UNC CHARLOTTE

The WILLIAM STATES LEE COLLEGE *of* ENGINEERING

Human-Robot Cooperation using EEG signals with Self-Learning

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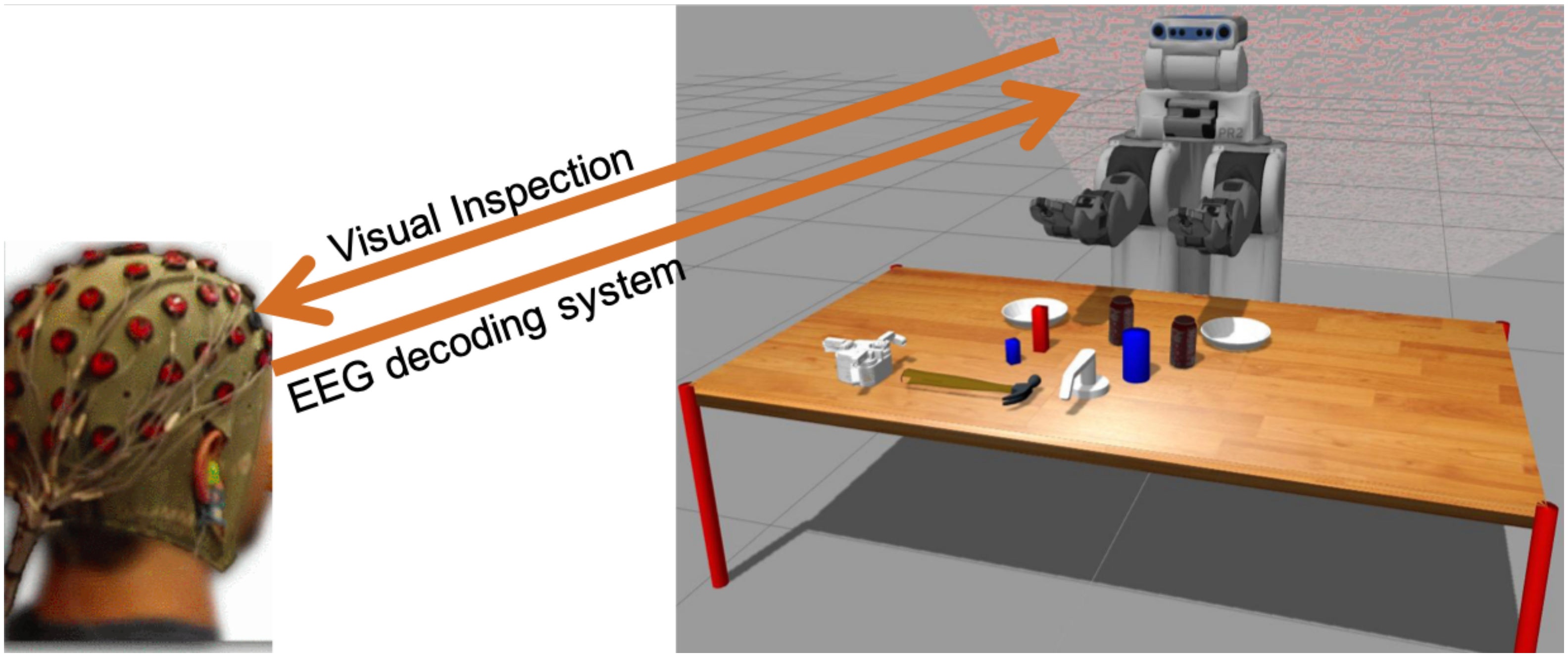
Outline

- **Contribution**
  - System overview
  - Block diagram
- **Problem statement**
- **Theory and Implementation**
  - Pick and place objects
  - ErrP classification
  - Self-learning
- **Results**
- **Conclusion**

My Contributions

- Developing a novel classifier to classify the normal EEG vs ErrPs using various deep learning techniques with high classification rate
- Demonstrating the applicability of error related potentials to robotic collaboration tasks
- Demonstrating the daily life tasks such as object sorting with the help of error related potentials as feedback for trajectory correction
- Developing a self learning algorithm that could learn on the go about the classification of objects in real time
- Demonstrate the adaptiveness of self learning algorithm with different user priorities

Overview of System

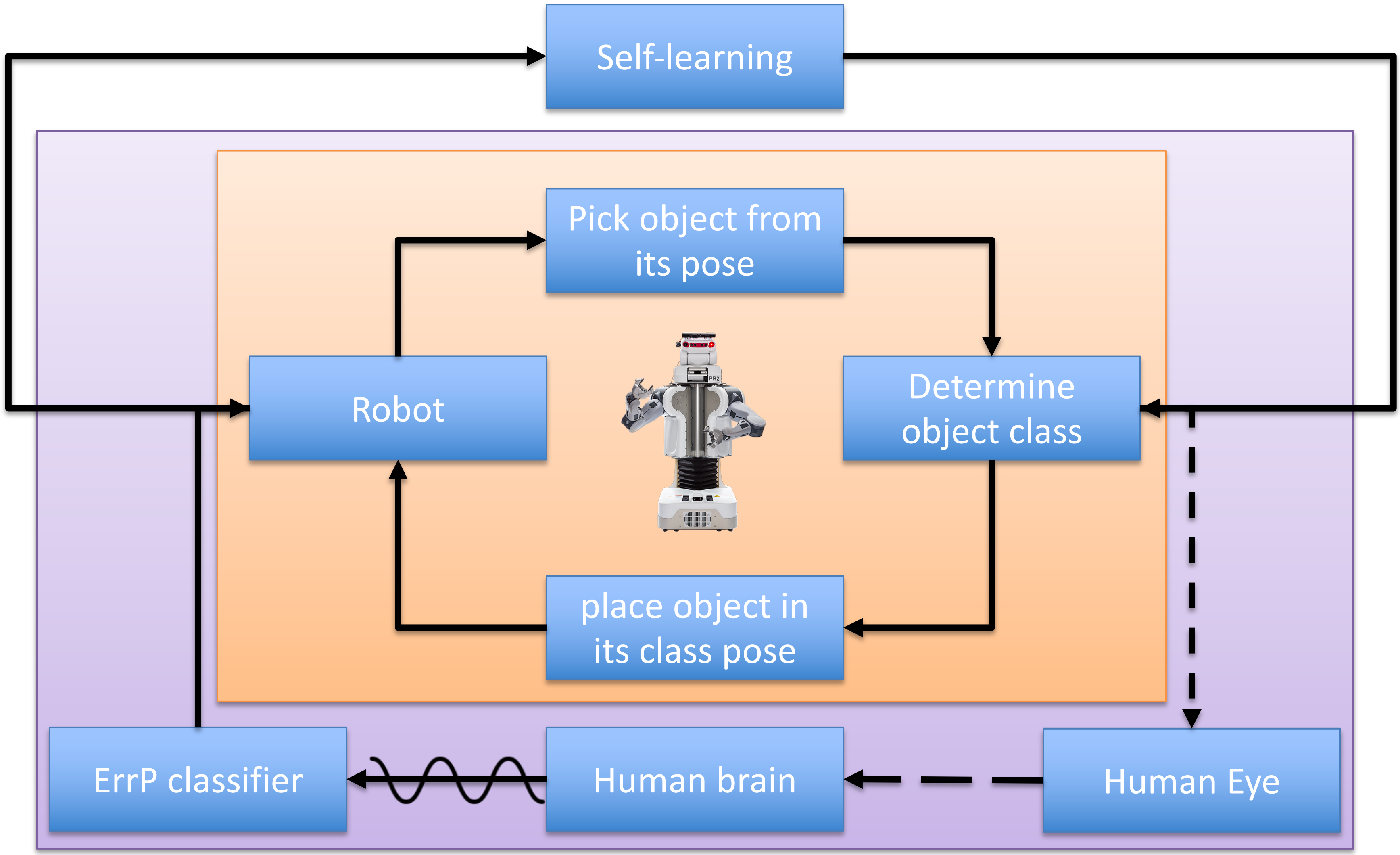


Pick and Place object

ErrP Classification

Self-learning

Block diagram



Assistive robot + Brain computer interface
+ Self learning = Current Research

Introduction

Human-Robot Cooperation

- Multidisciplinary research field with focus interactions between humans & robot

Assistance

Search and rescue

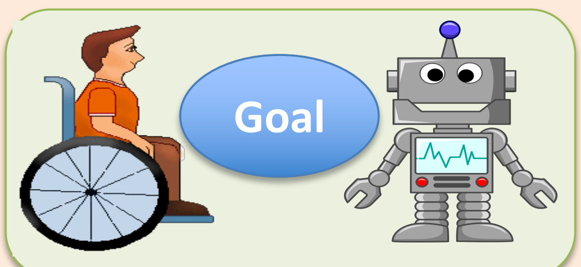
Military and police

Assistive Robotics

- Branch of robotics that assists people with physical disabilities with physical interaction

Capabilities

Activity requirement

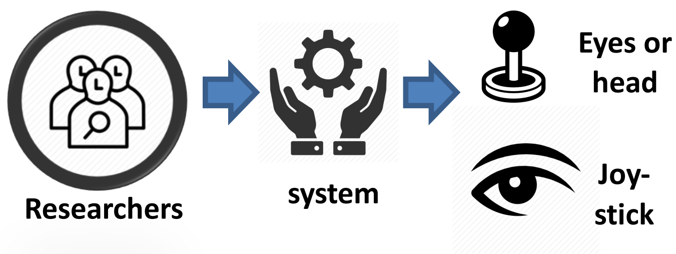


Activities:

dressing, hygiene, eating, communication, home management, education, and care of others

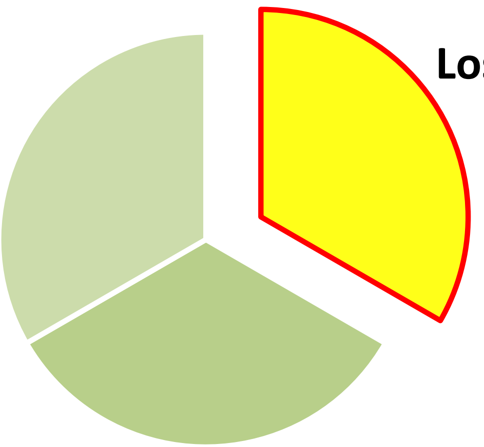
Problem Statement

There is an active area of research for disabled

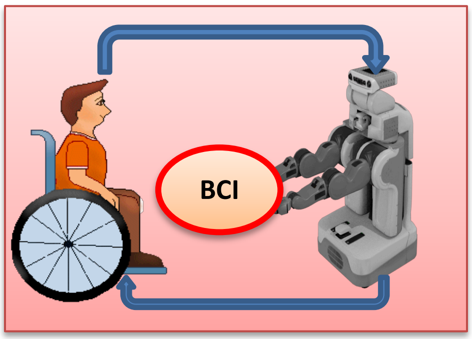


Communication plays major role

State-of-the-art



Lost ability to communicate



Locked-in Syndrome

Complete loss of control over their voluntary muscles where patients are unable to speak and move but are conscious and can think & reason

