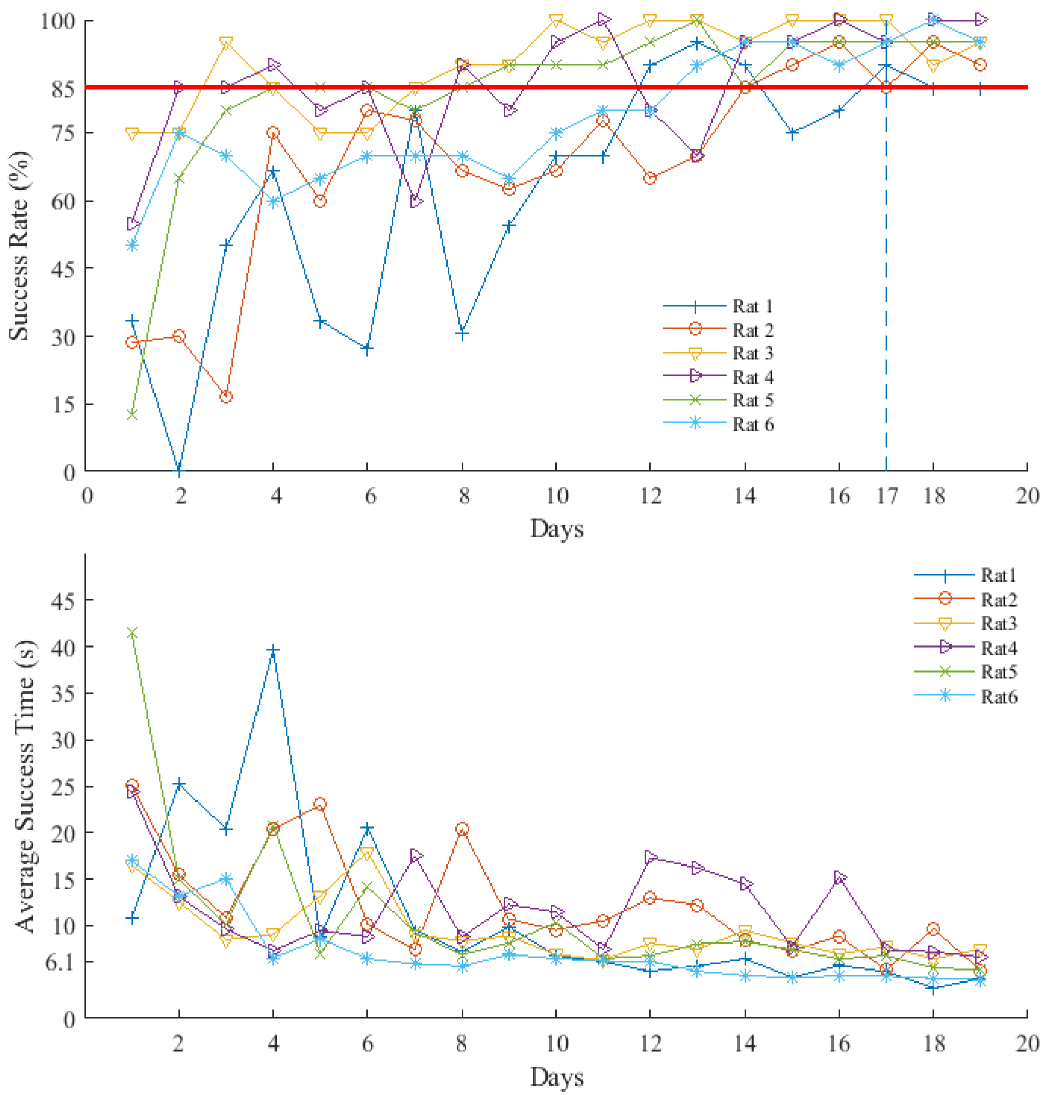


red light

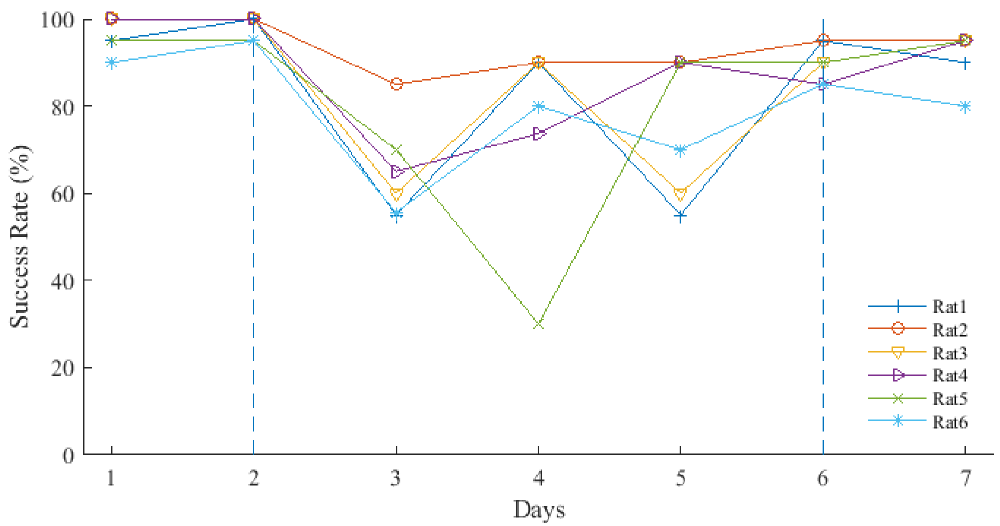


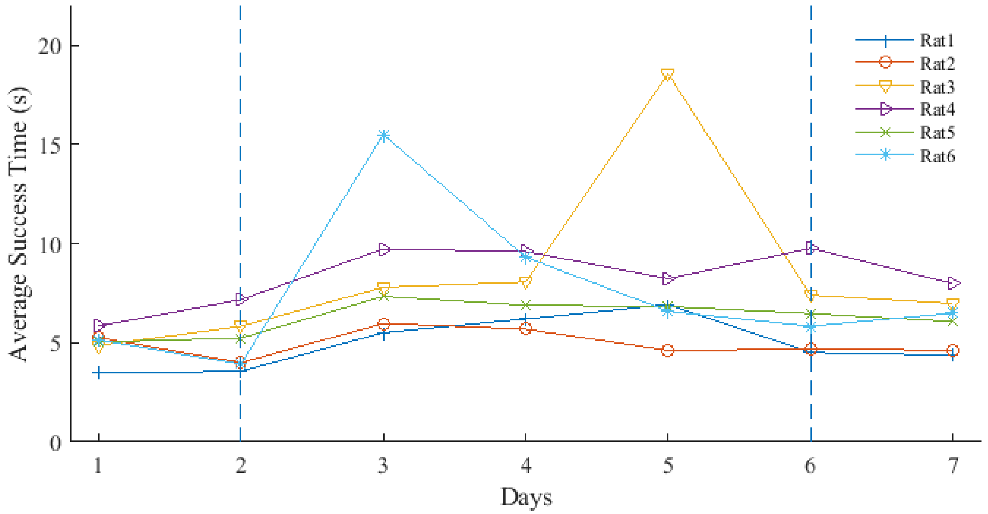
landmarks with green LEDs

BEHAVIOR RESULTS (Lighted Environment)



BEHAVIOR RESULTS (Dark Environment)





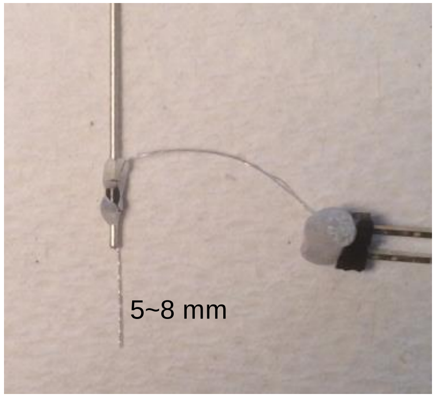
Electrodes implantation

- 3 bipolar twisted electrodes per rat

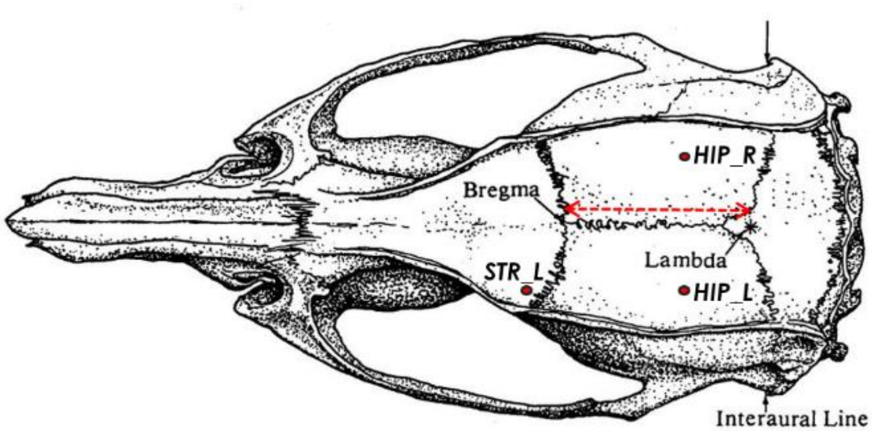
Coordinates	HPC	STR
AP – Antereo Posterior	- 4.92 mm	+0.96 mm
ML – Medio Lateral	± 2.5 mm	-3.6 mm
DV – Dorso Ventral	-2.3 mm	-3.5 mm

* Relative to bregma

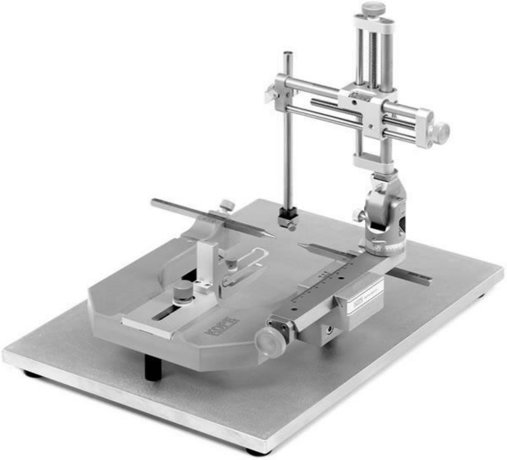
Perfluoroalkoxy alkane coated stainless-steel wire, Ø114.3μm



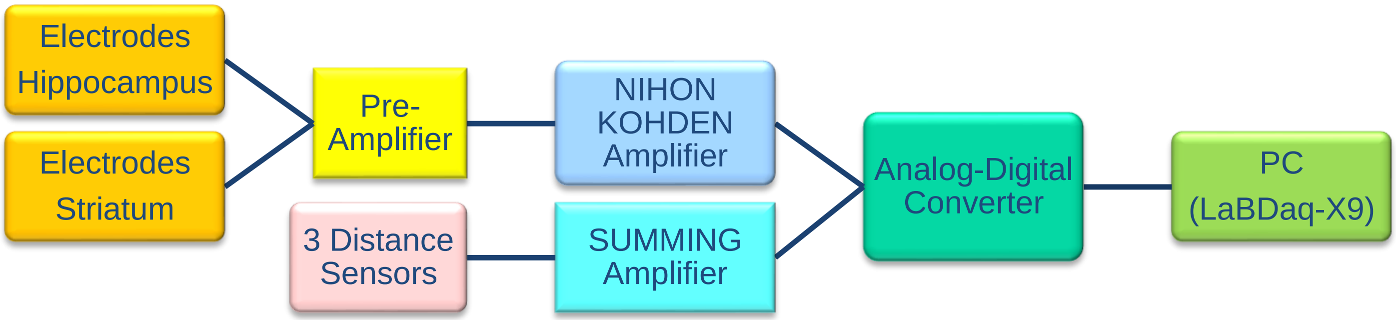
Rat skull

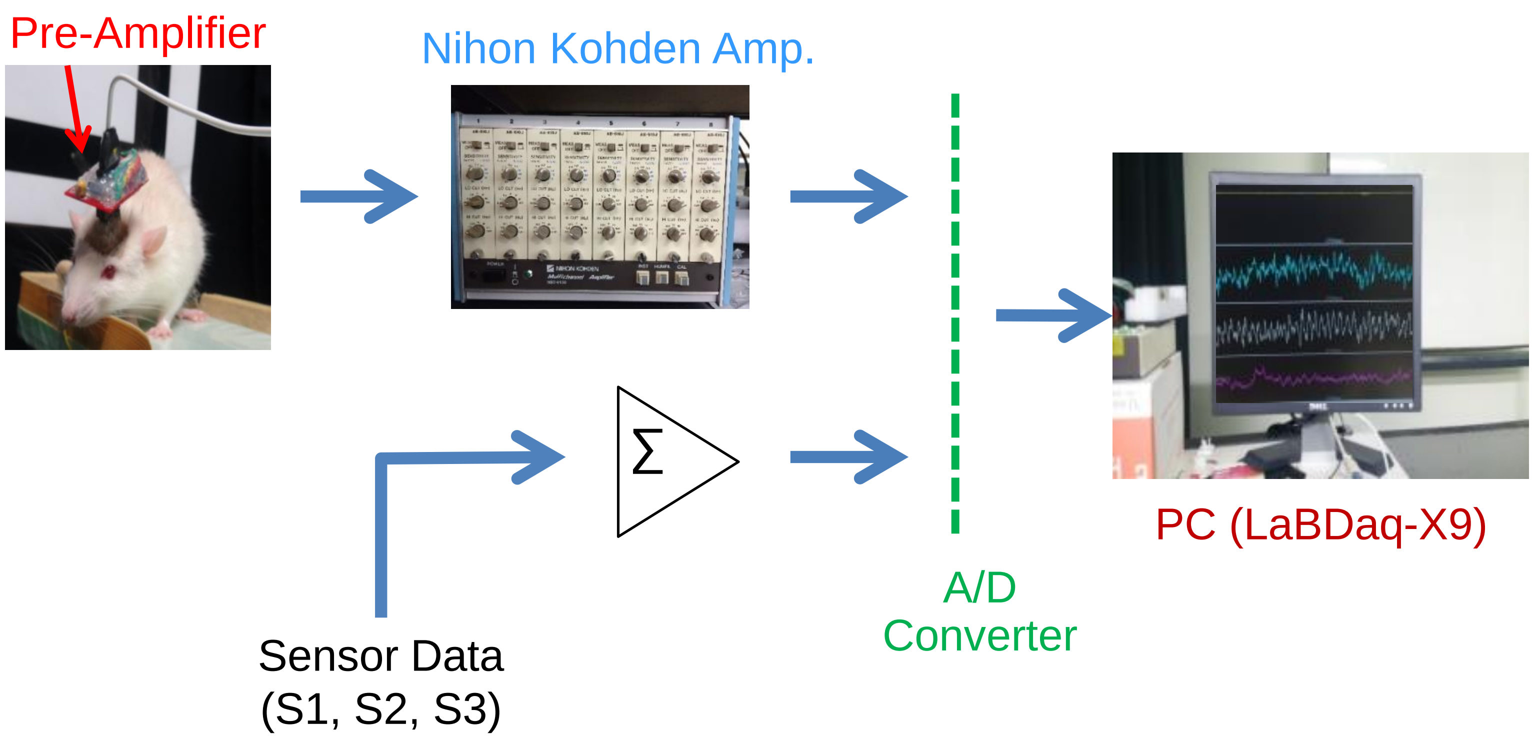


Stereotaxic instrument

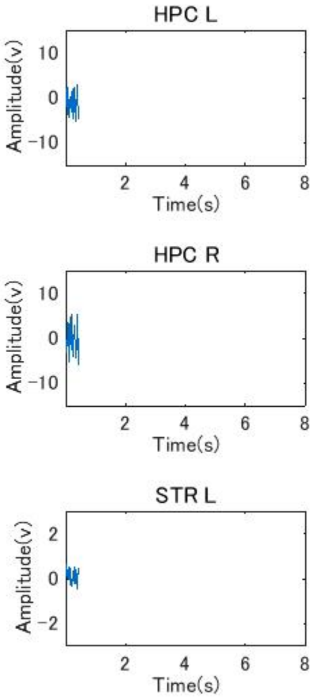


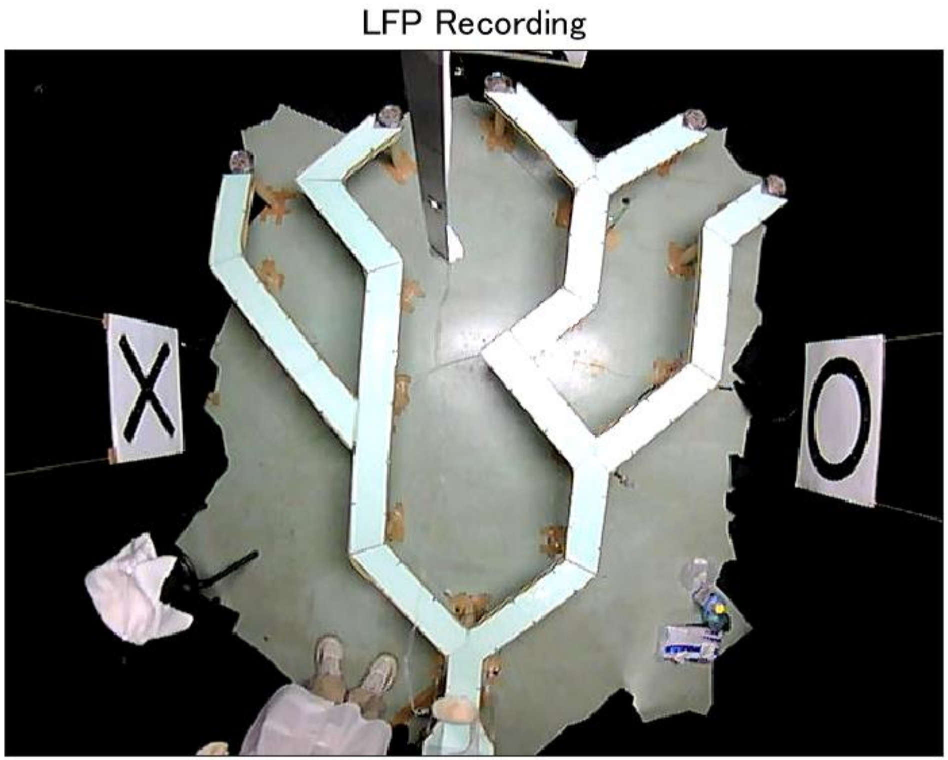
Data acquisition system



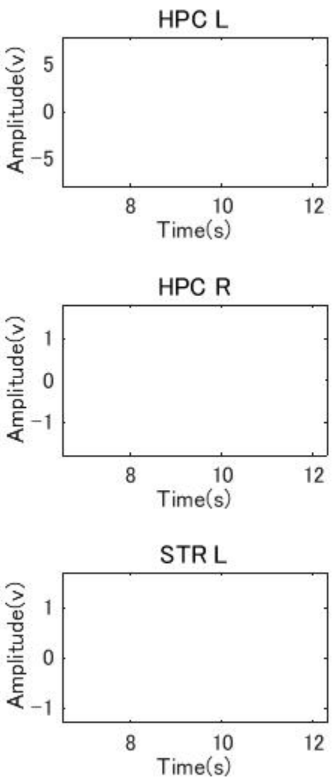


LFPs recording experiment

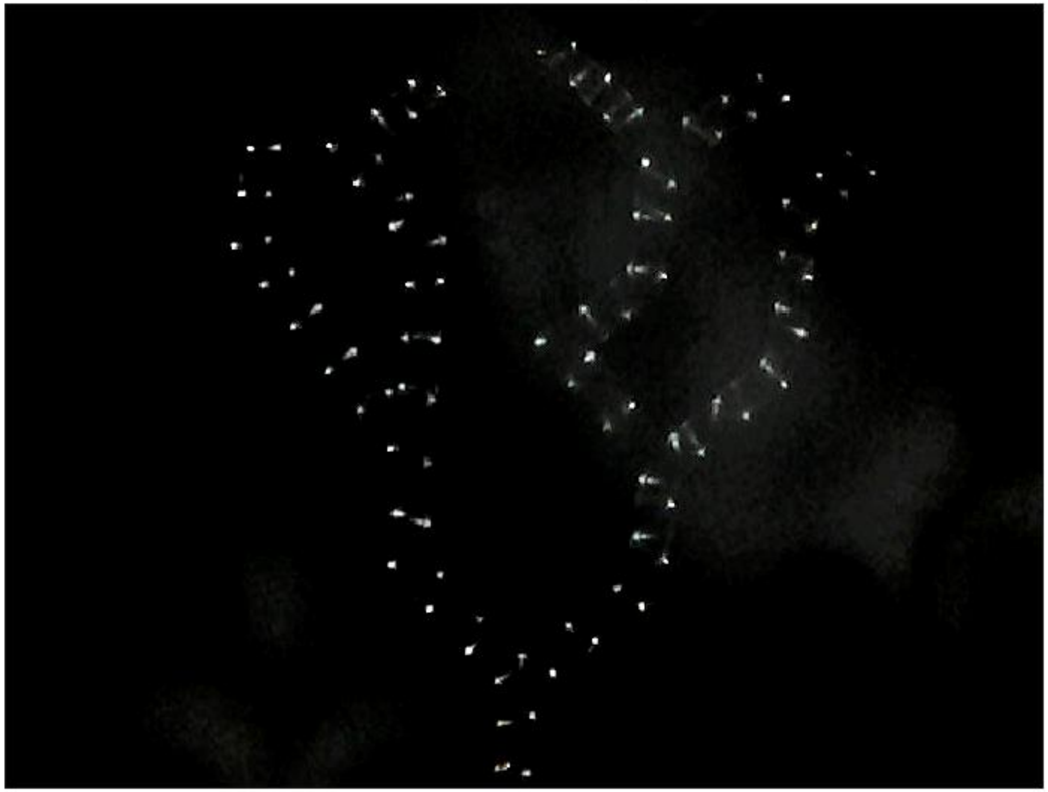




LFPs recording experiment

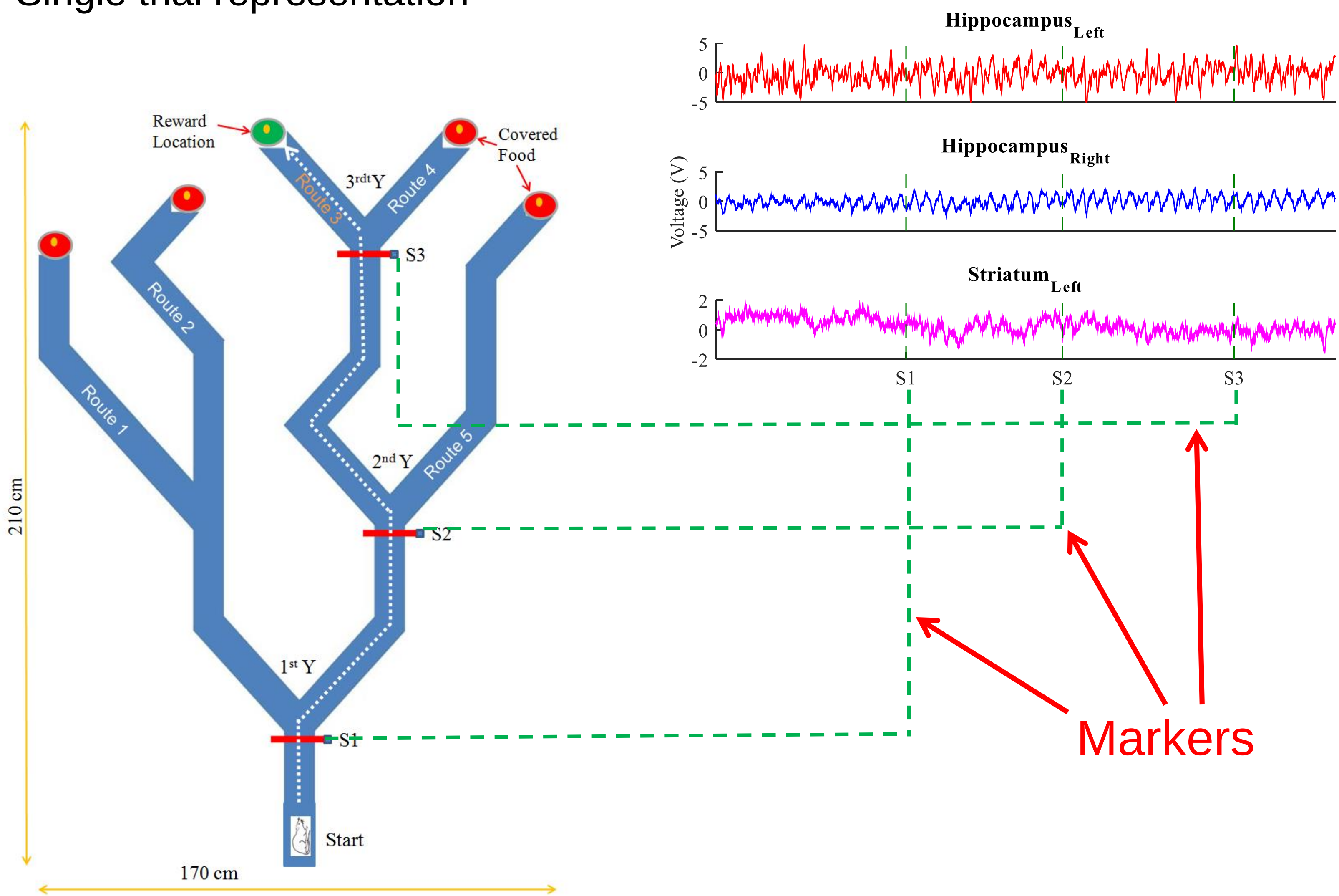


LFP Recording

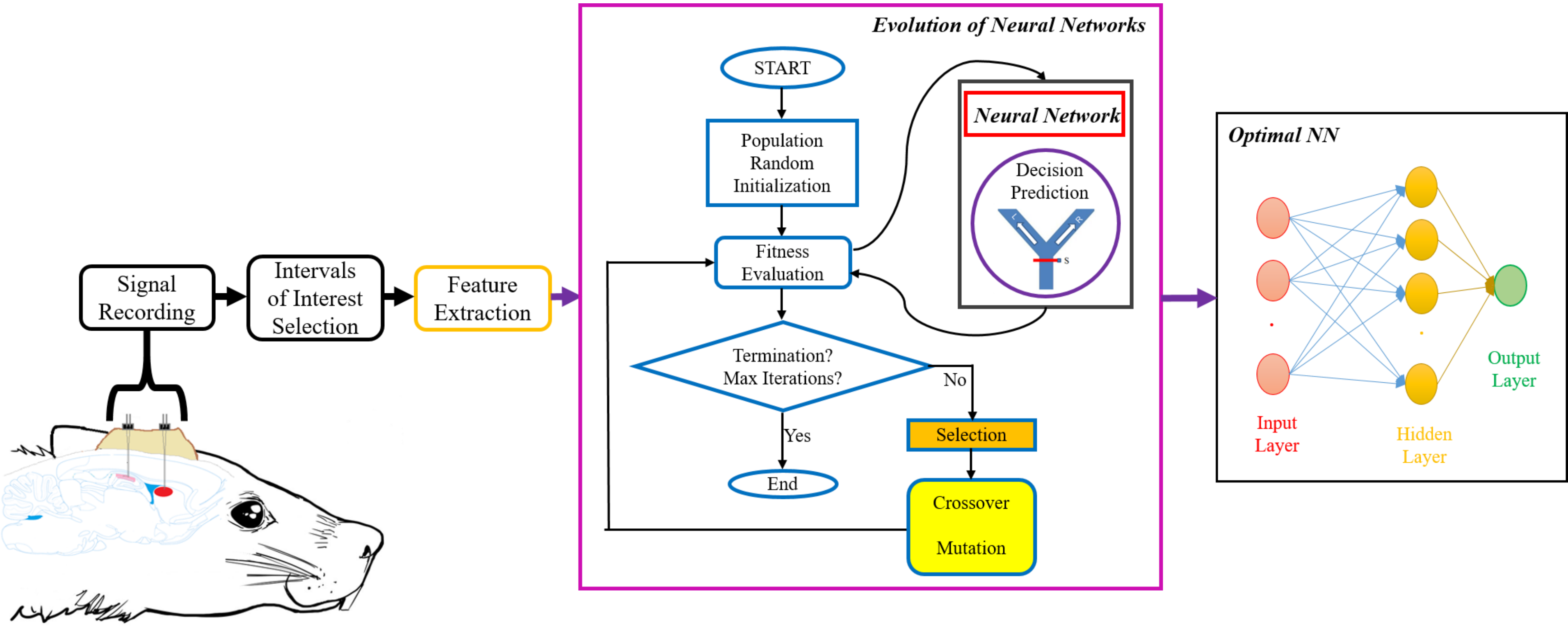


Raw LFPs

- Single trial representation



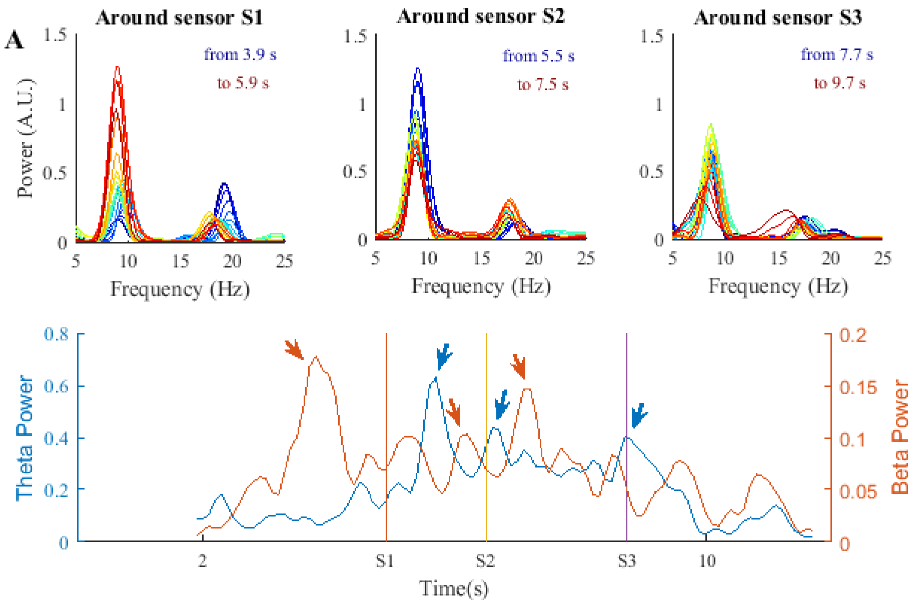
Flowchart of the proposed method



Brain activity analysis (Channel 1)

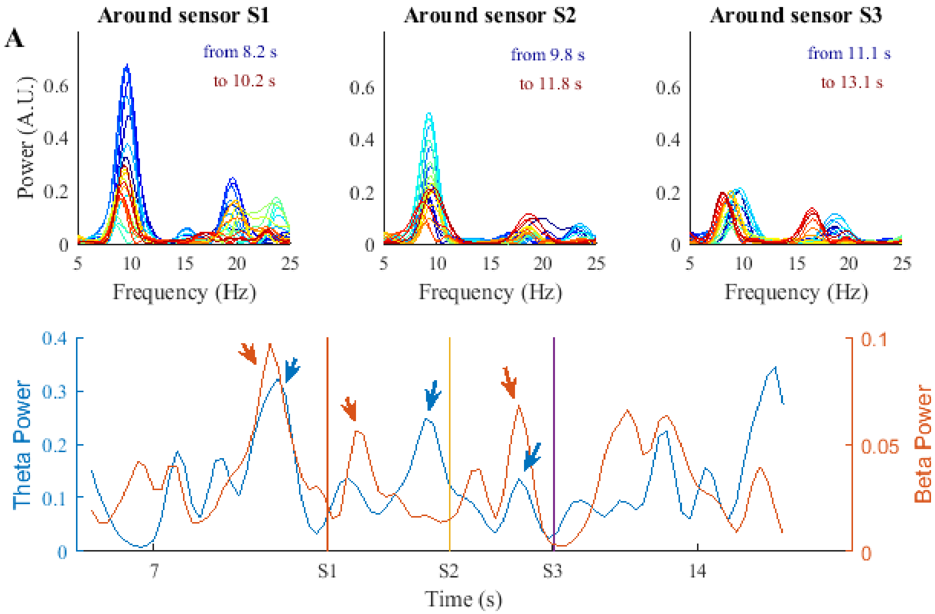
Rat 1

Hippocampus Left



Rat 2

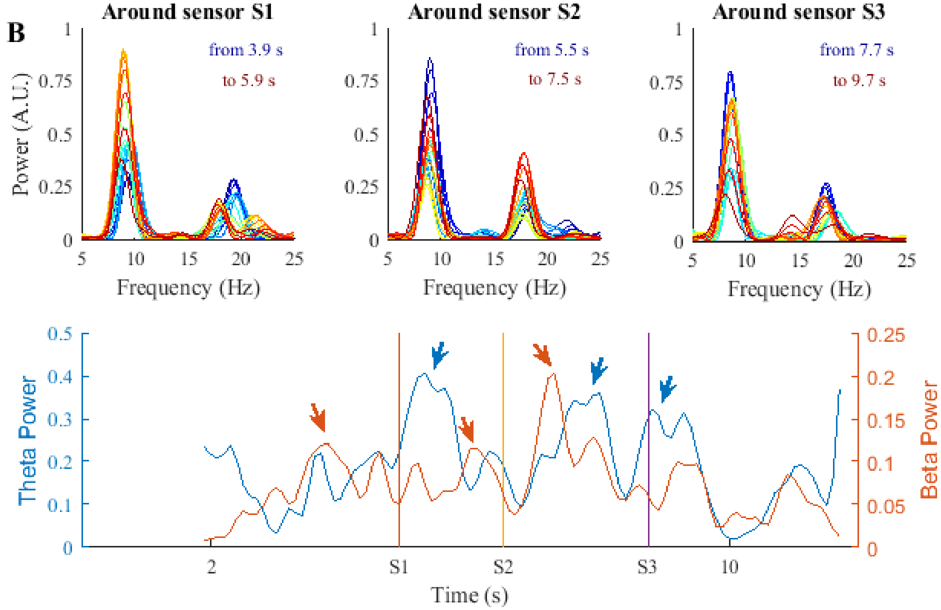
Hippocampus Left



Brain activity analysis (Channel 2)