Stroke, severe cerebral palsy, motor neuron disease, ALS

Smith, Eimear, and Mark Delargy. "Locked-in syndrome." *BMJ (Clinical research ed.)* vol. 330,7488 (2005): 406-9. doi:10.1136/bmj.330.7488.406

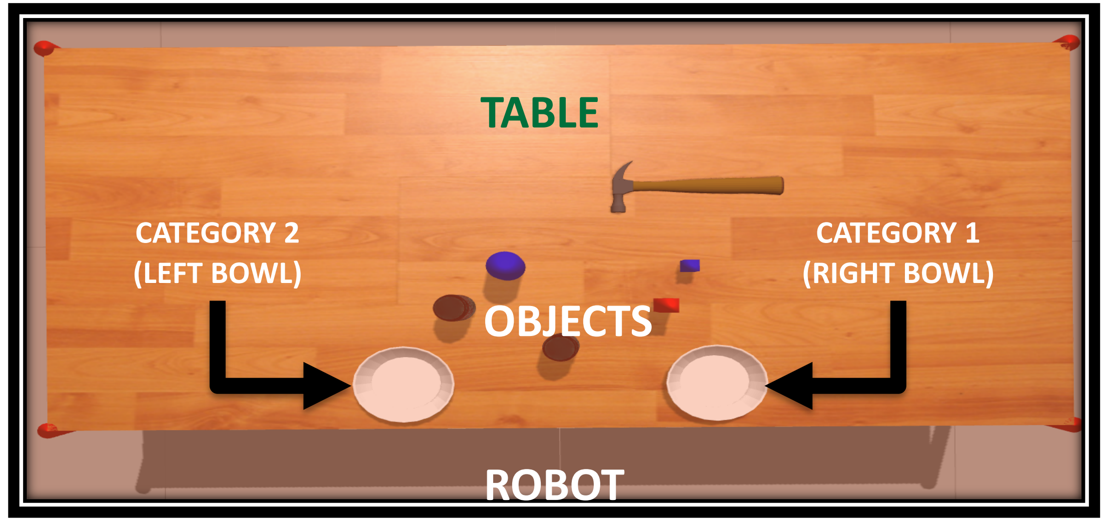
Theory & Implementation

- Pick and place objects
- ErrP Classification
- Self-learning

Pick and Place objects

Task: Object Retrieval

GAZEBO



Why object retrieval?

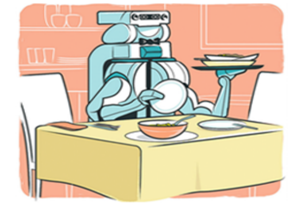
- Seven institutions across England and North America which reflect the views of over 200 potential users of such technology.
- They include predevelopment questionnaires that focus on user task ability and anticipated use of an orthosis or rehabilitation robot.

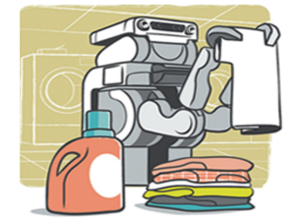
USER TASK PRIORITIES

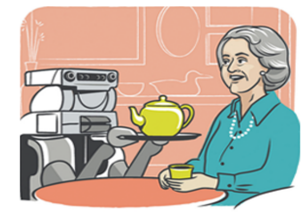
Priority	Task
High	Picking up misc. objects, esp. from floor or shell carrying objects
Moderate to High	Eating/Drinking, Preparing Food & drinks, Personal Hygiene, Leisure & Recreation

C. A. Stanger, C. Anglin, W. S. Harwin and D. P. Romilly, "Devices for assisting manipulation: a summary of user task priorities," in IEEE Transactions on Rehabilitation Engineering, vol. 2, no. 4, pp. 256-265, Dec. 1994

Pick and Place objects

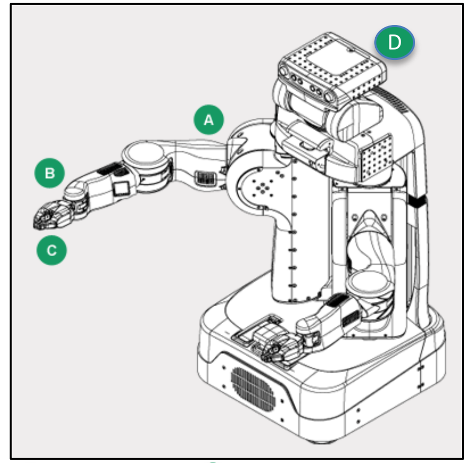






<u>Robot:</u> PR2

- Personal Robot 2
- Willow Garage
- Two 7 DOF arms
- Tilting head and a sliding joint



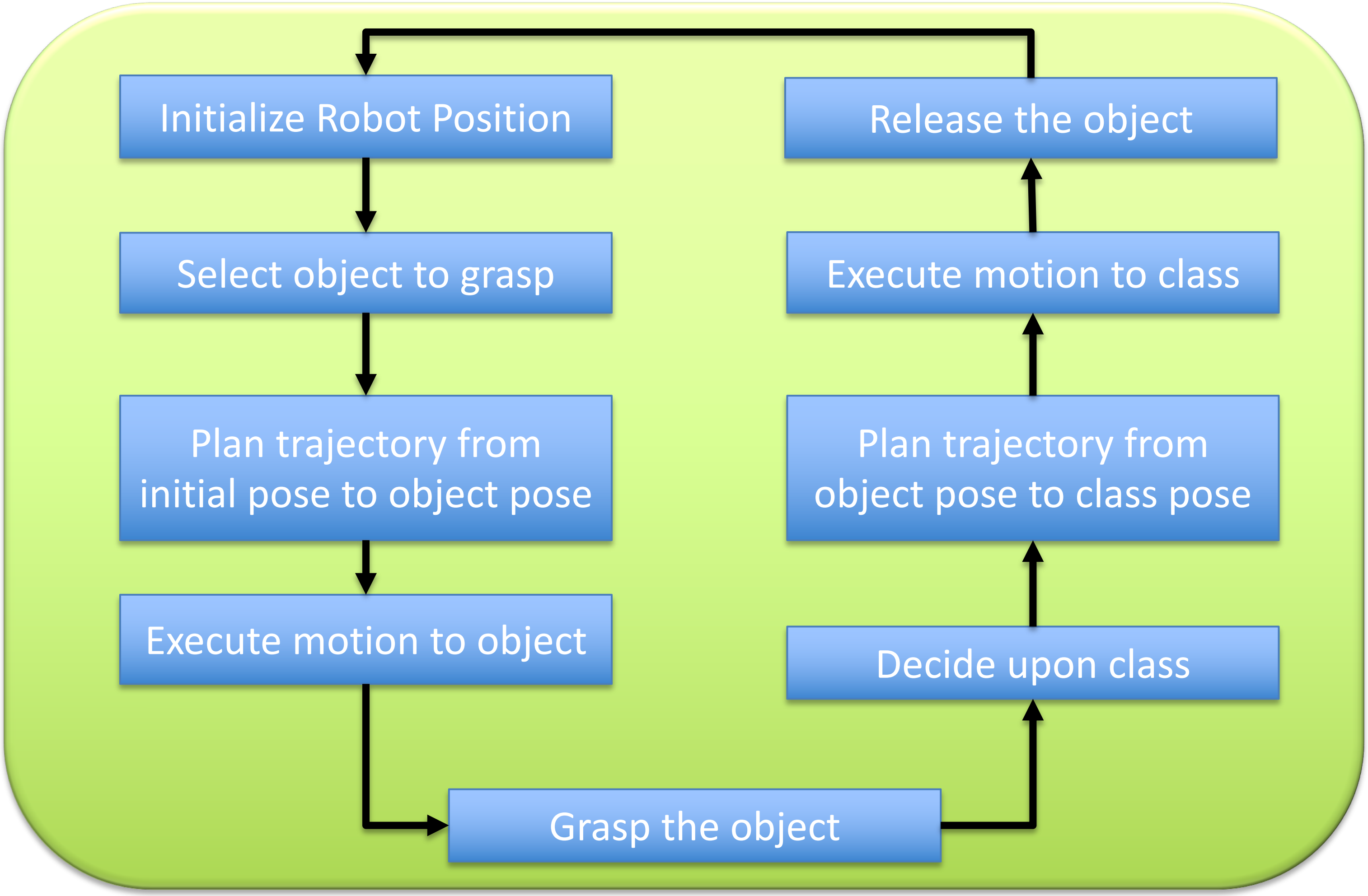
A Arm: 4
B Wrist: 3
C Gripper: 1
D Head: Pan & Tilt

<u>Why PR2?</u>

- A new study from the Georgia Institute of Technology
- They found that older and younger people have various preferences how their assistive robot should look like and have different minds about what robot should do
- Nearly 60% of older adults preferred a robot with human appearance

Akanksha Prakash, "Putting a Face on a Robot", https://www.news.gatech.edu/2013/10/01/putting-face-robot, 2013

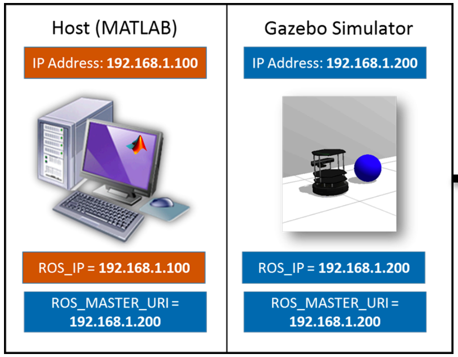
Pick and Place Objects



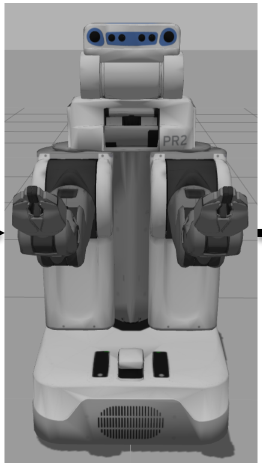
Block Diagram

Pick and Place Objects

Initialization

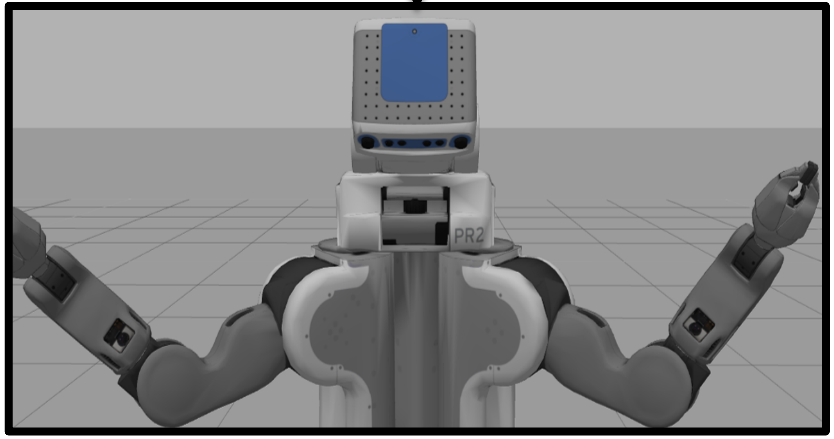


Initialize MATLAB and ROS network



Initialize Robot Joints → Set position for joints → Motion Execution

1. Right arm
2. Left arm
3. Head



Why Initialize?