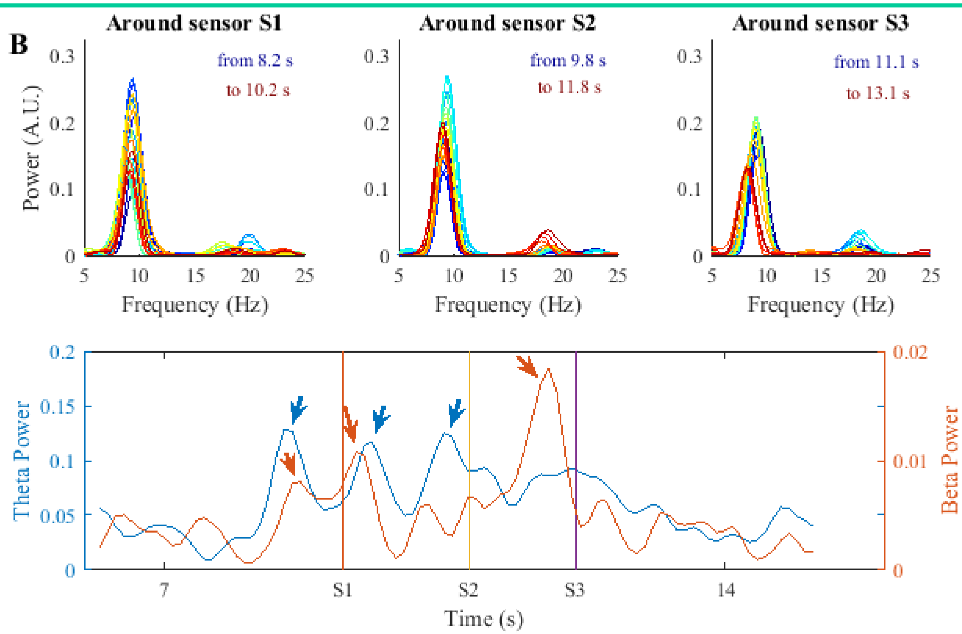
Rat 1

Hippocampus Right



Rat 2

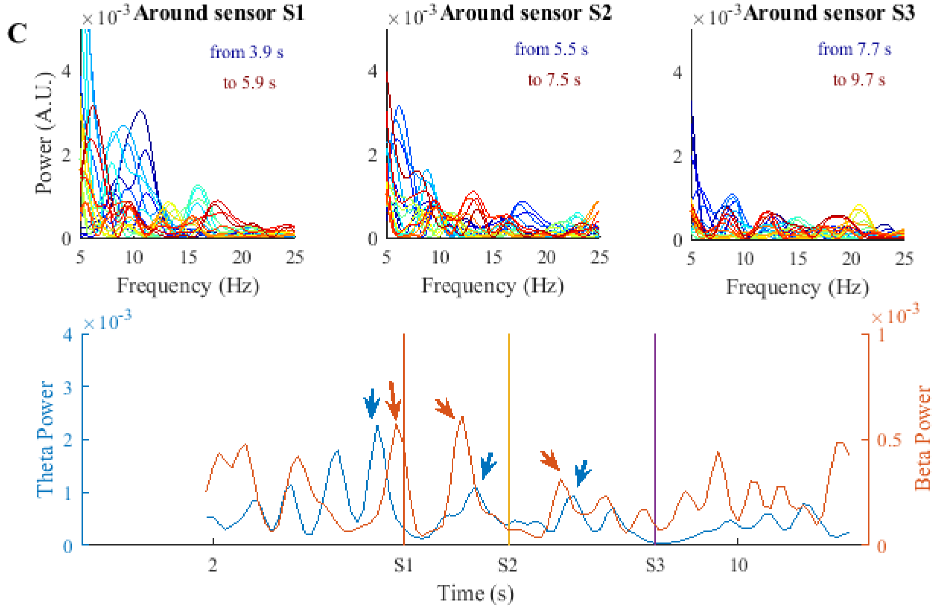
Hippocampus Right



Brain activity analysis (Channel 3)

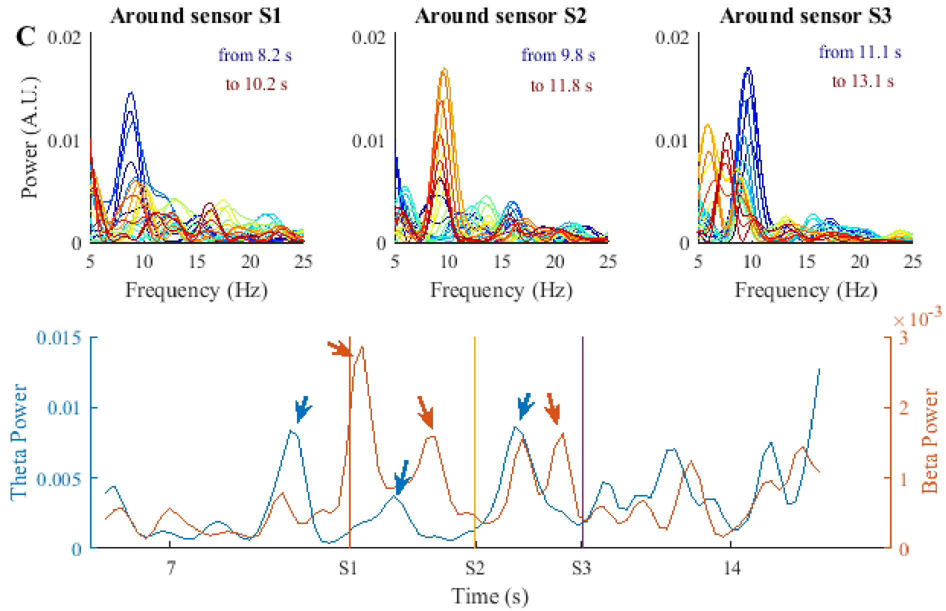
Rat 1

Striatum Left

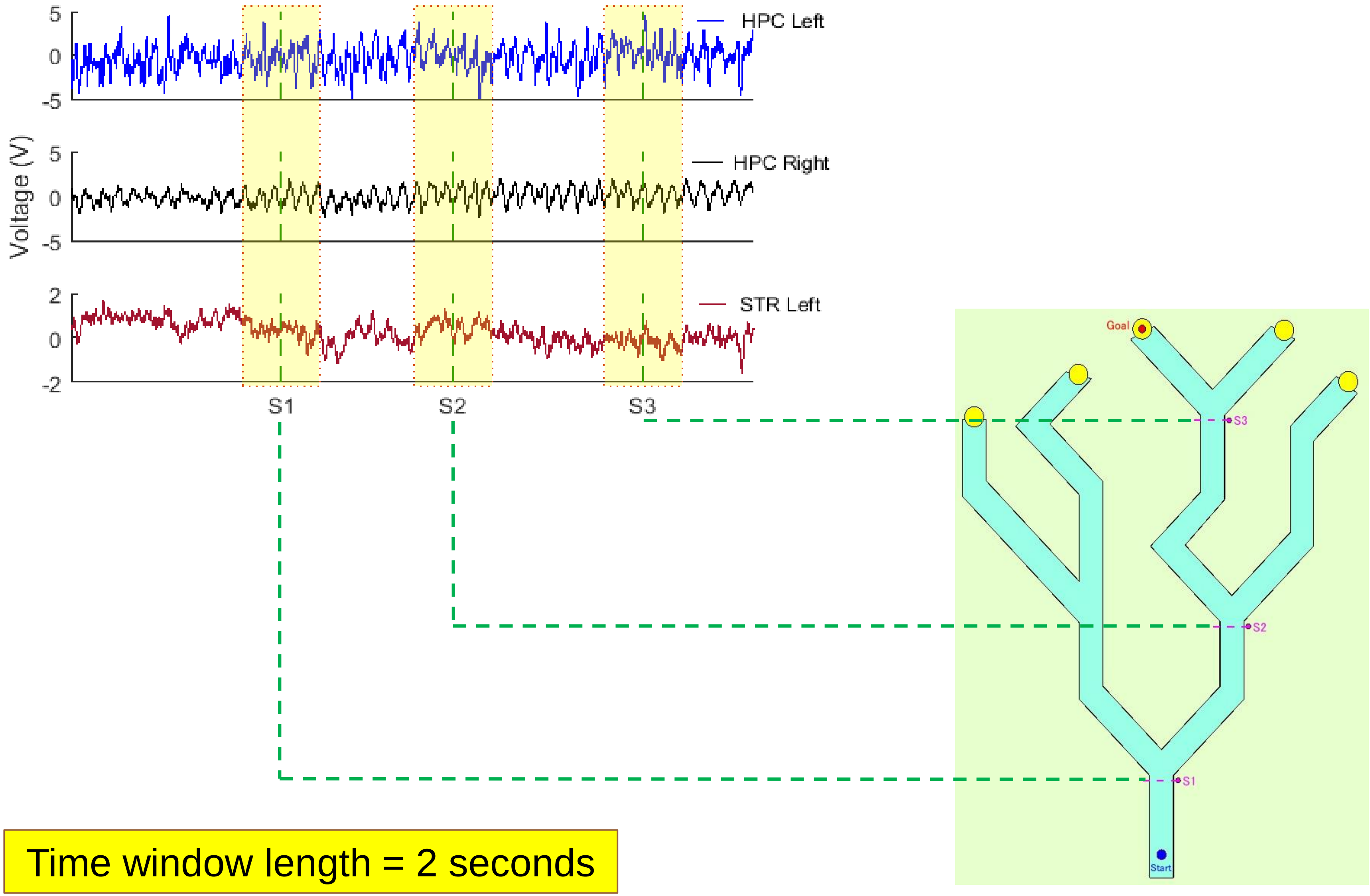


Rat 2

Striatum Left



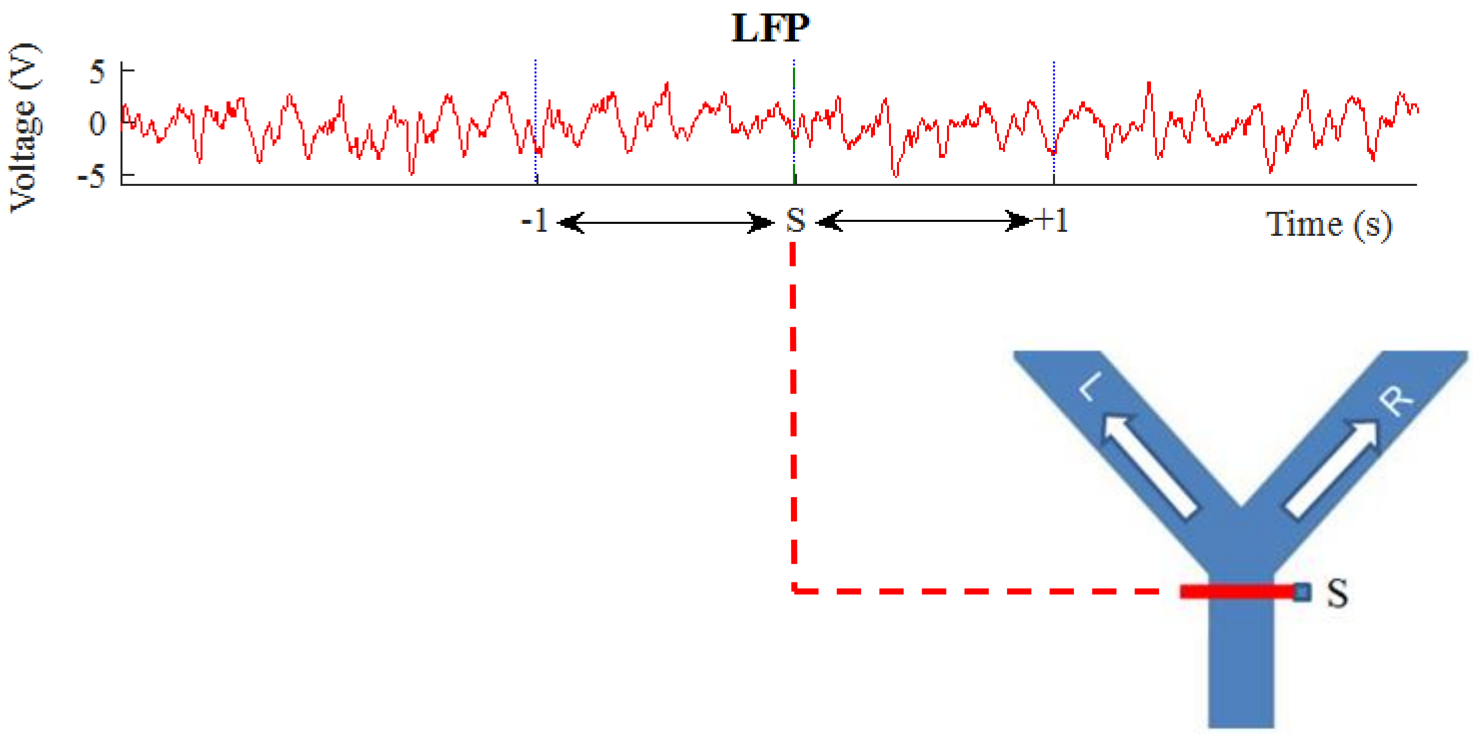
Signal's intervals of interest



Time window length = 2 seconds

Feature extraction time window

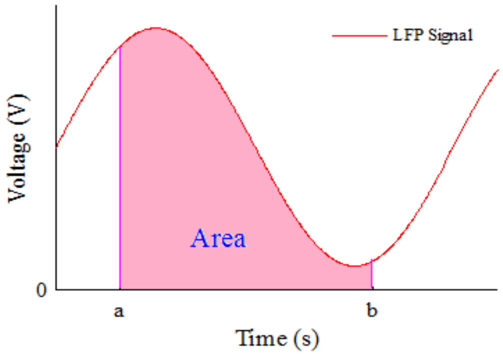
2 seconds time window length: 1 second before and after the turning point.



Selected features

1. Area

$$A = \frac{\sum_{i=1}^{W} |x_i|}{W}$$



2. Average peak amplitude

$$PA = log_{10}\left(\frac{\sum_{i=1}^{P} x_{P(i)}^2}{P}\right)$$

3. Average valley amplitude

$$VA = log_{10}\left(\frac{\sum_{i=1}^{V} x_{V(i)}^2}{V}\right)$$

4. Line length

$$L = \sum_{i=2}^{W} |x_i - x_{i-1}|$$

5. Mean energy

$$E = \frac{\sum_{i=1}^{W} |x_i^2|}{W}$$

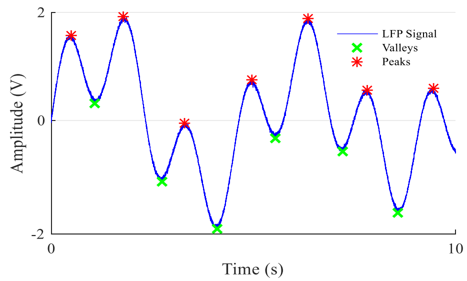
6. Normalized decay

$$ND = \left|\frac{\sum_{i=1}^{W-1} I(x_{i+1} - x_i < 0) - 0.5}{W - 1}\right|$$

Selected features

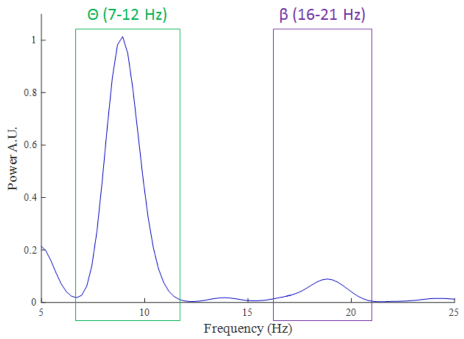
7. Normalized peak number $$N_P = \mathrm{P}\left(\frac{\sum_{i=1}^{W-1} |x_{i+1} - x_i|}{W-1}\right)^{-1}$$

8. Number of peaks



9. Number of valleys

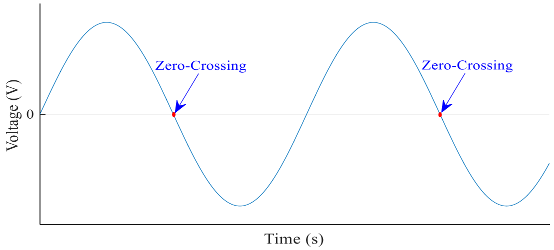
10. Peak variation $$\mathrm{PV} = \frac{1}{\sigma(PV)\sigma(x_{PV})}$$



11. Power of beta frequency band

12. Power of theta frequency band

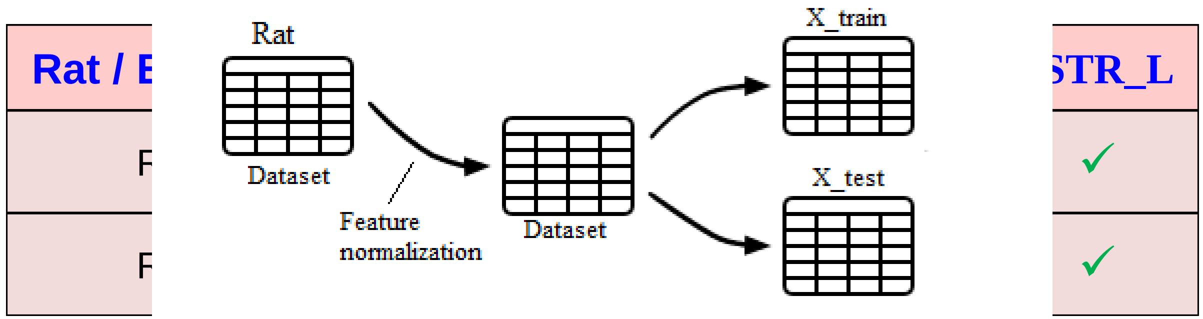
13. Root mean square $$\mathrm{RMS} = \sqrt{\frac{\sum_{i=1}^{W} x_i^2}{W}}$$



14. Zero crossing

Feature processing

Rat 1 & Rat 2 datasets: **14** extracted features x **3** channels = **42** features



Data was normalized (standardized) with the mean μ = 0 and the standard deviation σ = 1.

Rat 1

315x42 dataset is divided in:

$R1X_{train}$ = 267 training data (85%)

$R1X_{test}$ = 48 testing data (15%)

Rat2

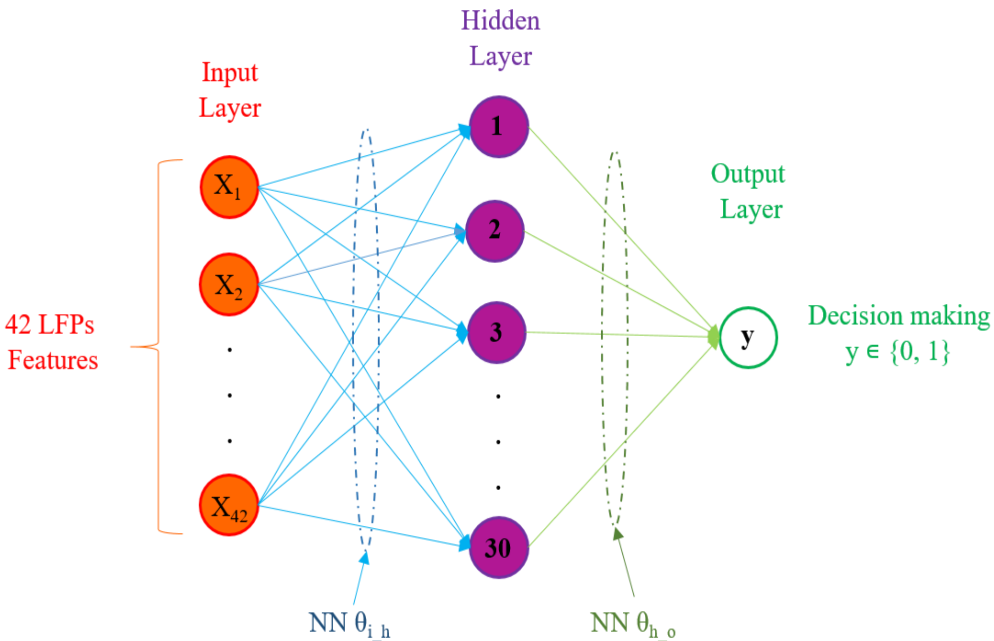
375x42 dataset is divided in:

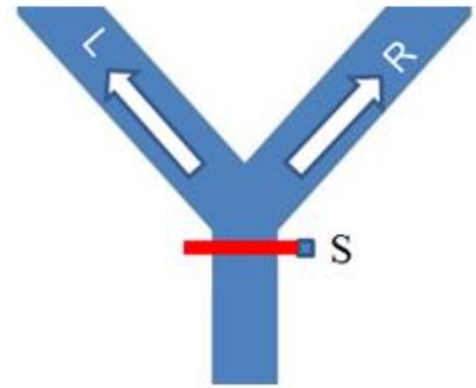
$R2X_{train}$ = 318 training data (85%)

$R2X_{test}$ = 57 data (15%)

Neural Network (NN) architecture

- 42 Input neurons, 30 Hidden neurons, 1 Output neuron

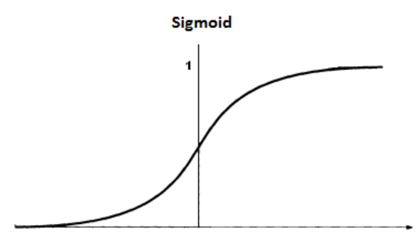




y = 1 ➔ robot turn Right
y = 0 ➔ robot turn Left

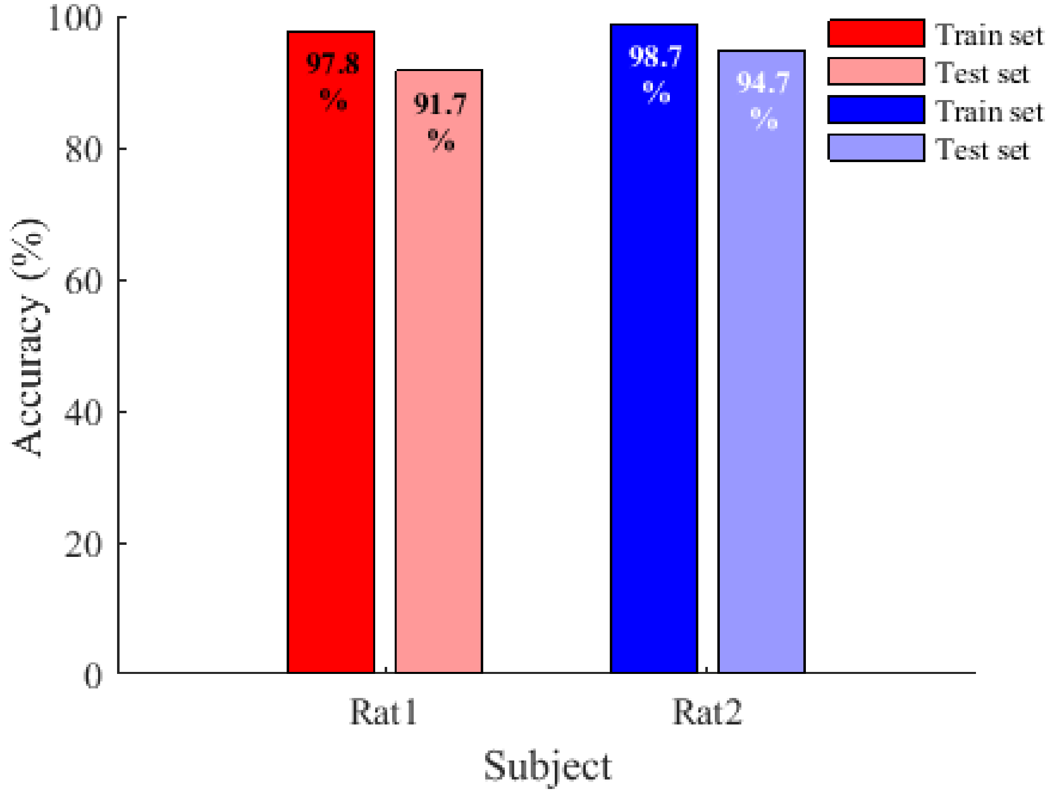
- Feed-Forward NN
- Sigmoid function is used as an activation function for hidden & output units

$$y(i) = \frac{1}{1 + e^{-x(i)}}$$



Results (Prediction accuracy)

Subjects	Number of wrong decisions prediction	
	Train Data	Test Data
Rat 1	6/267 (97.8%)	4/48 (91.7%)
Rat 2	4/318 (98.7%)	3/57 (94.7%)



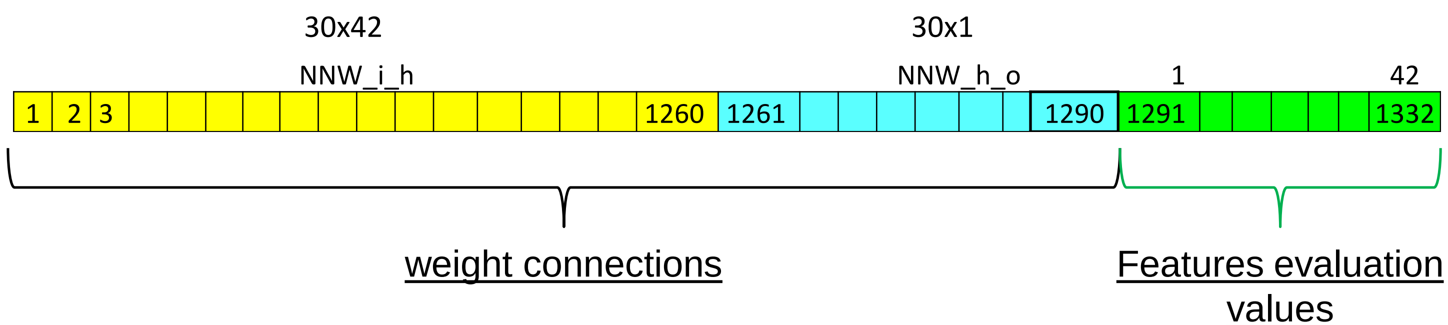
Best features selection

- Genetic Algorithm to determine features that mostly contribute to the rat's decision-making (most significance features).

Matrix of Features

1	2	3	4	5	…	…	…	…	38	39	40	41	42	
…	…	…	…	…	…	…		…	…	…	…	…	…	Data samples 1
…	…	…	…	…	…	…	…	…	…	…	…	…	…	Data samples 2

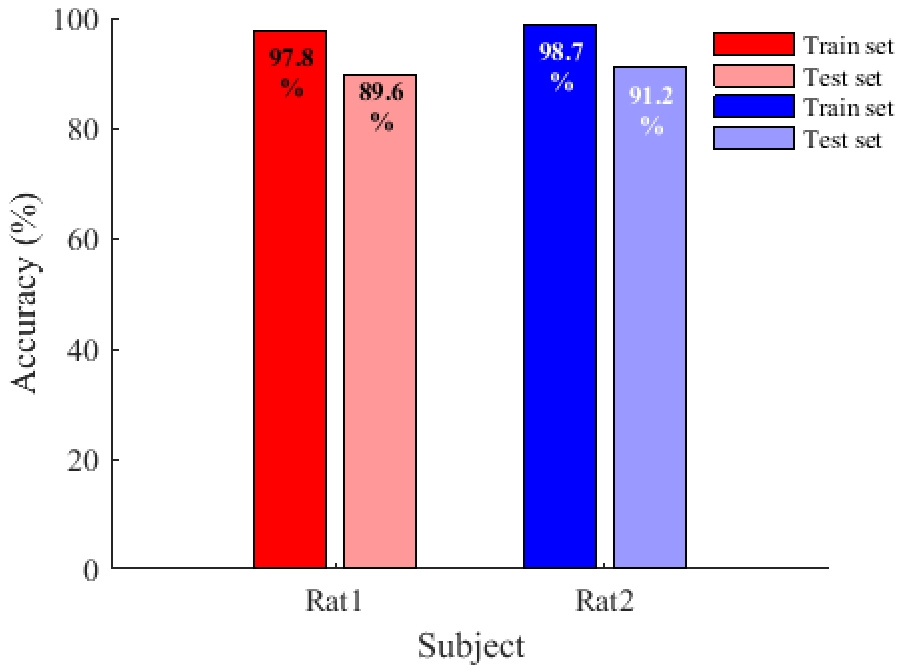
Genome of each individual of populations length = 1332



- Value close to 1 ➔ significant (feature is considered)
- Value close to 0 ➔ not significant (not considered)

Results (Prediction accuracy with key features)

Subjects	Number of wrong decisions prediction	
	Train Data	Test Data
Rat 1 (21 features)	6/267 (97.8%)	5/48 (89.6%)
Rat 2 (20 features)	4/318 (98.7%)	5/57 (91.2%)



Selected features by GA

Rat 1

Hippoc_Left	Area
	Av. peak amp.
	Av. valley amp.
	Line length
	Peak variation
	Power of theta osci.
Hippoc_Right	Av. peak amp.
	Av. valley amp.
	Mean energy
	Normal. peak no.
	No. of valleys
	Peak variation
	Power of theta osci.
	RMS
	ZC
Striatum_Left	Av. valley amp.
	Line length
	No. of peaks
	Peak variation
	RMS
	ZC

21 features

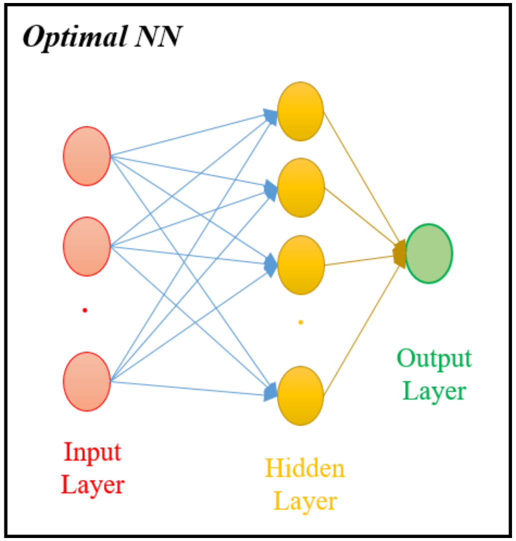
Rat 2

Hippoc_Left	Area
	Av. peak amp.
	Av. valley amp.
	Mean energy
	No. of valleys
	Power of theta osci.
	RMS
	ZC
Hippoc_Right	Av. peak amp.
	Line length
	Normal. decay
	No. of valleys
	Peak variation
	Power of beta osci.
Striatum_Left	Area
	Av. valley amp.
	Mean energy
	No. of peaks
	Power of theta osci.
	RMS

20 features

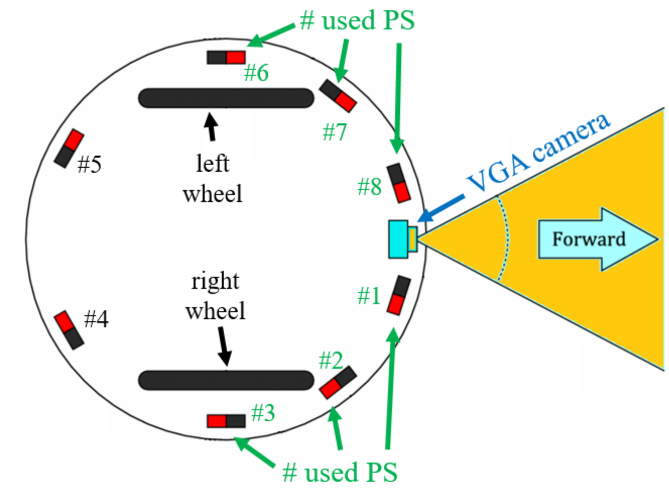
NN and e-Puck robot

NN architecture to predict the robot's decision on each Y-junction



Input layer	21 nodes (Rat 1)
	20 nodes (Rat 2)
Hidden layer	30 nodes
Output layer	1 nodes

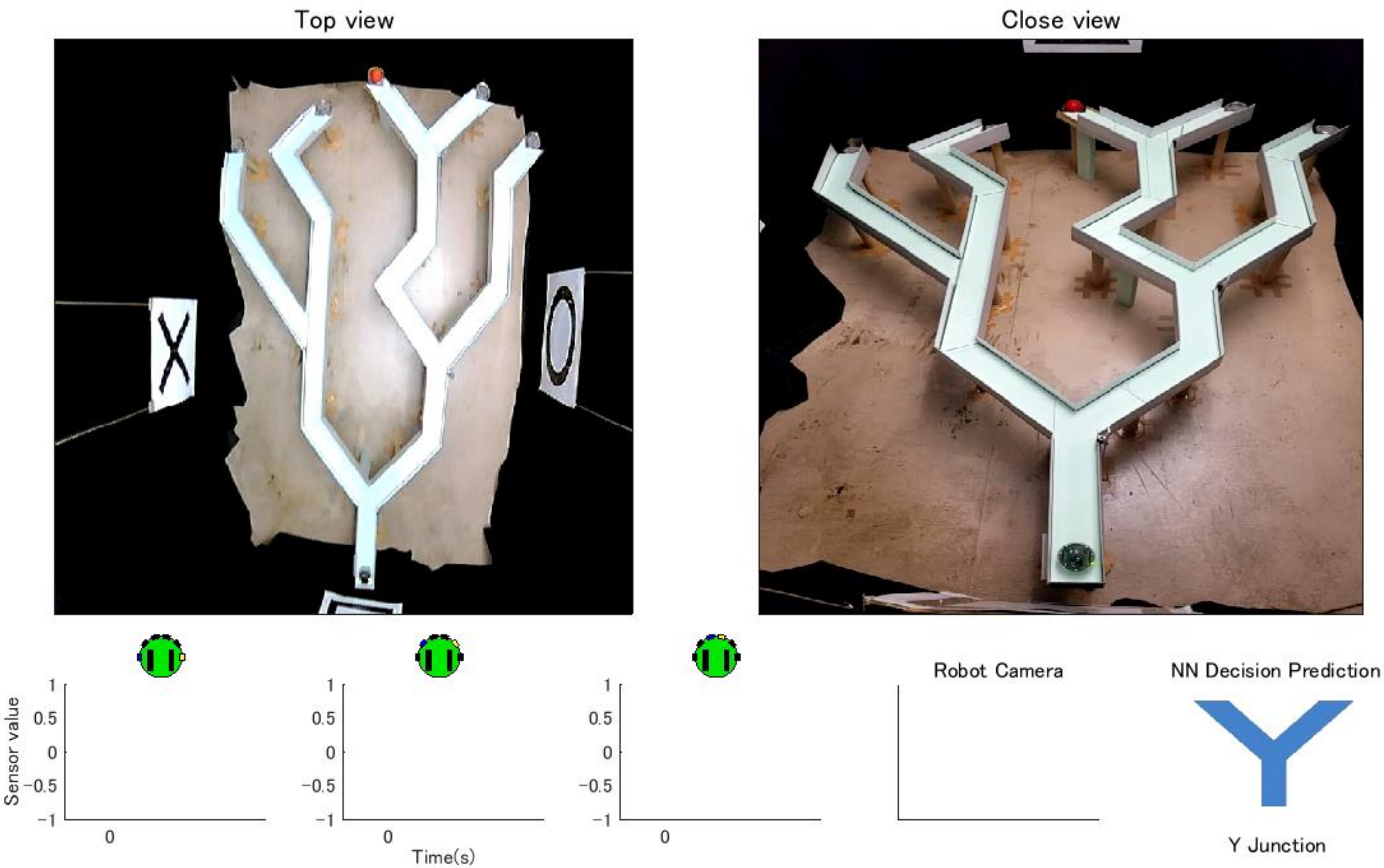
e-Puck robot



Navigating through maze:

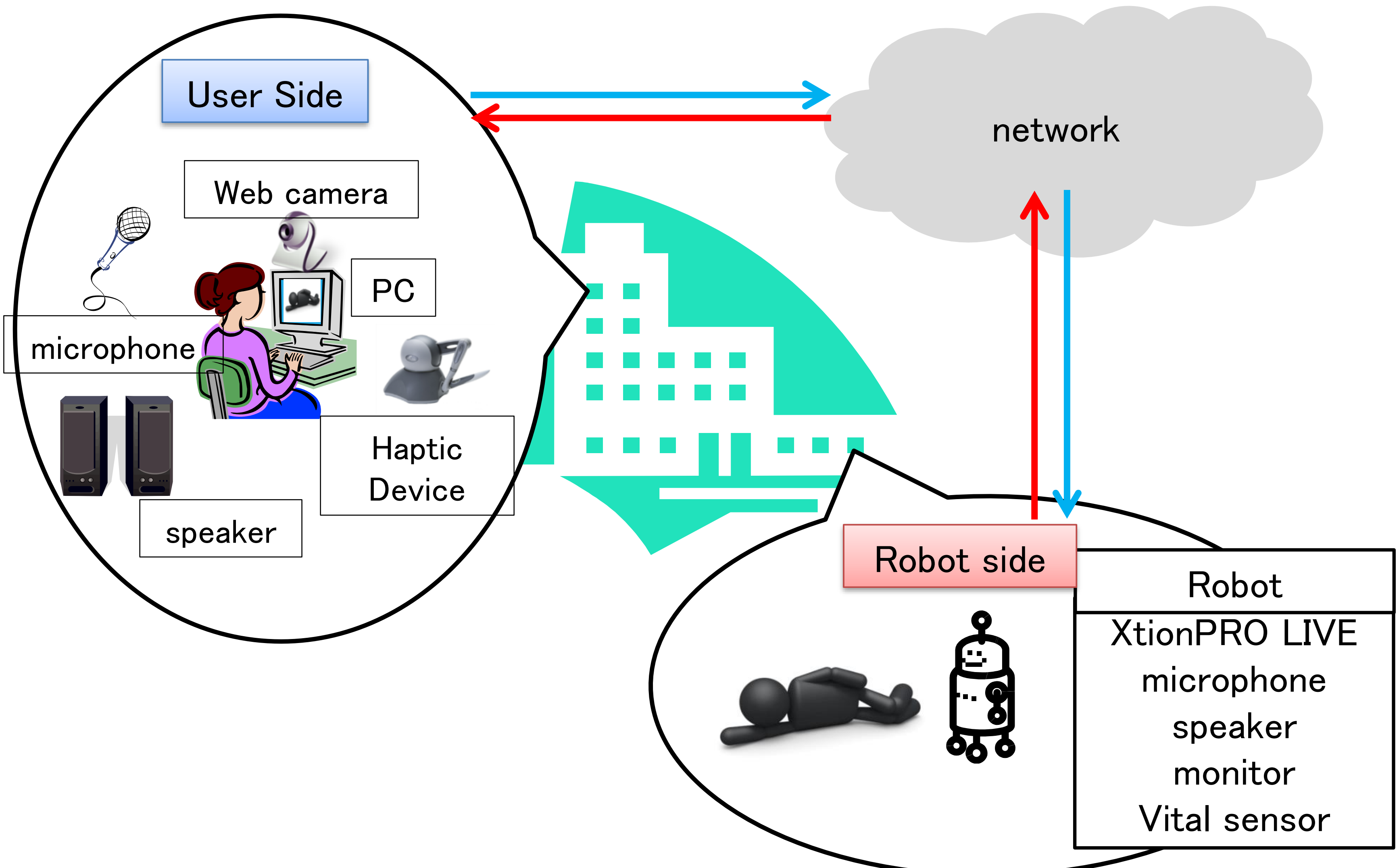
- proximity sensors
- camera (to verify the presence of reward)