- Arms are moved to not collide and keep away from the workspace
- Head is moved such that robot sees the table with objects on it

Pick and Place Objects

Pick the object

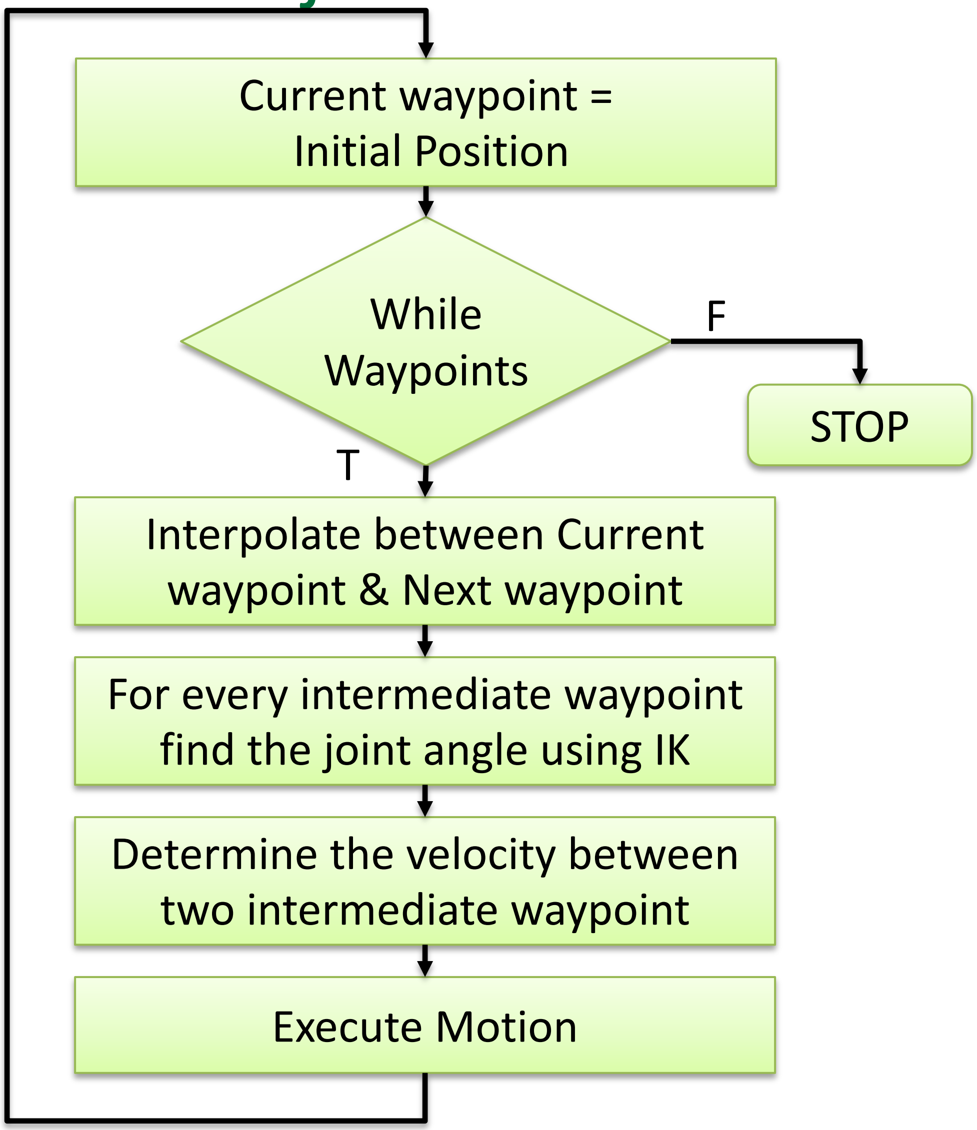
Given

- Way points along the trajectory
- Object pose to grasp
- Robot's end effector position

Place the object

Given

- Way points along the trajectory
- Class pose to place
- Grasped object pose



Pick and Place Objects

Why Interpolate/Waypoints

- Robot does not reach its maximum position
- For future use to verify for existence of error related potentials

Interpolation

- Given two SE3 poses and 'N' number of points, find 'N' SE3 poses

Determine Joint angles

- Inverse Kinematics – Given robot's end-effector position, calculate joint angles
  - Numerical method – BFGS projection algorithm (quasi-Newton method)
  - MATLAB's robotics.InverseKinematics object was used given rigid body tree of PR2

Determine Motion

- Inverse Instantaneous Kinematics – Given the position of all the joints, find the velocity of all the joints. Jacobian matrix helps to define a relationship between joint parameters and the end-effector velocities (Motion execution in 3 seconds)

Pick and Place Objects

Fetch the object

Release the object

Joint	Torque (Nm or N)	Type	Limit (+)	Limit (-)
*_caster_rotation_joint	-	continuous	-	-
*_caster_wheel_*_joint	-	continuous	-	-
torso_lift_joint	10000	prismatic	310 mm	0 mm
laser_tilt_joint	0.65	revolute	85°	-45°
head_pan_joint	2.65	revolute	168°	-168°
head_tilt_joint	15.00	revolute	60°	-30°
*_shoulder_pan_joint	30.00	revolute	40°	-130°
*_shoulder_lift_joint	30.00	revolute	130°	-40°
*_upper_arm_roll_joint	30.00	revolute	80°	-30°
*_elbow_flex_joint	30.00	revolute	44°	-224°
*_forearm_roll_joint	30.00	revolute	224°	-44°
*_wrist_flex_joint	10.00	revolute	133°	0°
*_wrist_roll_joint	10.00	continuous	-	-
*_gripper_joint	1000	revolute	130°	0°
		continuous	-	-
		prismatic	86 mm	0 mm

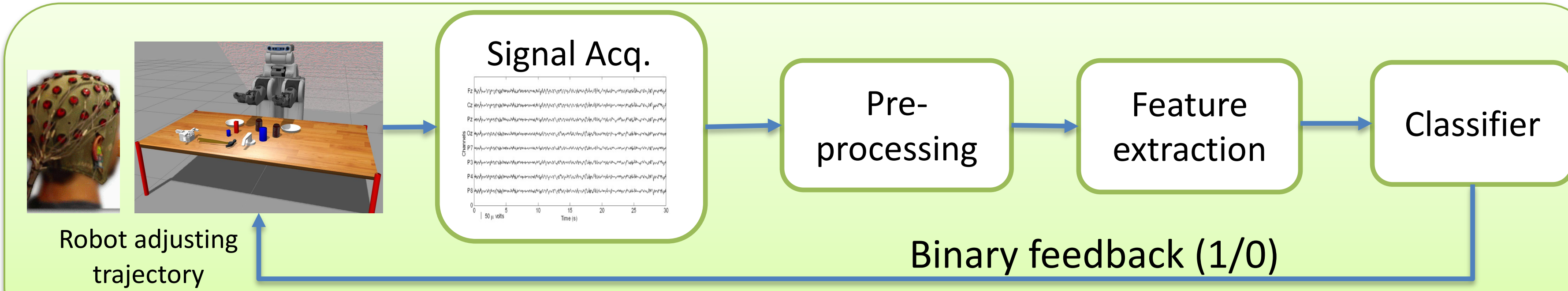
Given

gripper position: Position of prismatic gripper joint in meters (close or open)

maximum effort: Amount of torque required to move the gripper (close or open)

PR2 User Manual, Willow Garage, Oct 5th, 2012

ErrP Classification



Block diagram

Details

- Signal Acquisition
  – Electroencephalography (EEG)
- Preprocessing
  – Spectral & Spatial filtering
- Feature Extraction
  – Electrode selection
- Classifier
  – Convolutional Neural Network

Why EEG?

- Cost effective
- Portable
- High temporal resolution (in ms)
- Non-invasive
- Recording doesn't involve exposure of high intensity magnetic fields
- Studies related to event with simple setting

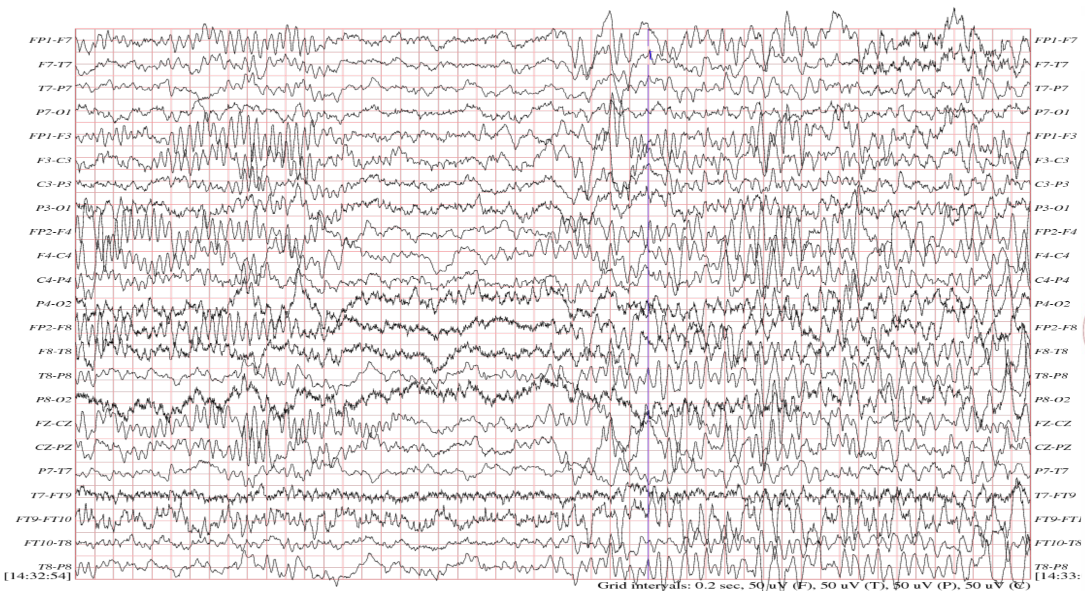
T. C. Major and J. M. Conrad, "A survey of brain computer interfaces & their applications," in IEEE SoutheastCon 2014, pp. 1–8, March 2014