Experiment with real robot



Surveillance robot

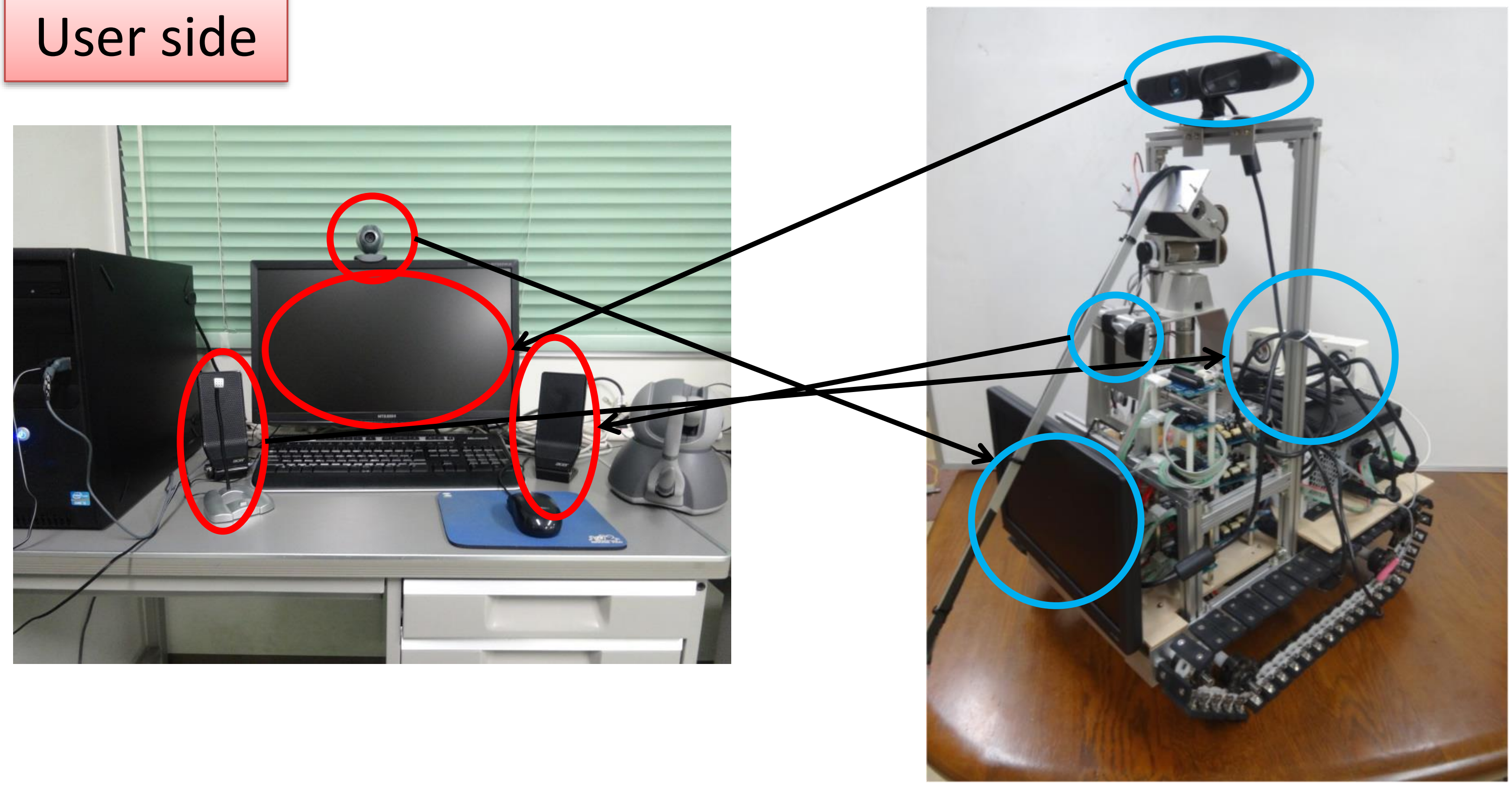
Developed system



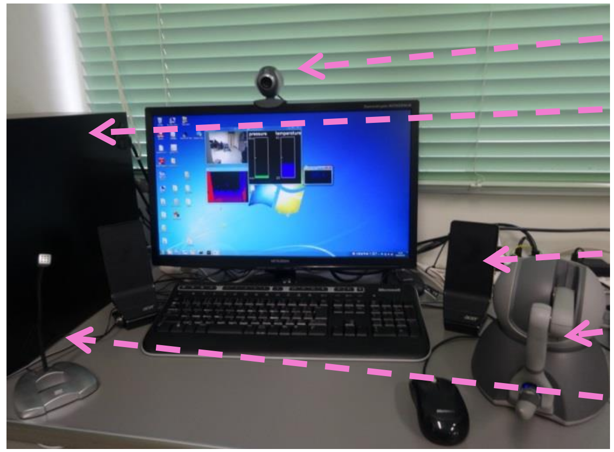
Developed system

Robot side

User side



User environment

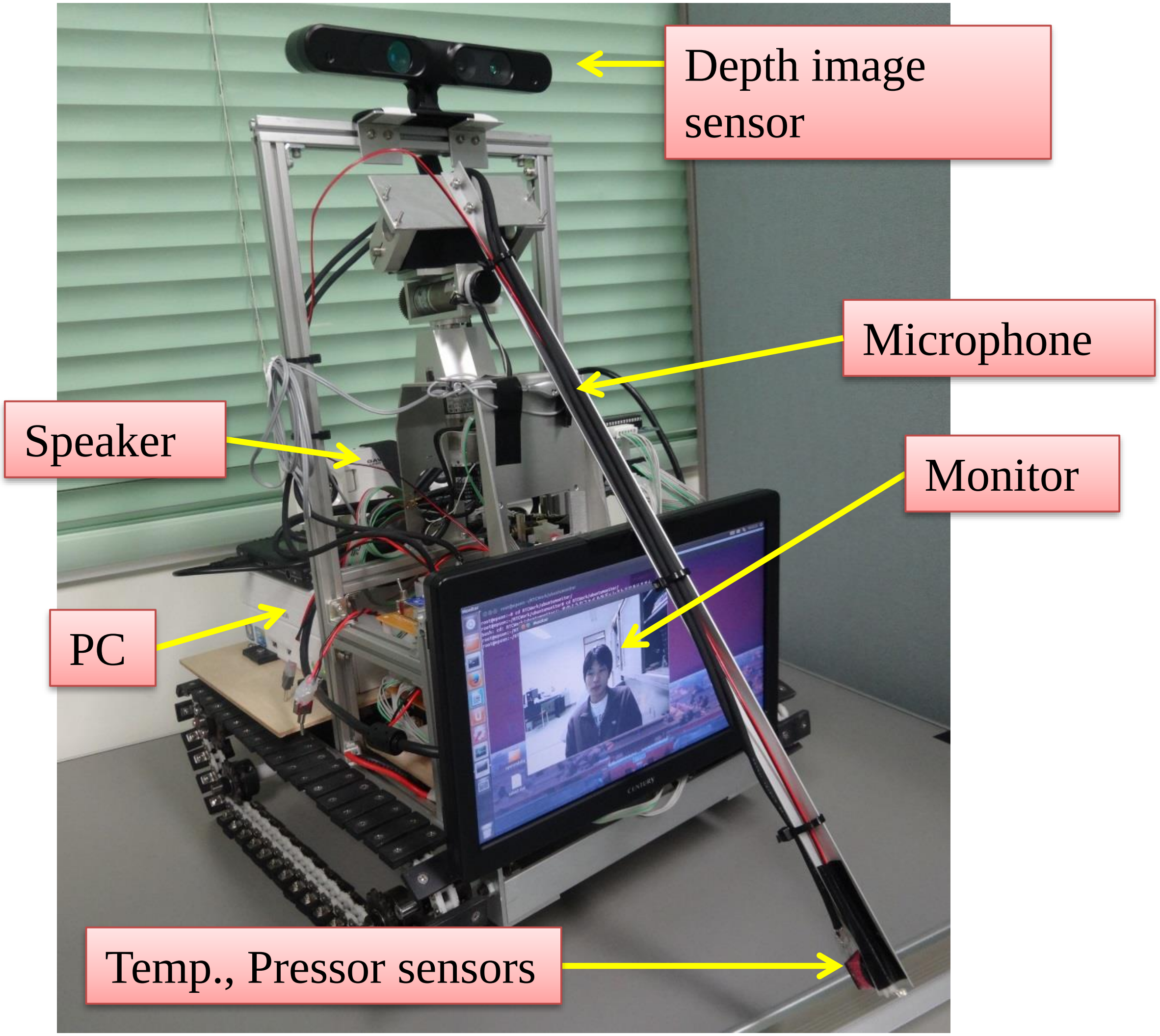


Web camera
PC
Speaker
Haptic Device
Microphone

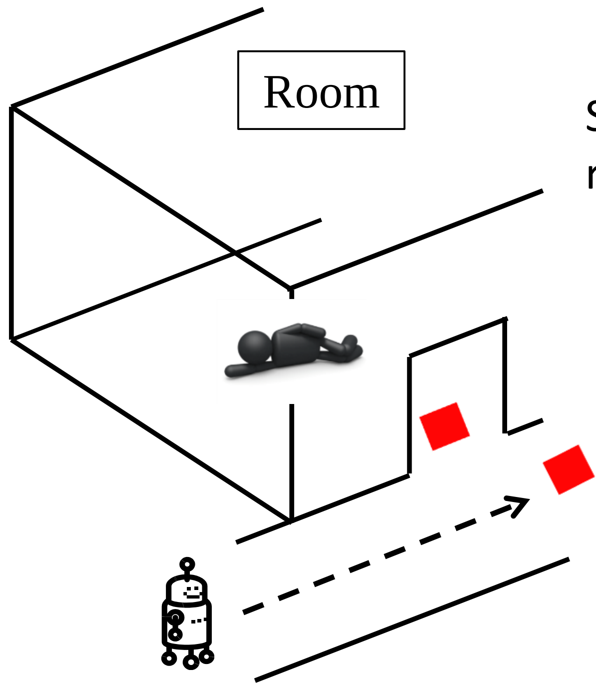
Monitor

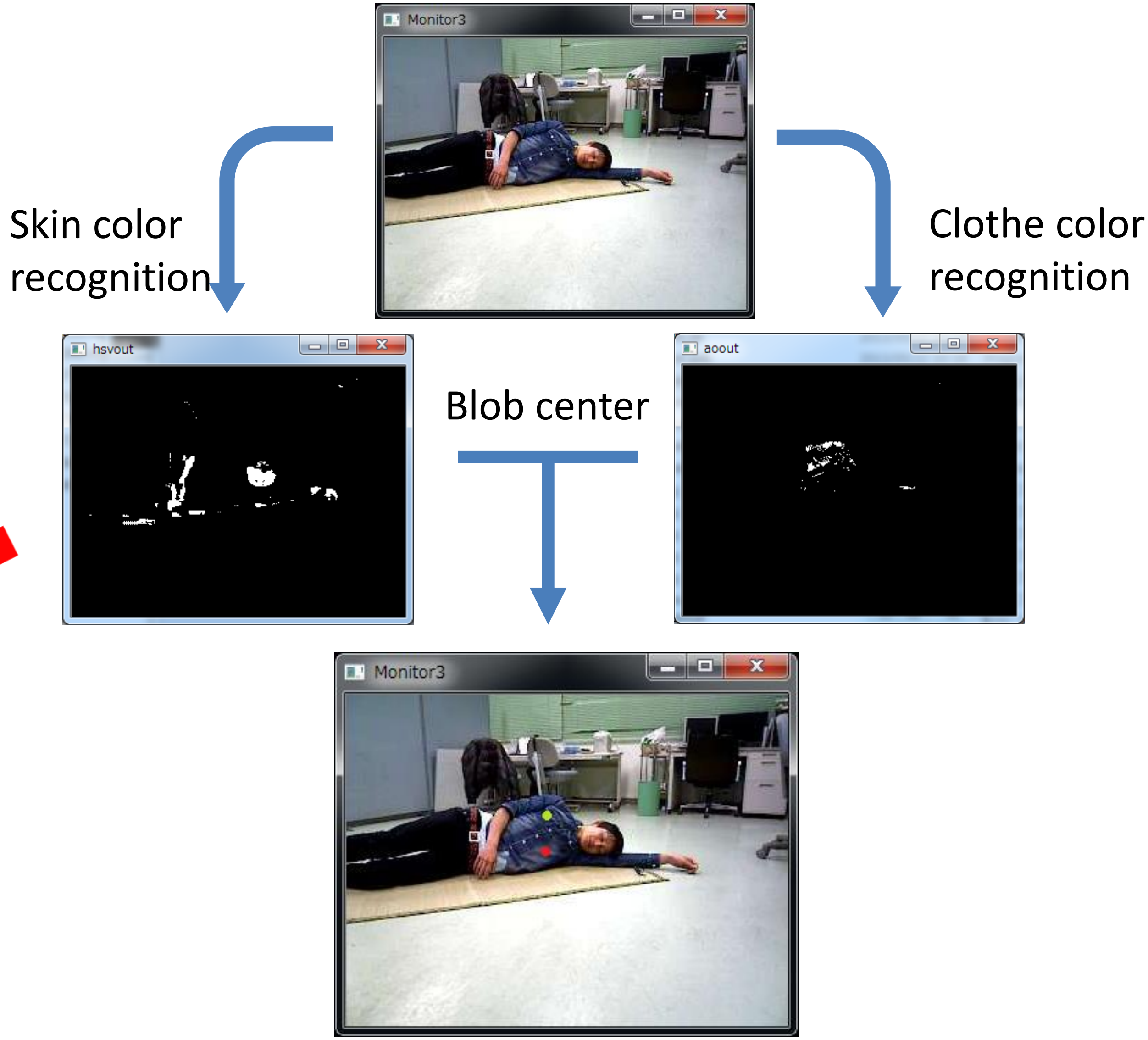
Robot’s image
Sensors data
temperature[°C]
Depth image