ErrP Classification

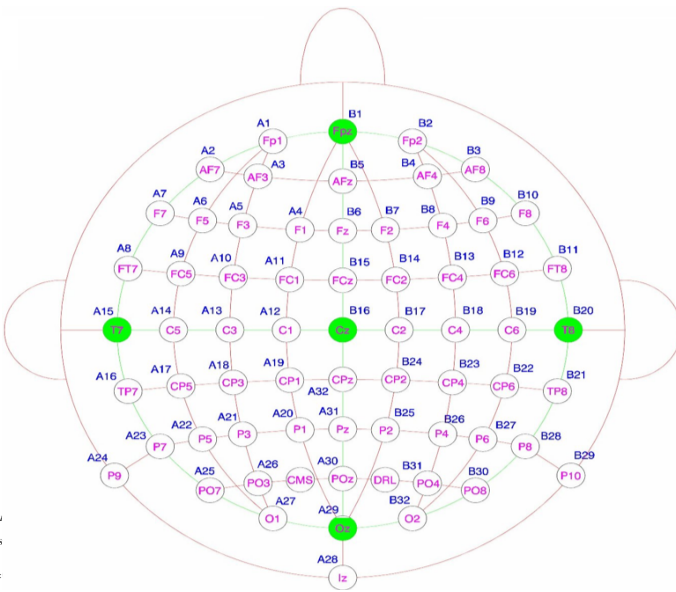
EEG

- EEG (Electroencephalography) is a recording of group of electrical potentials generated by neural activities in human brain

- EEGs are generally used to diagnose epilepsy, sleep disorders, depth of anesthesia, coma, encephalopathies and brain death



Raw EEG



10-20 system

ErrP Classification

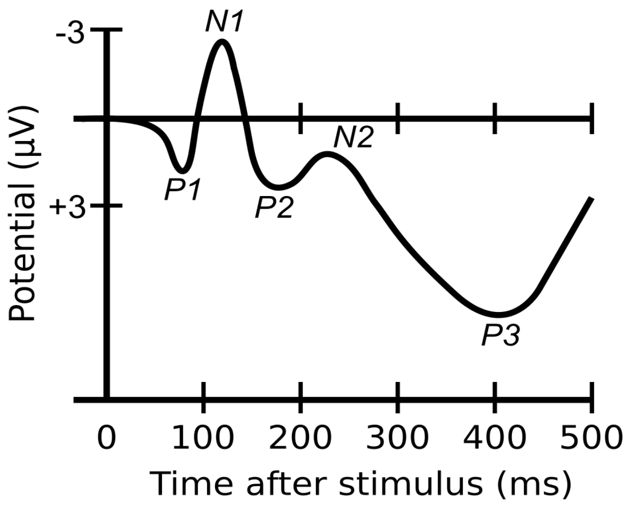
ERP

- EEG signals have many derivatives; one such is event-related potentials (ERP)
- ERP signals are generated by a population of neurons in response to a perceptual, cognitive or motor event, in opposition to spontaneous activity that reflects the brain activity related to volunteer self-paced tasks
- ERPs are widely used in the field of BCI for example to control wheel chair

Categorized according to latency and amplitude after the stimulus

P50 wave
N100 or N1 wave
P200 or P2 wave
N200 or N2 wave
N300 wave
P300 wave

N400 wave
Movement related cortical potentials
Contingent negative variation
Post imperative negative variation



T. C. Major and J. M. Conrad, “A Novel Principal and Independent Component Analysis Preprocessing Technique for Neural Network Classification of Electroencephalography Signals for Brain Computer Interface Development” May 2018.

ErrP Classification

ErrP

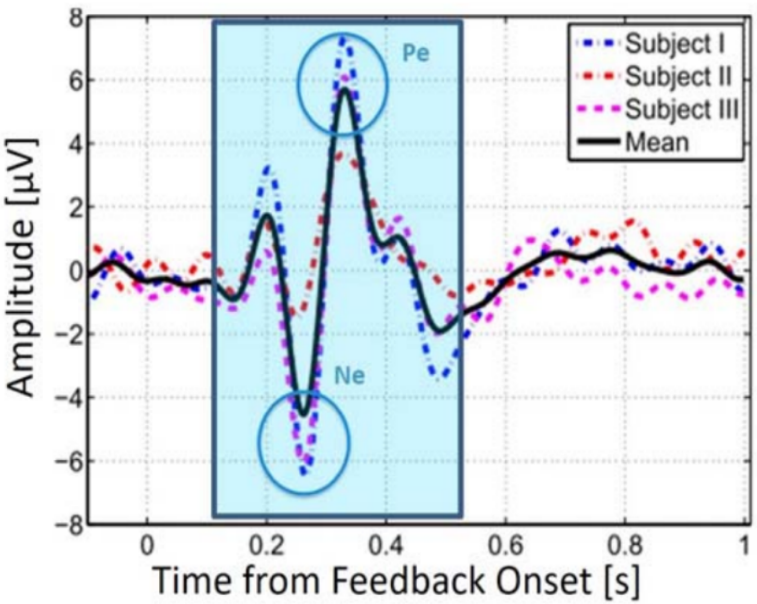
- In the late 1990s, an event-related potential where ErrPs were recorded in focused attention condition by presenting visual stimuli with correct and incorrect trials

- Later, several studies reported that such event related to error elicit a different characteristic pattern over medial-frontal areas appearing between 200 ms and 300 ms after an event has occurred

- **The ErrPs are characterized by an initial positive peak occurring at about 200ms after an event followed by a massive negative deflection at about 200-250ms and a second positive peak at about 320ms**

- These waveforms are reported to have a similar pattern in tasks using different modalities and maintained the almost identical when tested after several months

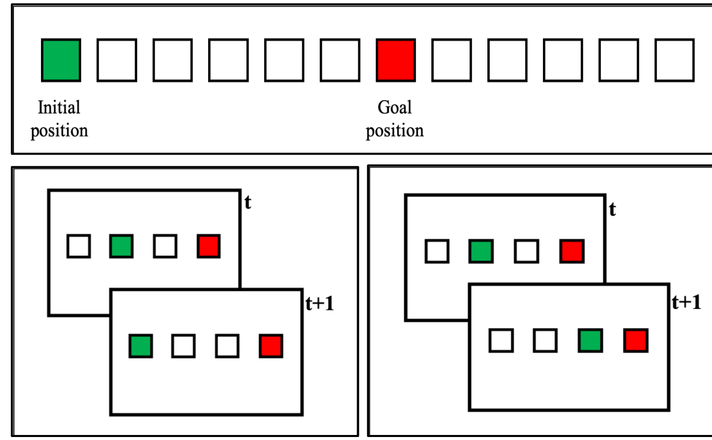
- the methods used to classify the signals can very well be generalized can be used in applications related to error processing



ErrP Classification

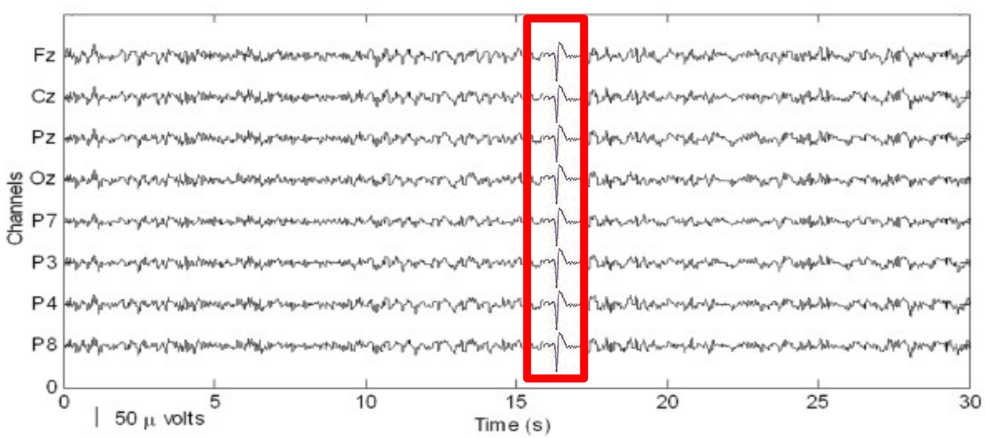
ERP: Dataset

- 64 electrode data was recorded as per 10/20 International system and sampled at 512 Hz
- 6 subjects of mean age about 27.83$\pm$2.23 separated by several weeks
- Error related potentials were elicit when the user monitors the behavior of an external device upon, he or she has no control



P_{err}	Subject 1	2	3	4	5	6
20%	51	50	54	211	628	643
40%	-	-	54	211	628	643

Dataset of 64 electrode system			
6 subjects	2 events	10 trails	120 datasets

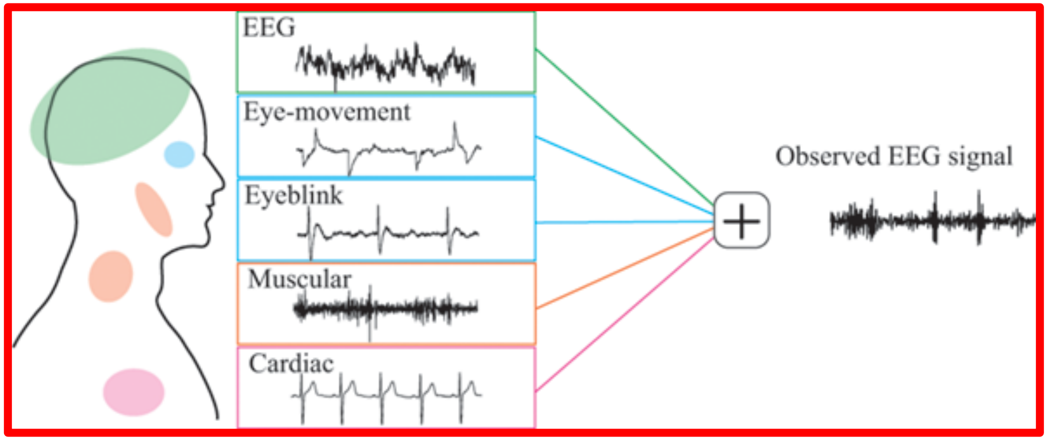


R. Chavarriaga, A. Sobolewski, and J. d. R. Milln, "Errare machinale est: the use of error-related potentials in brain-machine interfaces," Frontiers in Neuroscience, vol. 8, p. 208, 2014.

ErrP Classification

Preprocessing

- EEG signals are recorded using non-invasive methods
- The recorded output is a mixture of the EEG from the neural shooting potentials and other sources added.
- Raw EEG signals will have very low amplitude and are prone to low or poor signal-to-noise (SNR) ratio
- To obtain cleaner EEG signals, preprocessing is carried on the raw EEG which filters unwanted components combined with the raw EEG
- Thus it can reduce the computational load on the rest of the BCI components



EEG artifacts
Cardiac artifacts
Electrode artifacts
External device artifacts
Muscle artifacts
Ocular artifacts

Kanoga, Suguru, and Yasue Mitsukura. "Review of Artifact Rejection Methods for Electroencephalographic Systems." *Electroencephalography* (2017): 69.

ErrP Classification

Filtering

Spatial

Common average filter (CAR)

- The assumption is that the electrodes are spaced equally over the head such that the mean voltage distribution equals zero

$$V_i^{CAR} = V_i^{ER} - \frac{1}{n}\sum_{j=1}^{n} V_j^{ER}$$

- CAR provides EEG recordings which is reference free

Spectral

Bandpass filter

- Improve the accuracy and robustness of BMI by reducing the influence of the activities that lie out of the range of frequency of interest
- Bandpass filters can reduce the effects of power line noise, ECG, EMG and other noises outside the frequency range of interest
- EEG analysis higher order, Butterworth filter is used with a pass-band frequency of 1-10Hz because they are known to be relatively slow cortical potential

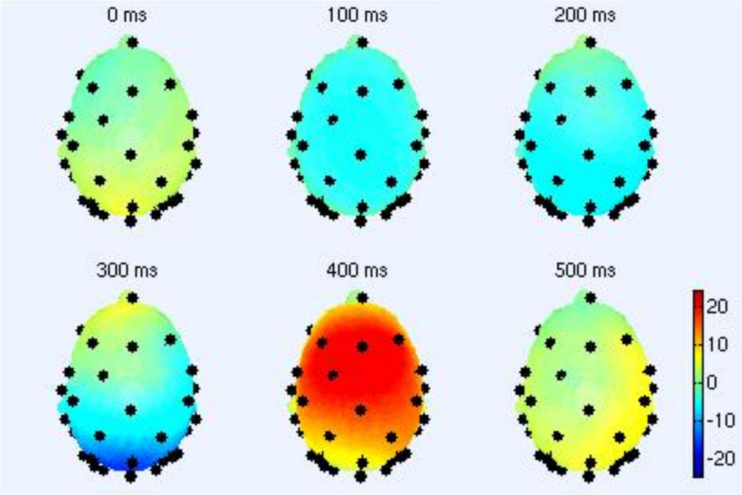
Alhaddad, Mohammed J. "Common average reference (CAR) improves P300 speller." *International Journal of Engineering and Technology* 2, no. 3 (2012): 21.

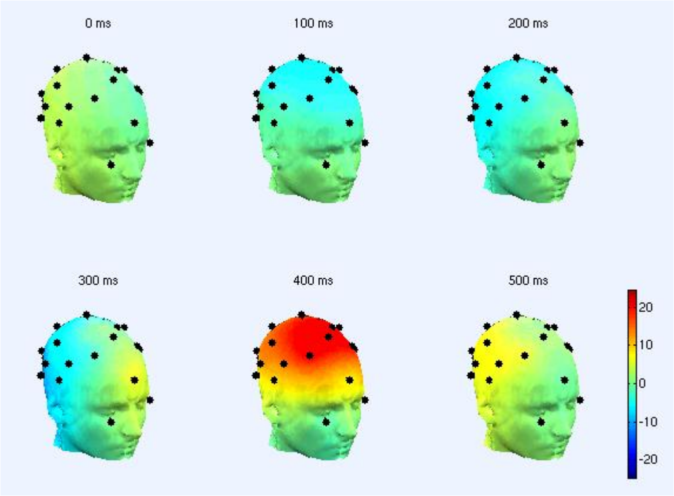
Arvaneh, Mahnaz, Cuntai Guan, Kai Keng Ang, & Chai Quek. "Optimizing EEG channel selection by regularized spatial filtering & multi band signal decomposition." In *IASTED Int. Conf. Biomedical Engg.*, pp. 86-90. 2010.

ErrP Classification

Electrode Selection

- EEG channel selection improves BMI performance by removing irrelevant channels
- Enhances user convenience from the use of lesser channels
- Decreases the number of features (dimensionality reduction)
- Removing of electrodes also removes the noise contamination





Delorme, Arnaud, and Scott Makeig. "EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis." Journal of neuroscience methods 134, no. 1 (2004): 9-21.

ErrP Classification

Classification: State of the art methods

Authors	Purpose	Classifier type	Accuracy
Ferraz and Milan, 2008	Initial ErrP	Gaussian classifier	75.8%
Iturrate and team, 2009	Exp protocol	Support vector machine	80%
Jiaxin and Zhang, 2015	EOG and EEG to control robot	LDA	77%
Ehrlich and Cheng, 2016	Neuro based method to detect error in robot action	LDA	73.2%
Zhang and Chen, 2018	Visual cues to control wheel chair	Elastic net	79%

- Gaussian Classifier, logistic regression, support vector machines, linear discriminant analysis and its variations
- As per 10-year BCI update in 2018, CNN were being used and performed best on P300 signal classification

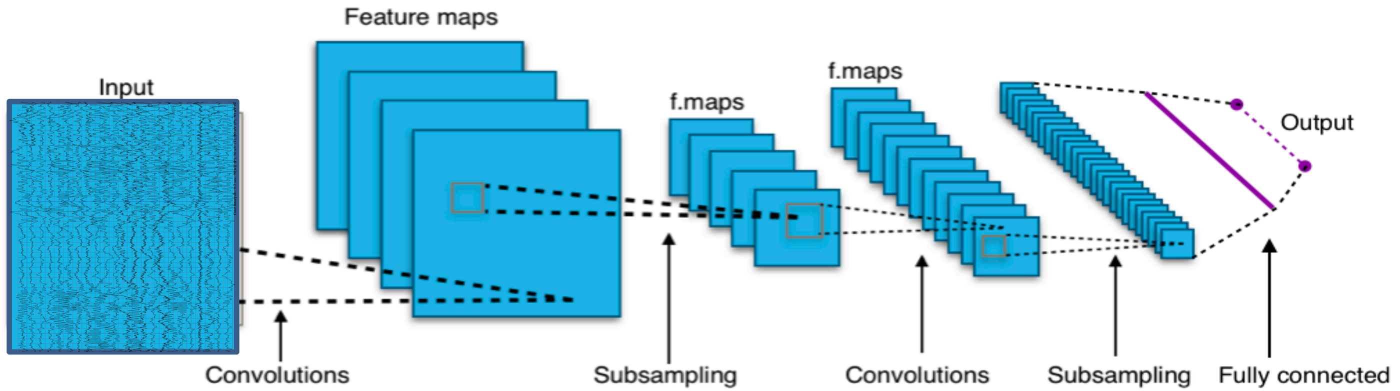
Lotte, Fabien, Laurent Bougrain, Andrzej Cichocki, Maureen Clerc, Marco Congedo, Alain Rakotomamonjy, and Florian Yger. "A review of classification algorithms for EEG-based brain–computer interfaces: a 10-year update." *Journal of neural engineering* 15, no. 3 (2018)

ErrP Classification

Classification: Convolutional Neural Networks

- ANNs that can learn local patters in data using convolutions
- Architectures varies from shallow to deep with multiple layers
- Advantage of using CNNs are they are well suited for end to end learning
- These architectures have outperformed in the field of computer vision, speech processing, yet new to EEG signals classification

Layers
Convolutional layer
Pooling layer
ReLU activation
Fully Connected
Batch Normalization
Dropout layer



Schirrmeister, Robin Tibor et al. "Deep learning with convolutional neural networks for EEG decoding and visualization." *Human brain mapping* vol. 38,11 (2017): 5391-5420. doi:10.1002/hbm.23730

Self-learning

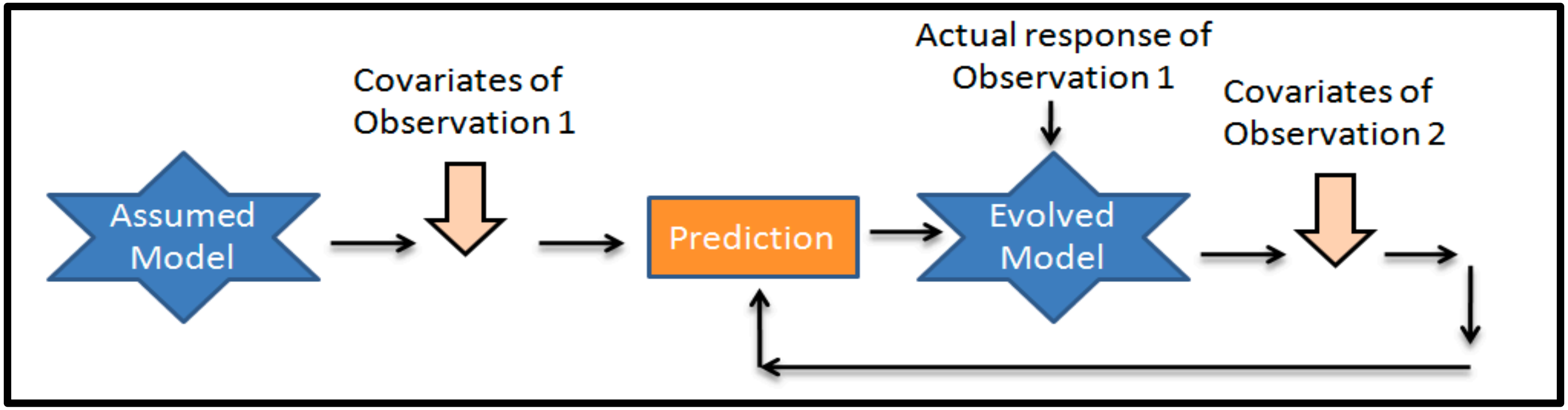
Robot learning

- Studies techniques allowing a robot to acquire novel skills or adapt to its environment through learning algorithms
- Learning can happen either through autonomous self-exploration or through guidance from a human teacher, like for example in robot learning by imitation

Online machine learning

- Type of machine learning in which data becomes available in a sequential order
- Used in situations where it is necessary for the algorithm to dynamically adapt to new patterns in the data in real time like stock market prediction
- Disadvantage is it is prone to catastrophic interference which can be addressed by increment learning approaches

Self-learning



Why Online learning?