Surveillance robot

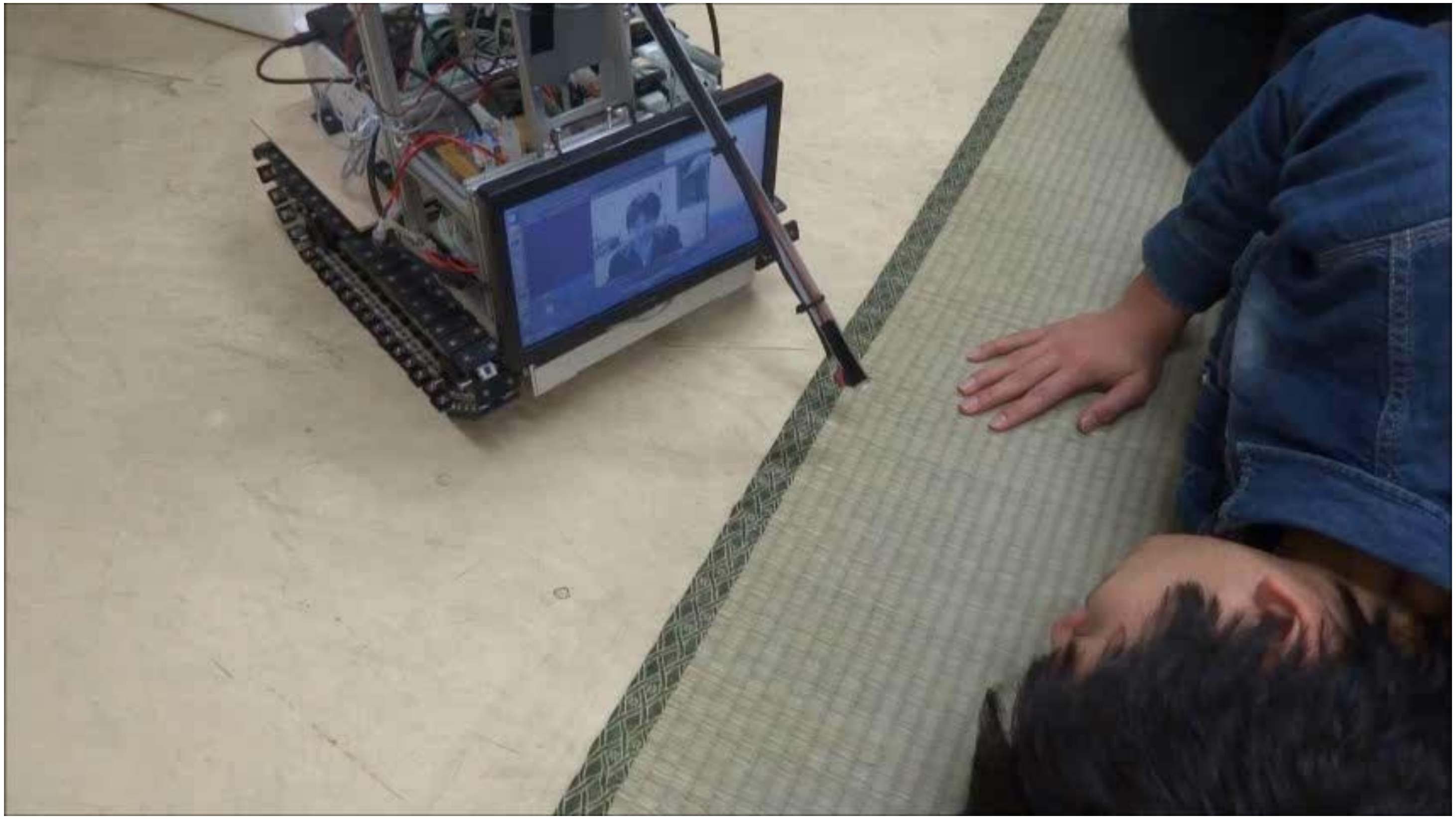


Human recognition

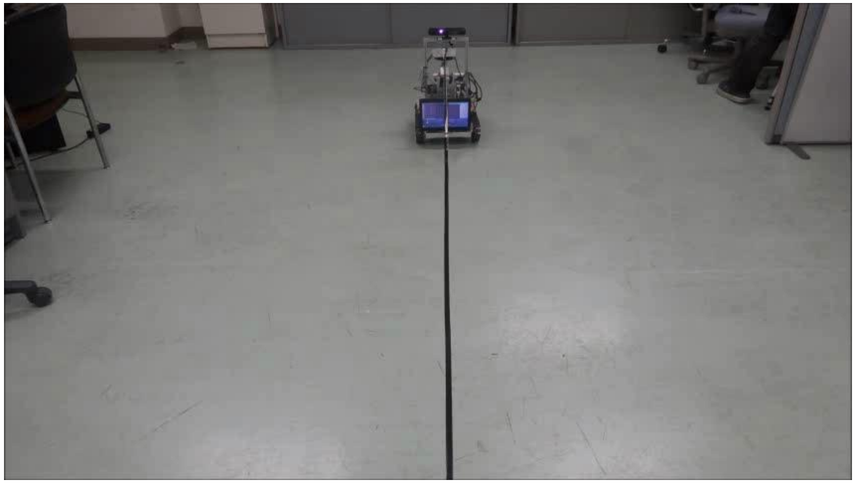


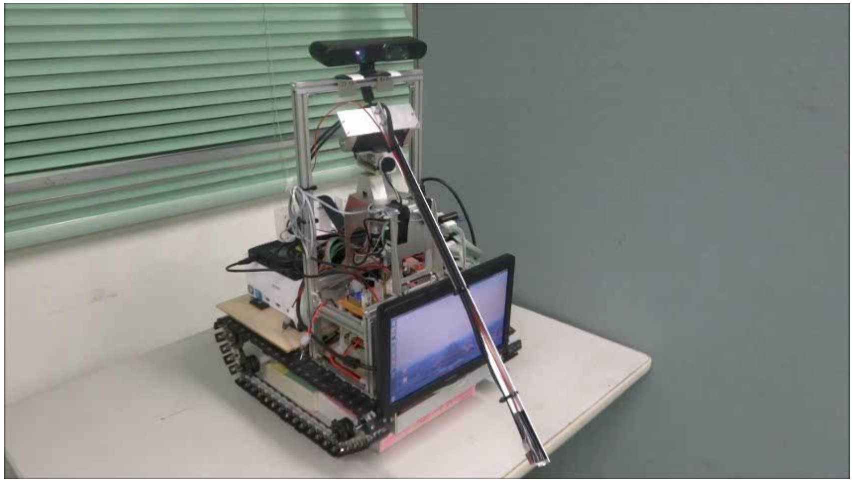


Communication



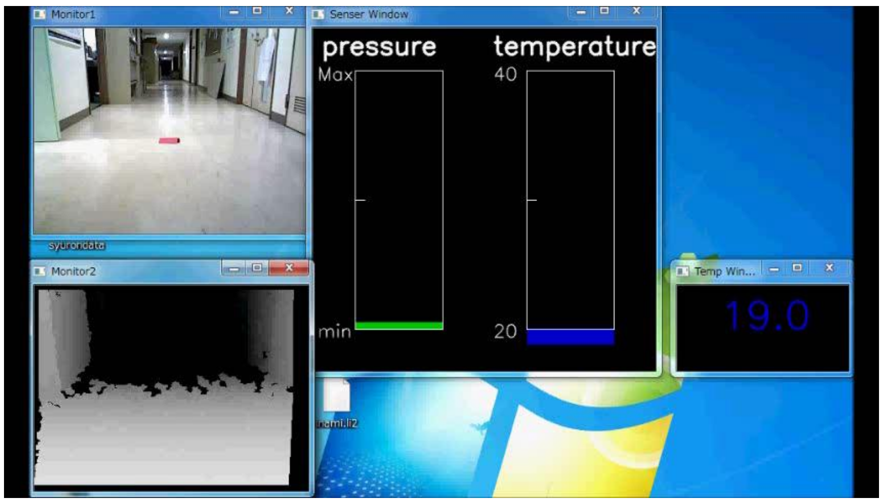
Wireless robot control



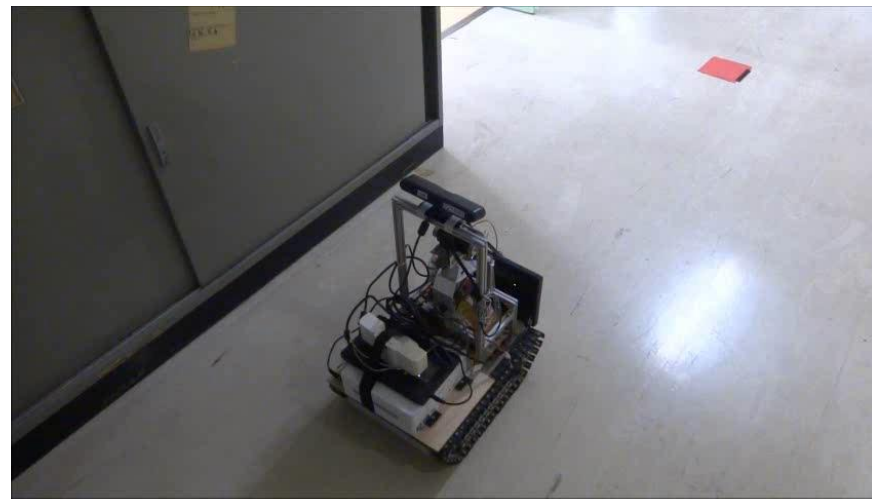


Enviromennt exploration

User side

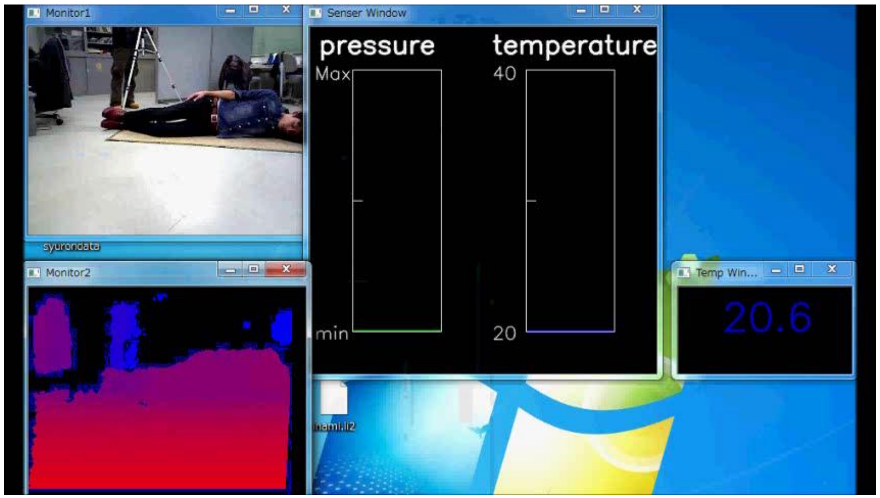


Robot side

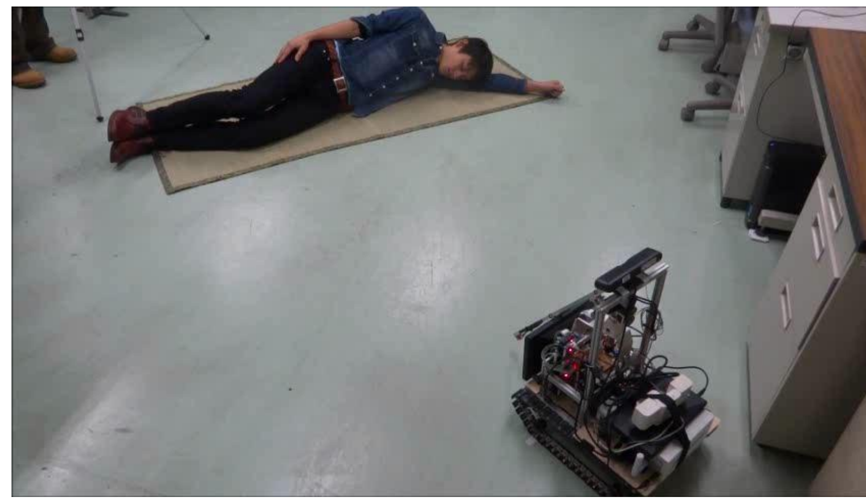


Experimental results

User side



Robot side



Application of Deep Belief Neural Network for Robot Object Recognition and Grasping

Introduction

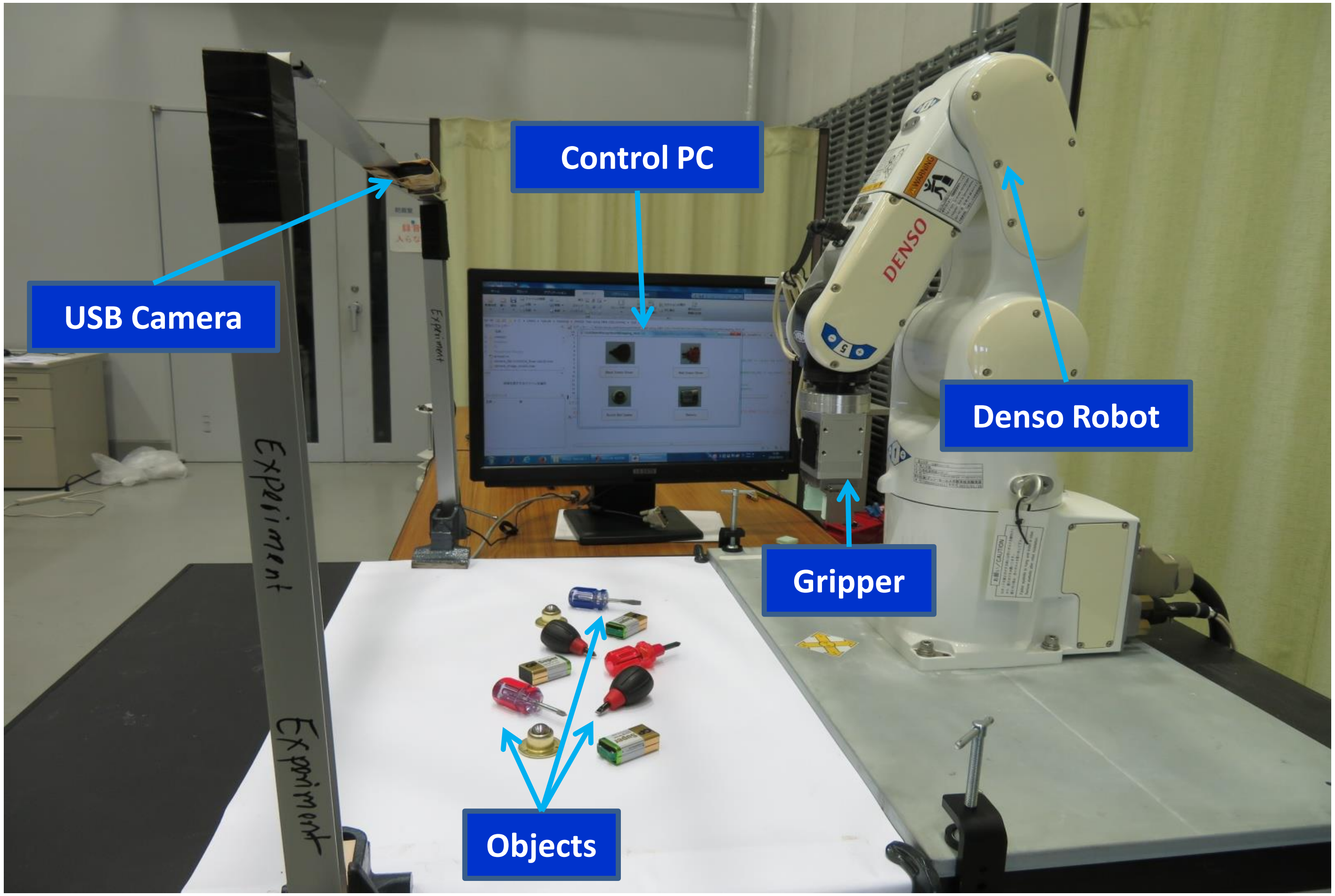
- Small size robot is widely used for assembly task.
- Real time object recognition and robot pick-place operation.
- Deep Learning needs processing time.
- We propose a method to optimize the Deep Learning parameters using Genetic Algorithm for object recognition and robot grasping.

Why DBNN and Evolutionary Method?

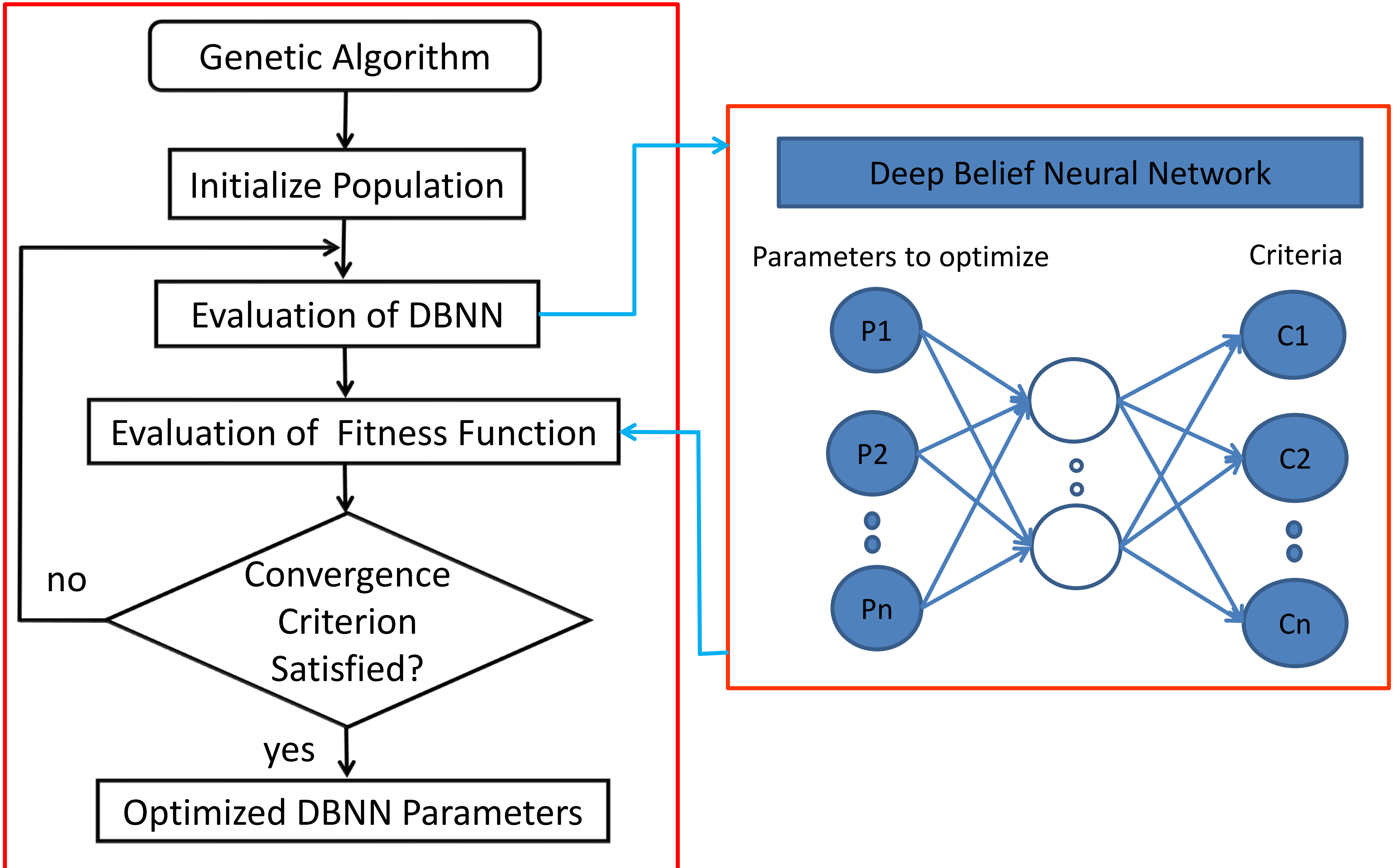
- DBNN makes it easy adding of new objects.
- It can be implemented using low-cost USB camera, without the need for depth image sensor.
- A single DBNN is utilized to recognize several objects, which reduce the computational cost and time.
- Evolutionary method is used to optimize DBNN parameters in order to reduce the error rate and training time.

Robot Task

❑ Task for the robot is to pick up the specific object required by the user and place it in the target location.