- Data is available one at a time
- Robot needs to dynamically adapt to classifying objects in real time i.e., as per the person choice
- It will learn faster
- Learning on the go

Self learning

What type of objects?

- Researchers from Georgia Tech have put efforts in understanding the needs of motor impaired patients with amyotrophic lateral sclerosis (ALS)

- The survey was conducted to 23 patients by performing needs assessment (8) and in-person interviews (15).

43 objects classes were prioritized

Choi, Young Sang, Travis Deyle, Tiffany Chen, Jonathan D. Glass, and Charles C. Kemp. "A list of household objects for robotic retrieval prioritized by people with ALS." In *2009 IEEE International Conference on Rehabilitation Robotics*, pp. 510-517. IEEE, 2009.

Dataset

- Robot learning Lab, Cornell University

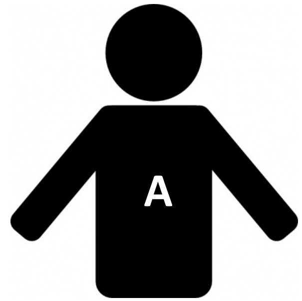
- Deep learning for detecting robotic grasps

Out of 43 only 15 were found

Lenz, Ian, Honglak Lee, and Ashutosh Saxena. "Deep learning for detecting robotic grasps." *The International Journal of Robotics Research* 34, no. 4-5 (2015): 705-724.

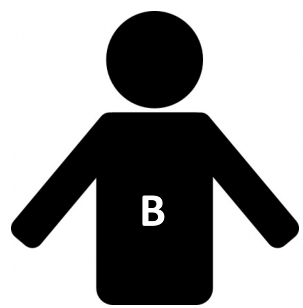
Self learning

Kitchen



Dressing

Study table



Washroom

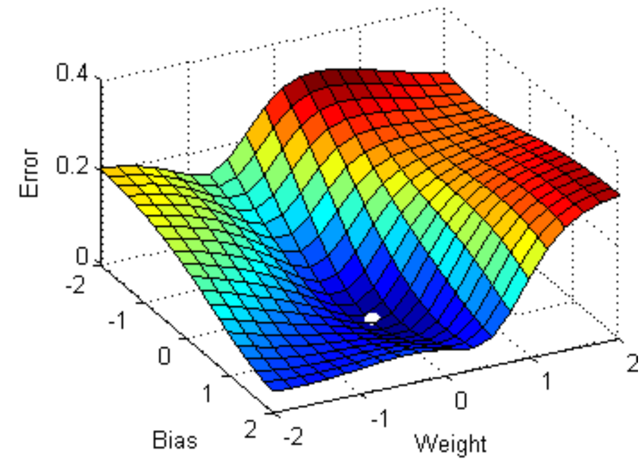
Self learning

Stochastic Gradient descent

- SGD is a type of gradient descent which is a first-order iterative optimization algorithm for finding the minimum of a function.

- Gradient descent is used to find local minima of any function; hence it is known as steepest descent.

- SGD is iterative method which is also used to optimize an objective function which is differentiable which is nothing but performing a stochastic an approximation of gradient descent optimization.



$$\theta = \theta - \eta . \nabla_\theta J(\theta; x^{(i)}; y^{(i)})$$

θ	Weight update
η	Learning rate
$x^{(i)}$	Input example
$y^{(i)}$	Target example

H. Robinds and S. Monro, "A stochastic approximation method," Annals of Mathematical Statistics, vol. 22, pp. 400–407, 1951.

Self learning

Stochastic Gradient descent

- The main difference between a standard GD and that of SGD is that, in gradient descent the samples are selected as a single group or the way they appear in the training set where as in SGD the samples are randomly selected or shuffled.

- SGD tries to find the global min. by adjusting its configuration of the network at every training example rather than decreasing the error by finding its gradient for the entire dataset, SGD decreases the error by approx. the gradient of one training example

- Another important aspect of using SGD is that it adjusts the network parameters such that if the model is struck at the local minimum, it makes a way to move out and approach towards global minimum. During this process, there are changes of increasing the error of the network, but this will make the algorithm reach the global minimum point.

H. Robinds and S. Monro, "A stochastic approximation method," Annals of Mathematical Statistics, vol. 22, pp. 400–407, 1951.

Self learning

Stochastic Gradient descent

- Advantages of using SGD is that it requires less memory to store the data as it sees one data at a time, it requires less computation when compared to true gradient descent and most of the times it stops at the global minimum

- Choose an initial vector of parameters w and learning rate η.
- Repeat until an approximate minimum is obtained:
  - Randomly shuffle examples in the training set.
  - For $i = 1, 2, \ldots, n$, do:
    - $w := w - \eta \nabla Q_i(w)$.

Algorithm

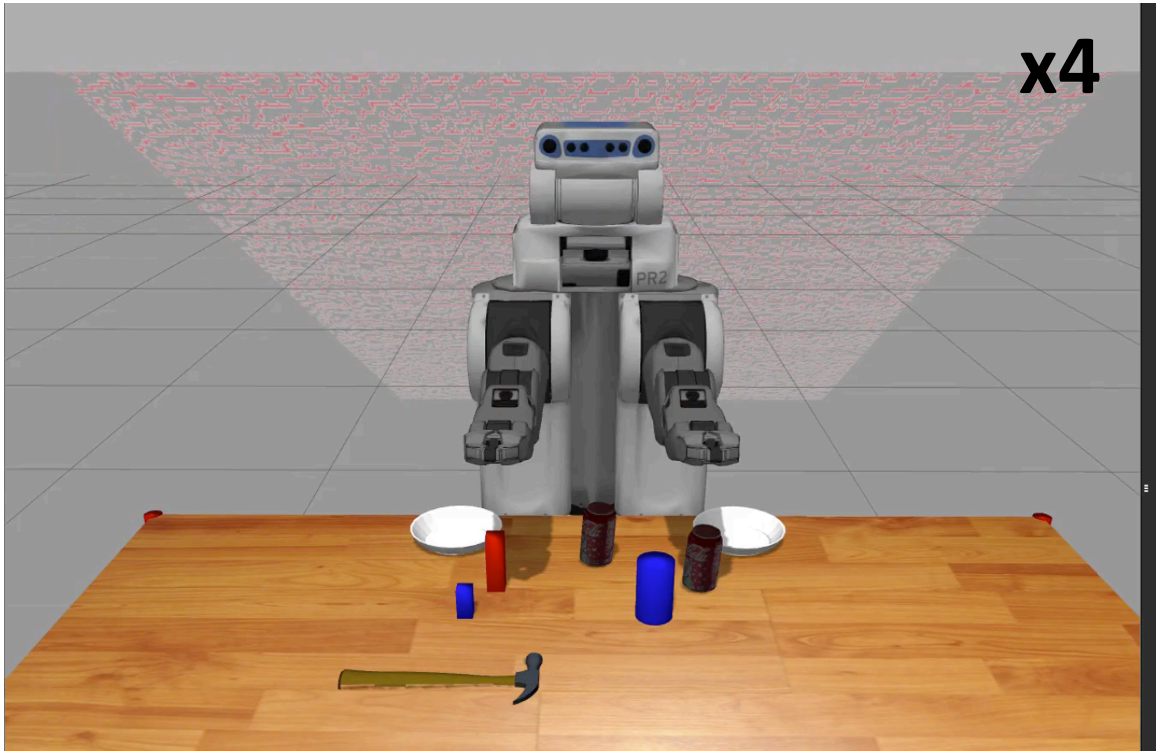
H. Robinds and S. Monro, "A stochastic approximation method," Annals of Mathematical Statistics, vol. 22, pp. 400–407, 1951.

Results

- Pick and place objects
- ErrP Classification
- Self-learning

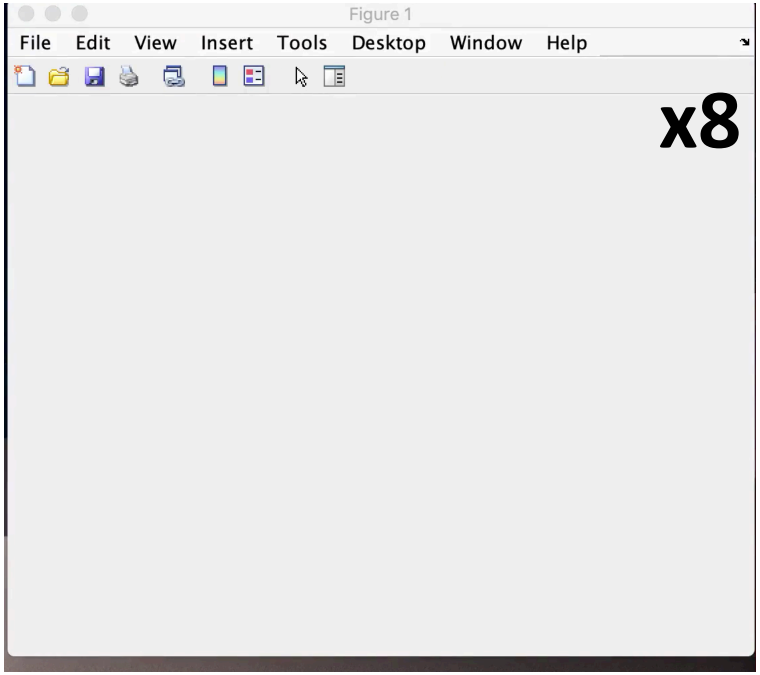
Pick and Place Objects

Initialization

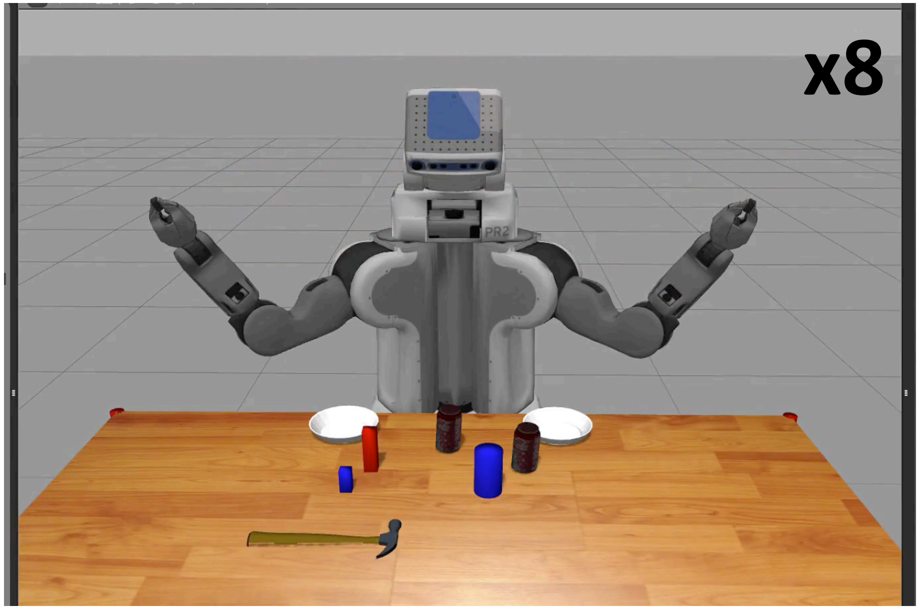


Pick and Place Objects

Objects classified as Class 1



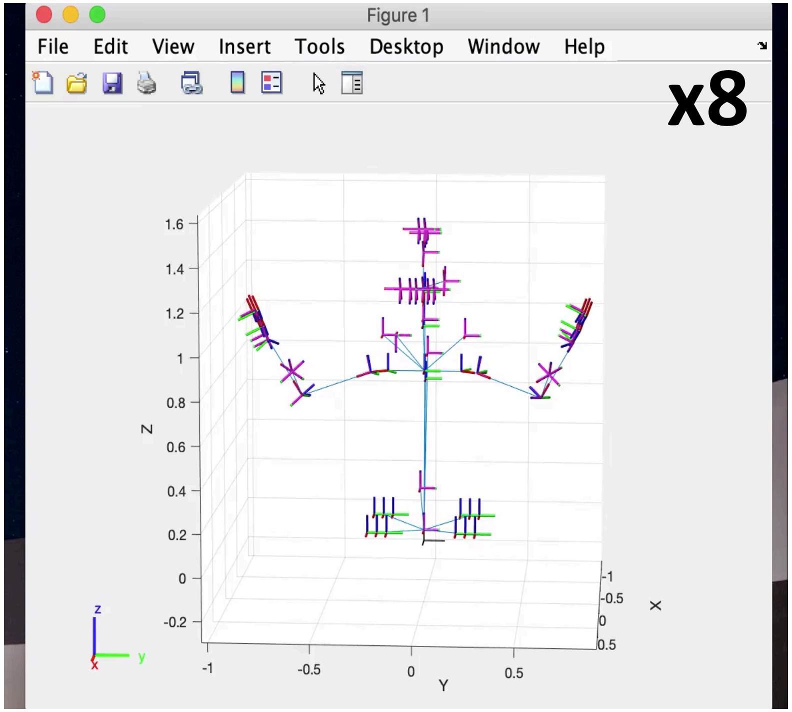
Trajectory Planning

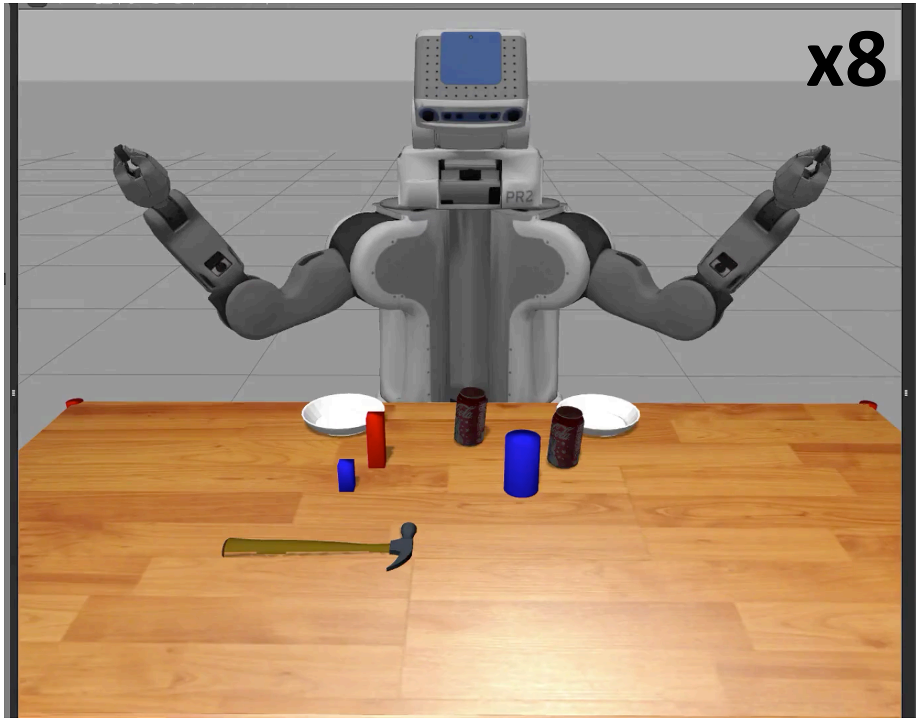


Robot view

Pick and Place Objects

Objects classified as Class 2



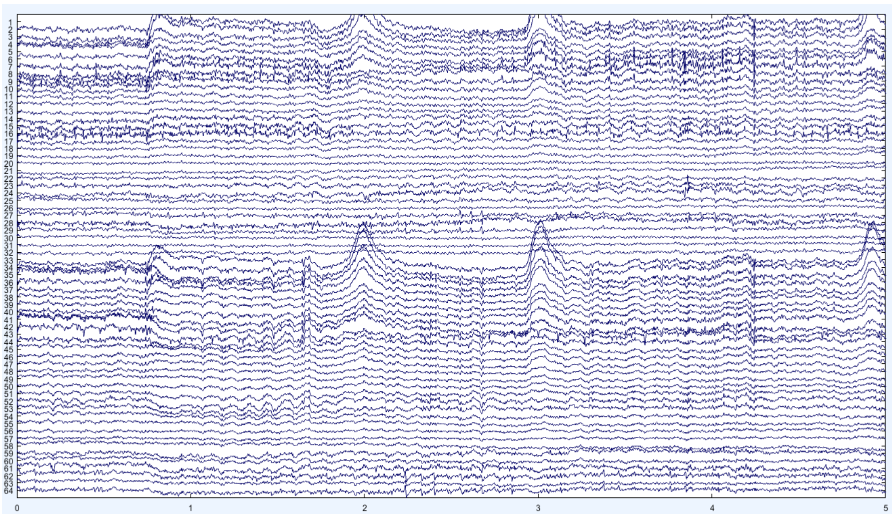


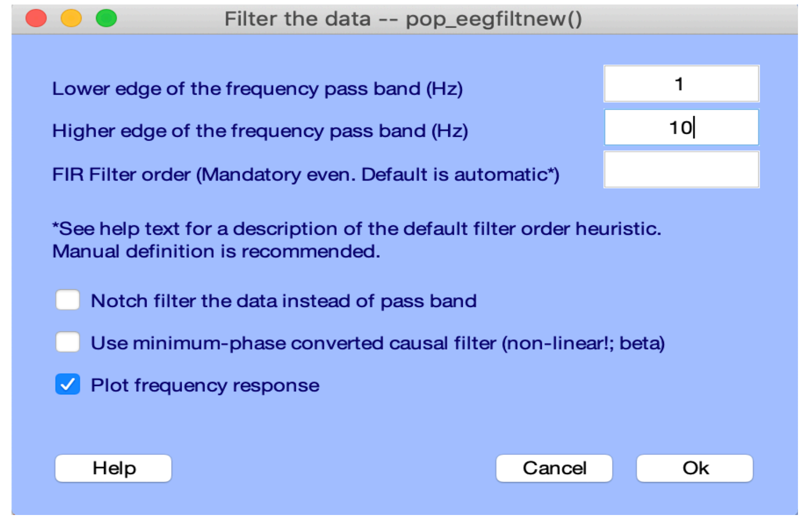
Trajectory Planning

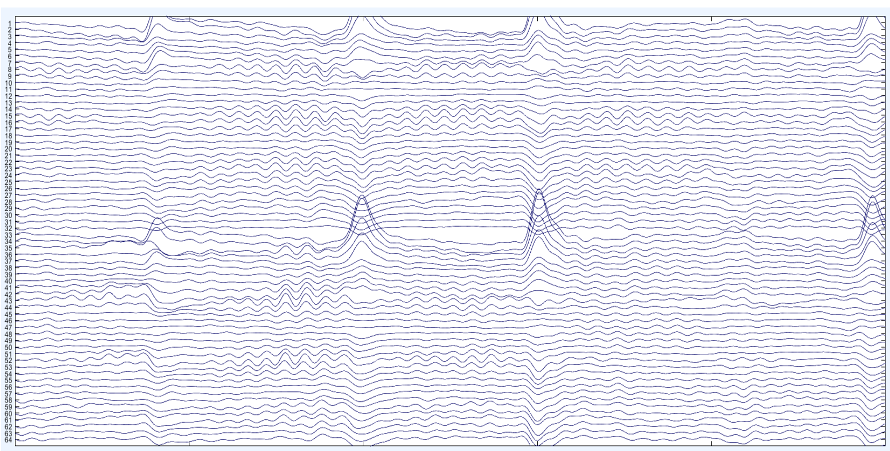
Robot view

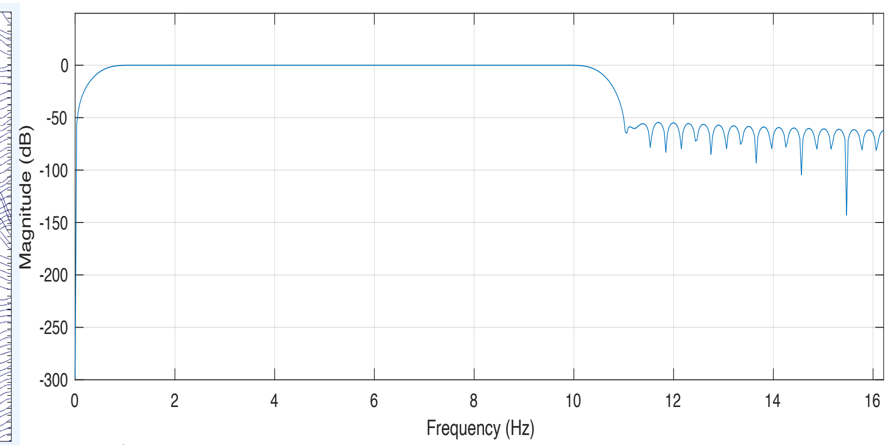
ErrP Classification

Preprocessing



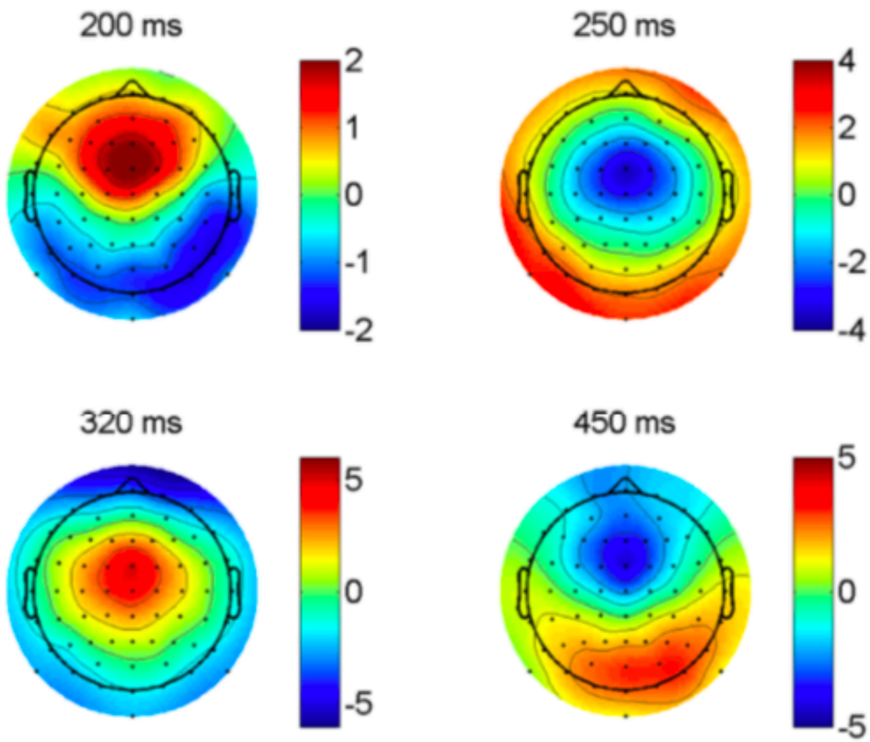


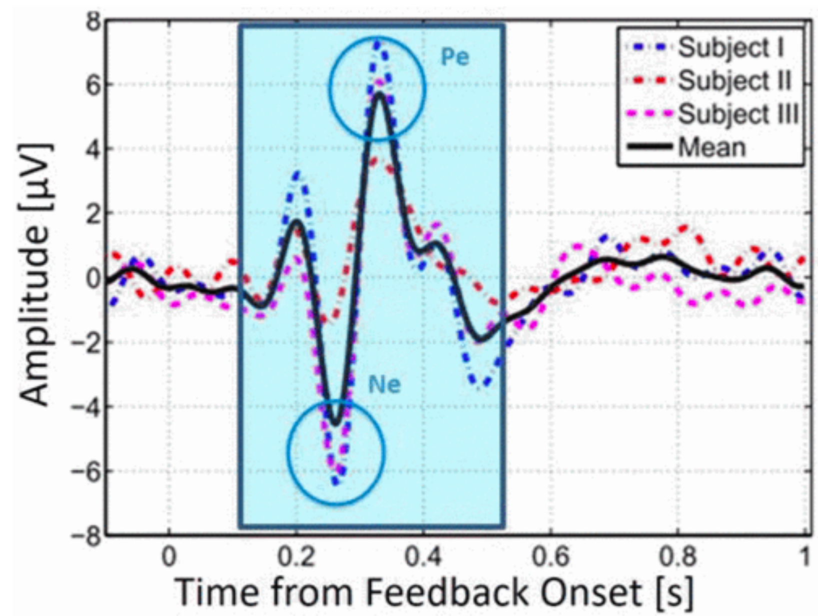




ErrP Classification

Electrode Selection





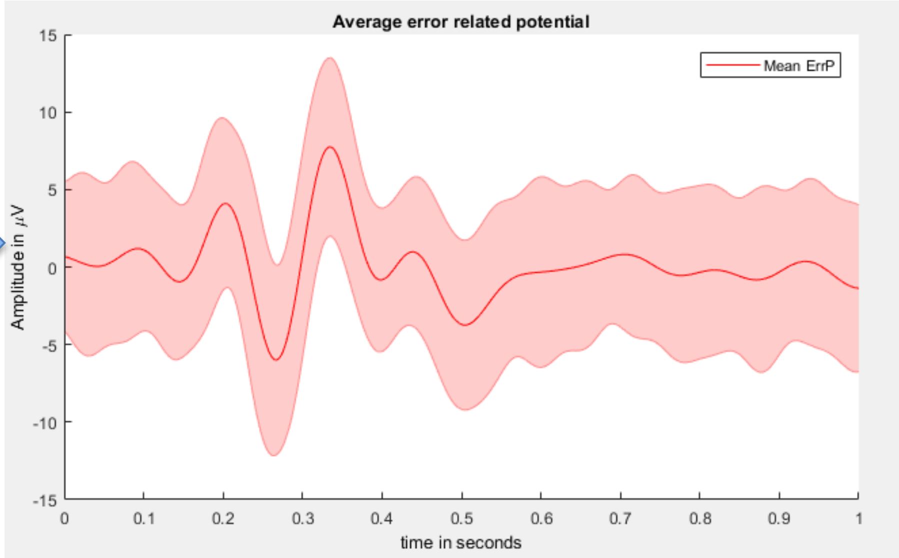
As most variation is at the region of Anterior Cingulate Cortex (ACC)