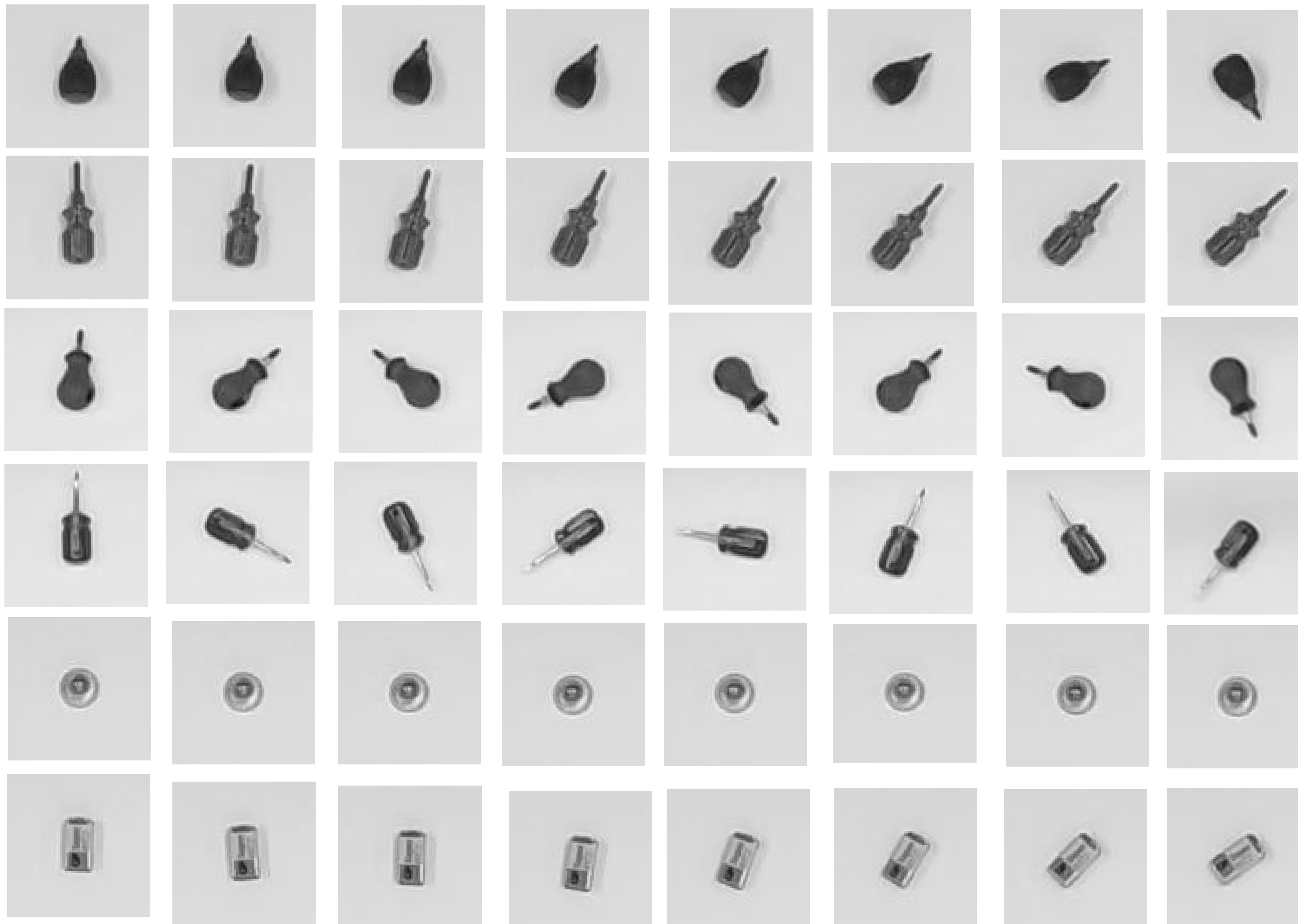


Evolution of DBNN Parameters



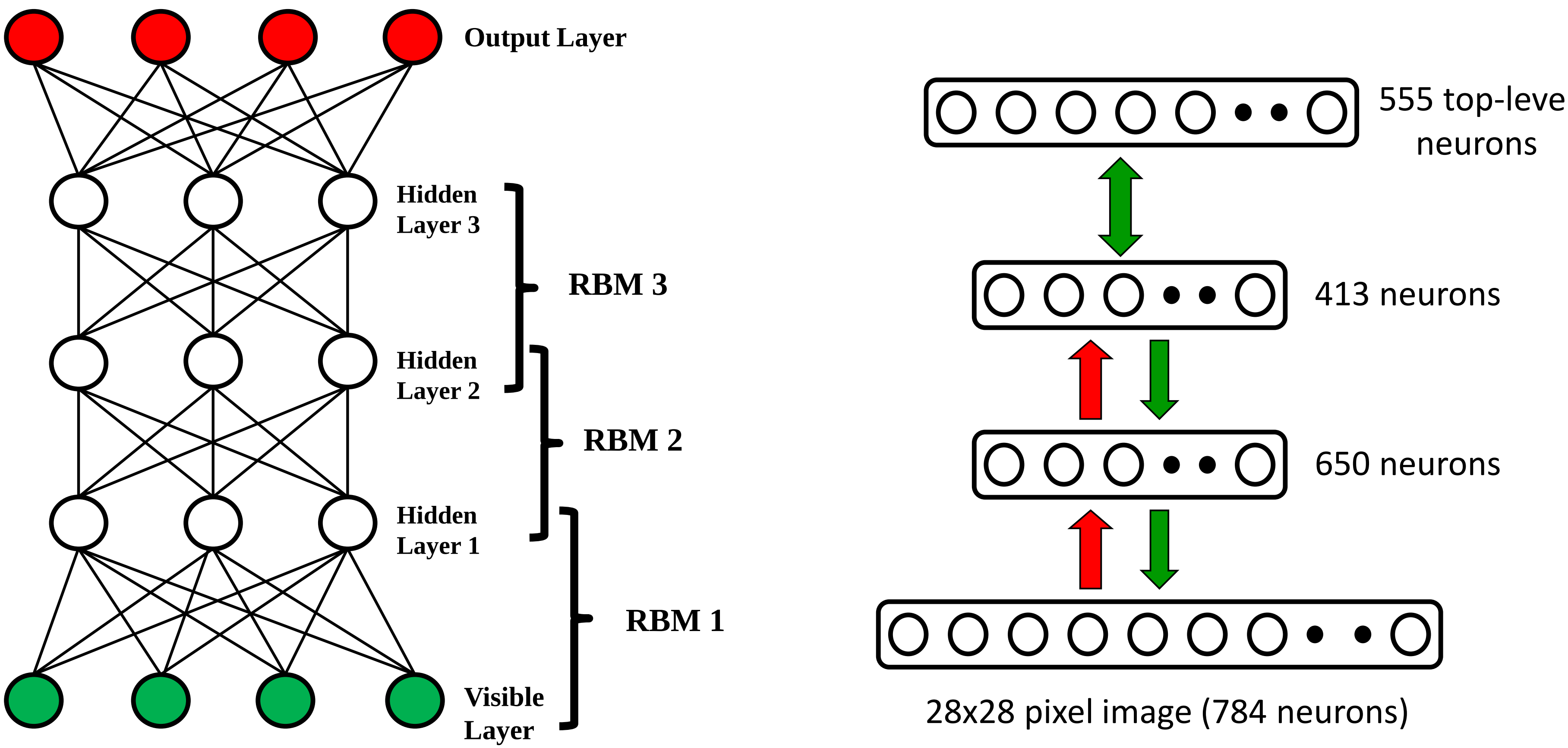
Sample Training Dataset

- 1200 images of 6 objects (200 images for each object).
- To make robustness of the recognition system.

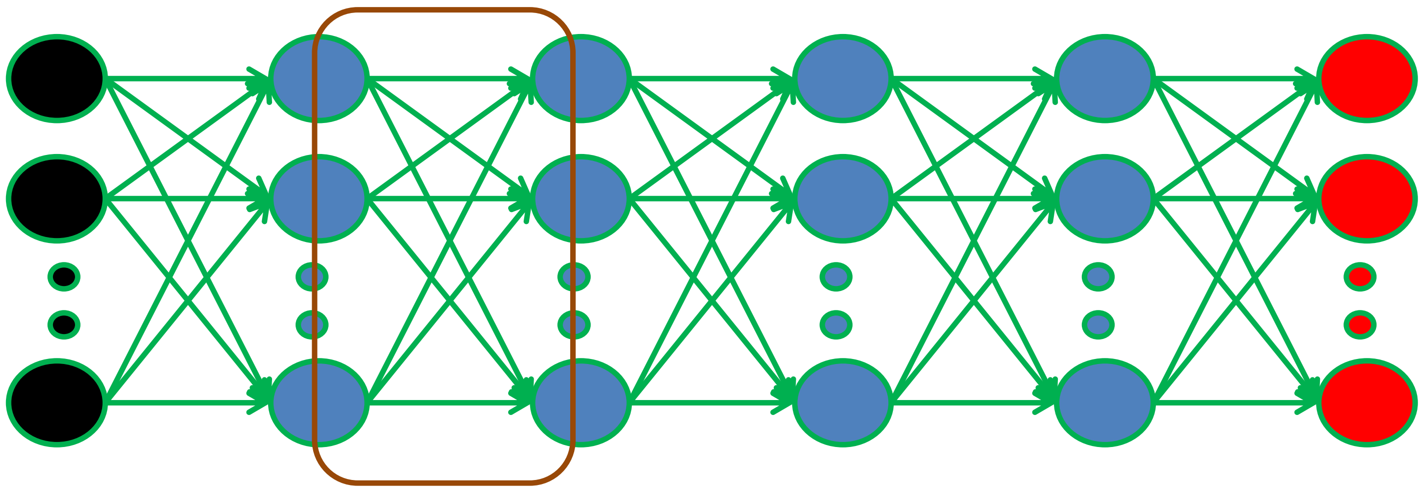


Deep Belief Neural Network (DBNN)

DBNN is the probabilistic generative model, which is constructed by many layers of Restricted Boltzmann Machines (RBMs).



Training DBNNs...

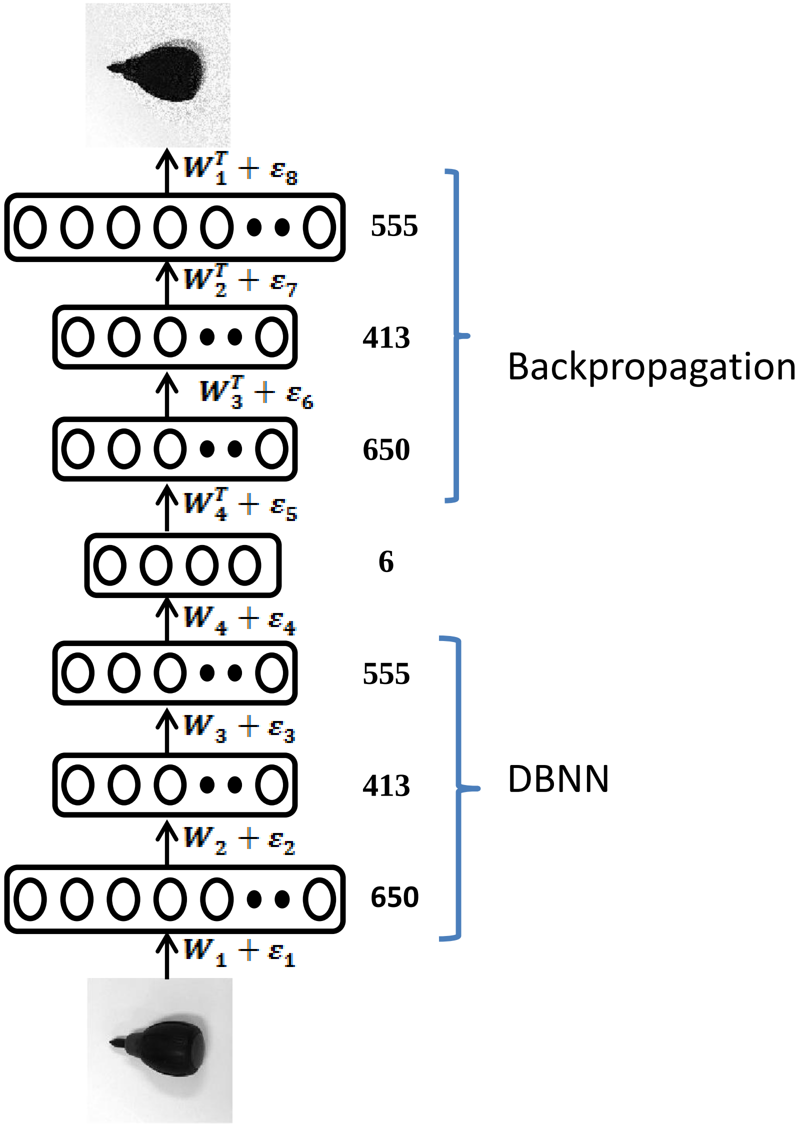


First train visible and hidden layer

then repeat this process several times

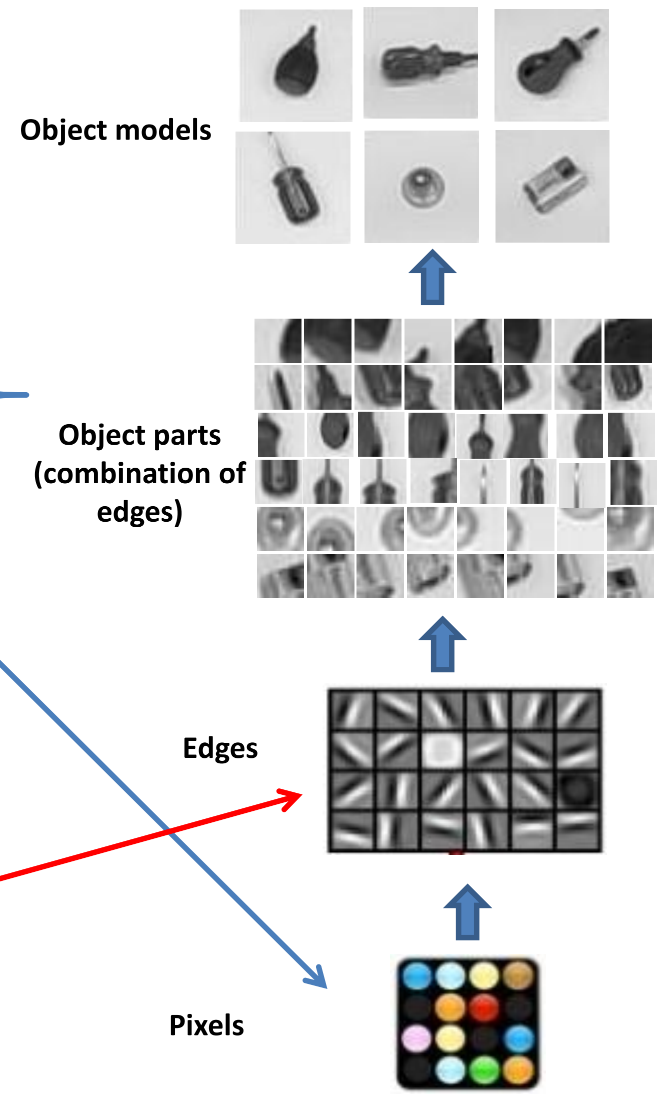
Fine-tuning using Backpropagation

❑ Fine-tuned the weights for better object recognition.
❑ The required gradients are easily obtained by using the chain rule to backpropagate error derivatives.
❑ Discriminative learning is used to separate class labels.
❑ "Softmax" label units represent the object class.

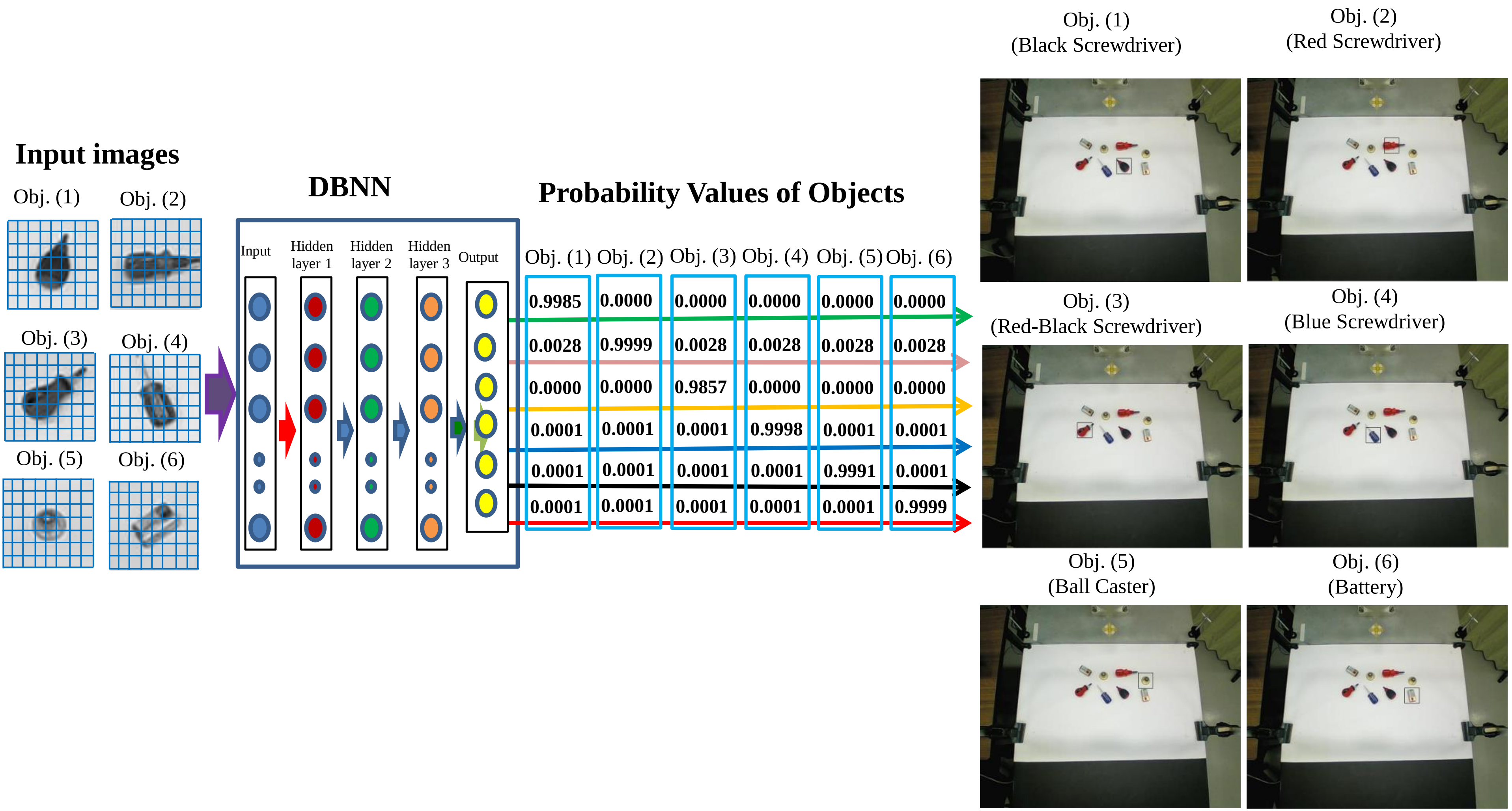


DBNN for Object Recognition

❑ Input vector is produced by reshaping the extracted picture of 28x28 pixels.
❑ Normalization and shuffling operations are performed.
❑ A nonlinear transformation is applied on the input vector.
❑ The vector is used as input of the DBNN.
❑ To generate features from RBM, we start with binary state of each feature from random state of visible units.



Object Recognition using DBNN



Obj. (1)	Obj. (2)	Obj. (3)	Obj. (4)	Obj. (5)	Obj. (6)
0.9985	0.0000	0.0000	0.0000	0.0000	0.0000
0.0028	0.9999	0.0028	0.0028	0.0028	0.0028
0.0000	0.0000	0.9857	0.0000	0.0000	0.0000
0.0001	0.0001	0.0001	0.9998	0.0001	0.0001
0.0001	0.0001	0.0001	0.0001	0.9991	0.0001
0.0001	0.0001	0.0001	0.0001	0.0001	0.9999

DBNN Parameters to Optimize

- Number of units in three Hidden Layers

Hidden Layer	Searching Range
First	[50 1500]
Second	[50 1500]
Third	[200 2500]

- Number of epochs in three Hidden Layers

Hidden Layer	Searching Range
First	[20 250]
Second	[20 250]
Third	[20 250]

- Learning rates in three Hidden Layers

Hidden Layer	Searching Range
First	[0.0001 0.09]
Second & Third	[0.01 0.9]

- Momentum values

	Searching Range
For five epochs in each hidden layer	[0.001 0.9]

Genetic Algorithm (GA)

We use a parallel GA where the population is divided into subpopulation.

Basic Components

- **Successor function(s)**
  - Mutation, Crossover
- **Fitness function**
- **Some parameters**
  - Population size
  - Generation limit

Genetic Algorithm Parameters Summary

Function name	Parameters
Number of subpopulations	4
Number of individuals	25, 25, 25, 25
Crossover probability	0.8
Mutation rate	0.1, 0.03, 0.01, 0.003
Migration rate	0.1
Results on screen	Every 1 generation
Termination	30 generations

Fitness Function

The fitness function is defined as to minimize the error rate and network training time.

$$Fitness = 100 \times (E_{BBP} + E_{ABP}) + \frac{(T_{BBP} + T_{DBP})}{40}$$

$$e.g. \quad Fitness = 100 \times \left(\frac{19}{600} + \frac{8}{600} \right) + \frac{(32.7221 + 49.2779)}{40} = 6.55$$

where

$$E_{BBP} = \frac{number\ of\ \ misclassification\ before\ backpropagation}{total\ number\ of\ \ test\ data}$$

$$E_{ABP} = \frac{number\ of\ \ misclassificationbe\ after\ backpropagation}{total\ number\ of\ \ test\ data}$$

$$T_{BBP} = time\ required\ to\ train\ DBNN\ before\ Backpropagation\ (\mathrm{sec})$$

$$T_{DBP} = time\ required\ to\ \ fine - tune\ during\ \ Backpropagation\ (\mathrm{sec})$$

Optimized DBNN Parameters

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- Number of units in three Hidden Layers

Hidden Layer	Searching Range	Best Value
First	[50 1500]	698
Second	[50 1500]	432
Third	[200 2500]	1464

- Number of epochs in three Hidden Layers

Hidden Layer	Searching Range	Best Value
First	[20 250]	164
Second	[20 250]	148
Third	[20 250]	164

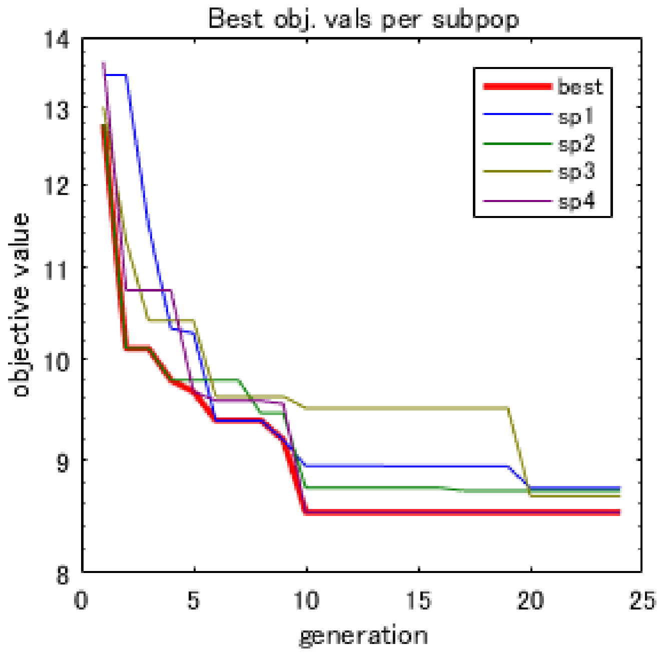
- Learning rates in three Hidden Layers

Hidden Layer	Searching Range	Best Value
First	[0.0001 0.09]	0.04474
Second & Third	[0.01 0.9]	0.44727

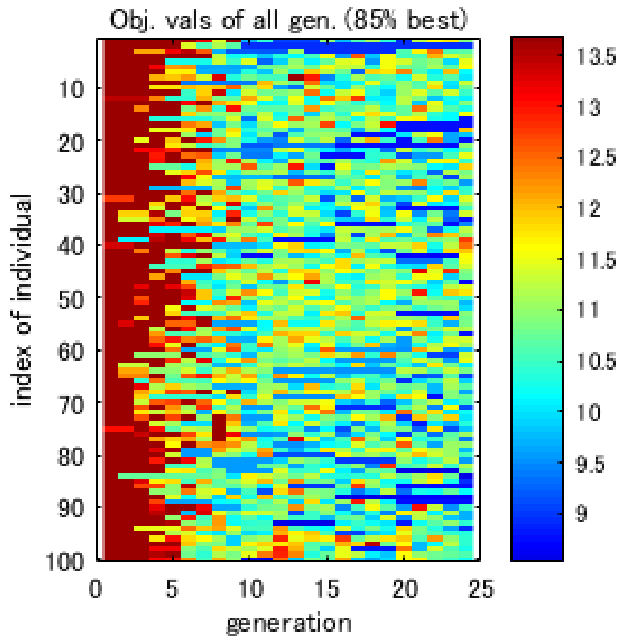
Momentum values	Searching Range	Best Value
For five epochs in each hidden layer	[0.001 0.9]	[0.28,0.28, 0.15,0.55,0.026]

Genetic Algorithm Results

Best objective values per subpopulation



Fitness value of individuals for all generation



Best fitness value is 8.52528 on 10th Generation

Object Detection

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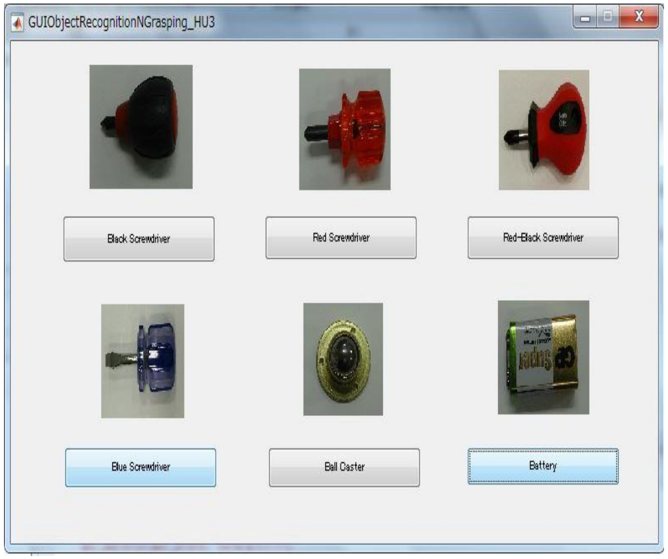
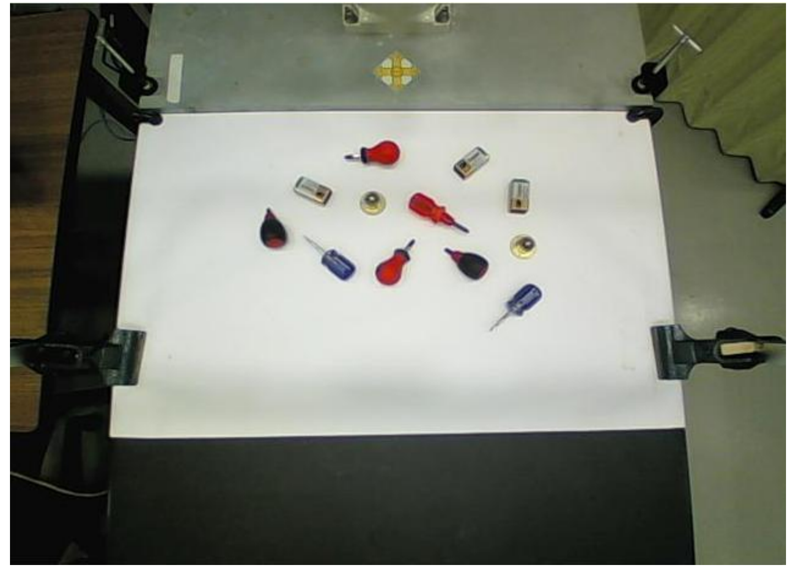
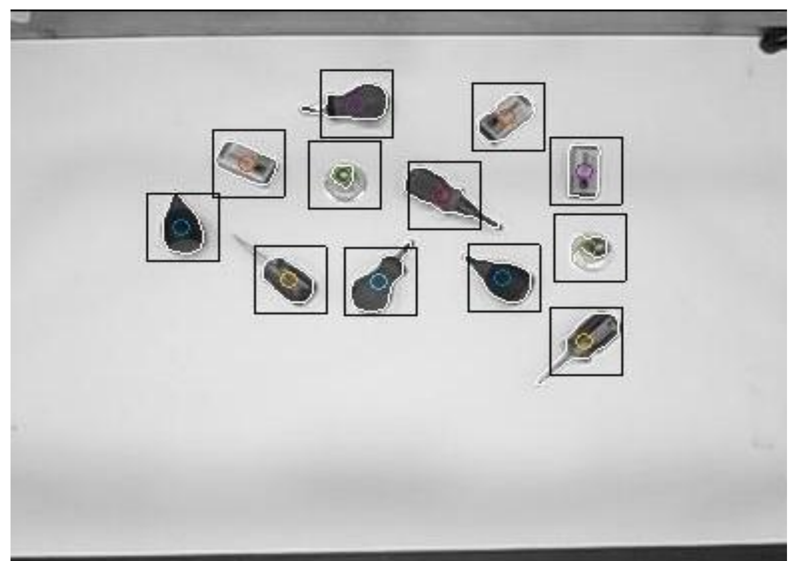
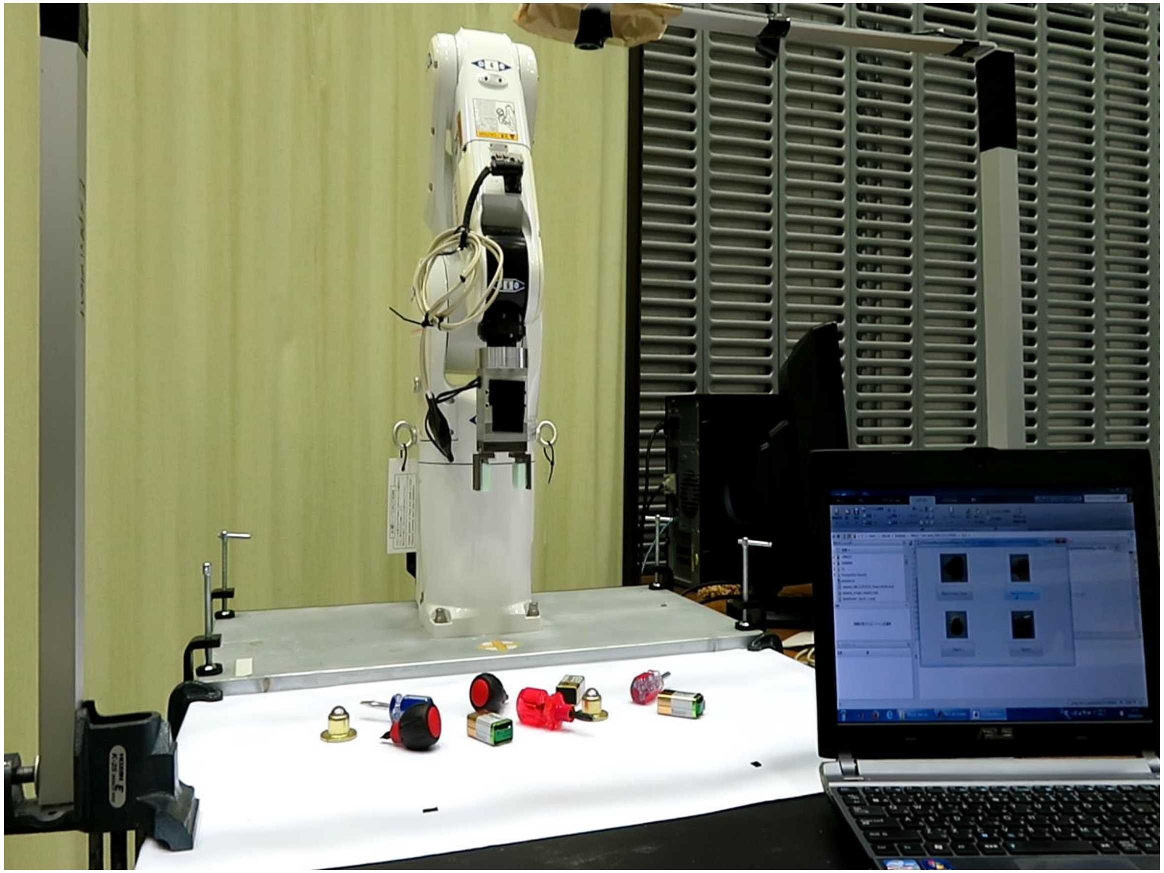
HOSEI University





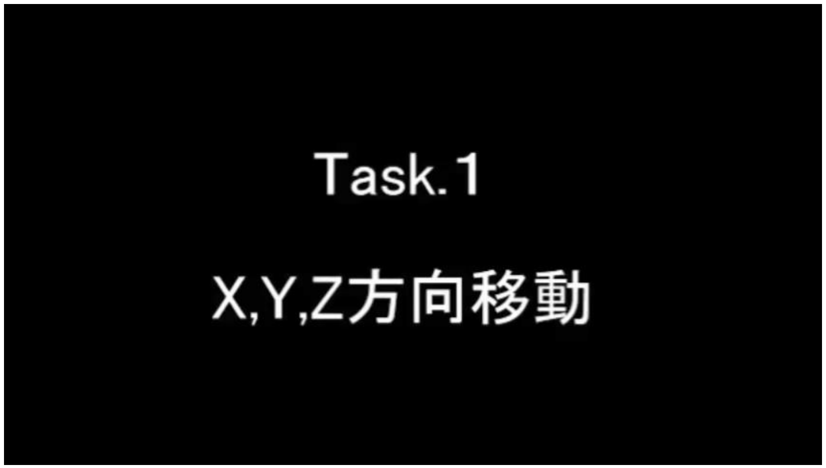


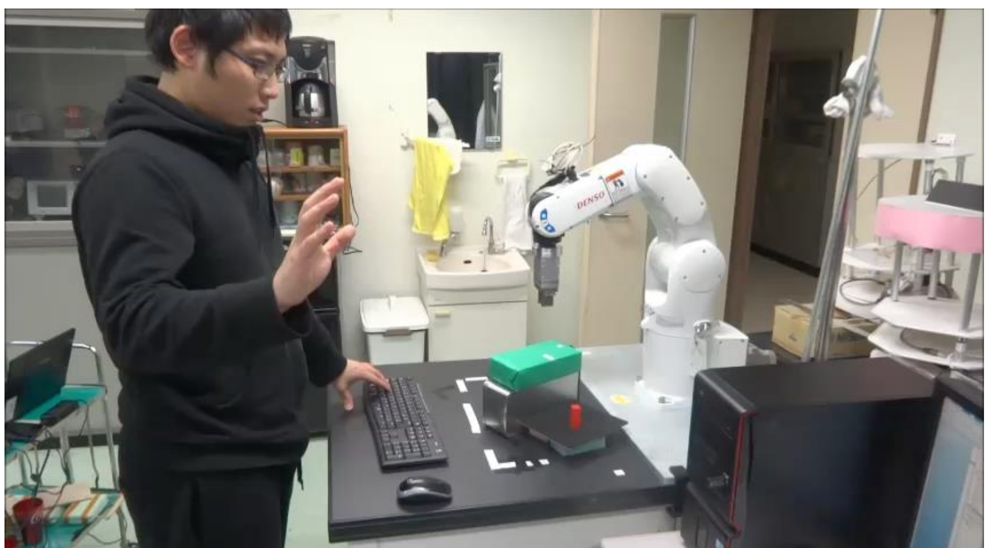
Experimental Results for Object Recognition and Robot Grasping



Multi-robot formation

Experimental results for teaching robot manipulators





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Surveillance robotic system

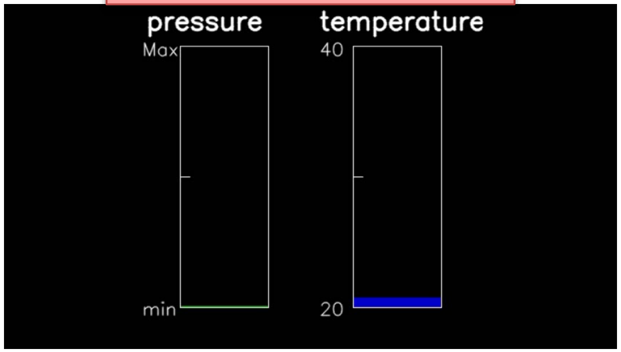
Server

Client

Depth image

RGB image

Sensor data



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