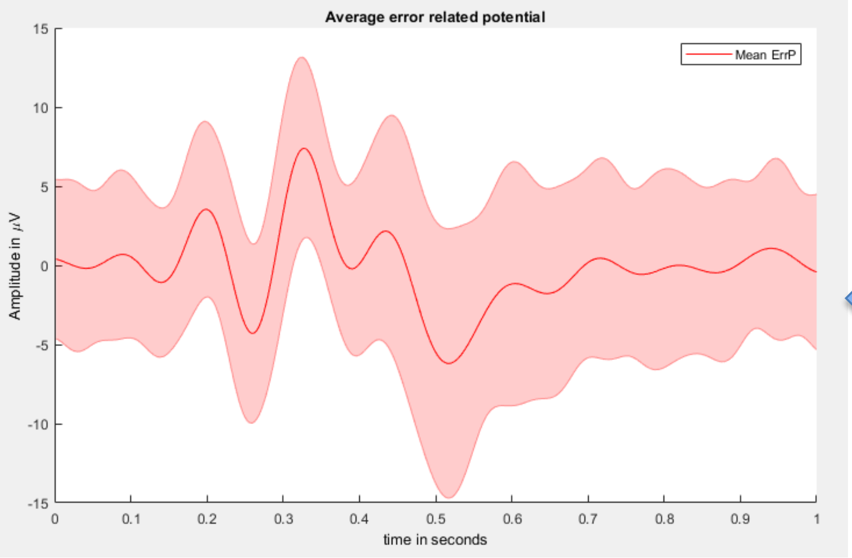
2 out of 64 were selected from that region

Holroyd, Clay B., and Michael GH Coles. "The neural basis of human error processing: reinforcement learning, dopamine, and the error-related negativity." *Psychological review* 109, no. 4 (2002): 679.

ErrP Classification

Averaged ErrP for electrode 'Cz'





Averaged ErrP for electrode 'FCz'

ErrP Classification

Classification

Layer	stage	kernel	filters
Input	-	-	0
Convolution	1	2x64	16
Convolution	2	1x64	32
ReLU activation	2		0
Max Pooling	2	1x2	0
Convolution	3	1x32	32
ReLU activation	3		0
Max Pooling	3	1x2	0
Convolution	4	1x16	64
ReLU activation	4		0
Max Pooling	4	1x2	0
Fully Connected	5	2	2
Softmax activation	5		0
Total Learnable Parameter : 239938			

Case 1:
Train Session 1 and Test Session 2

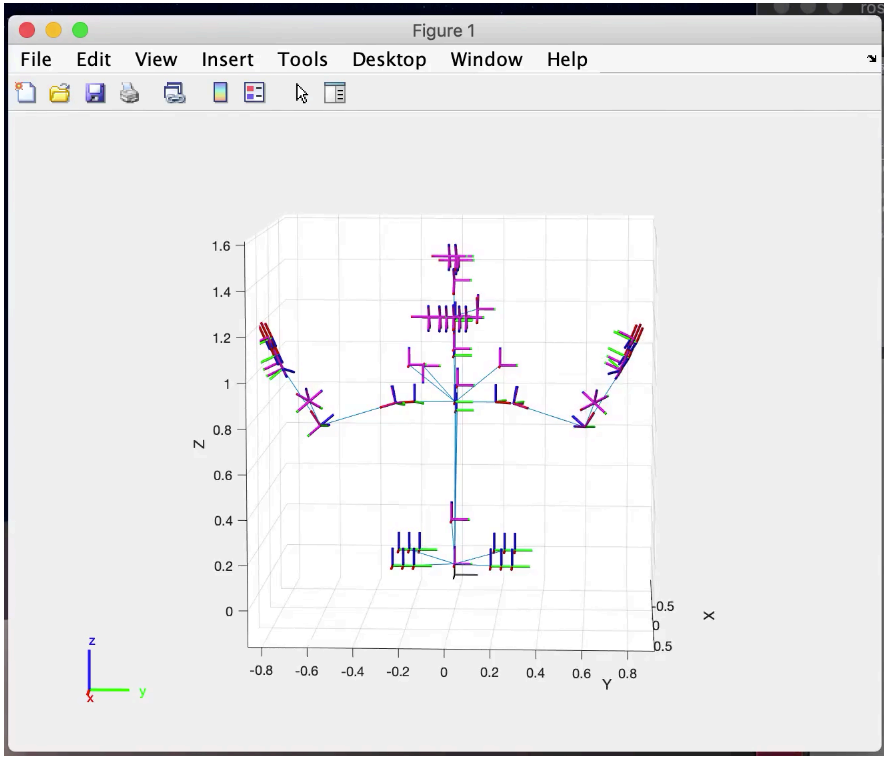
Case 2:
Train Session 2 and Test Session 1

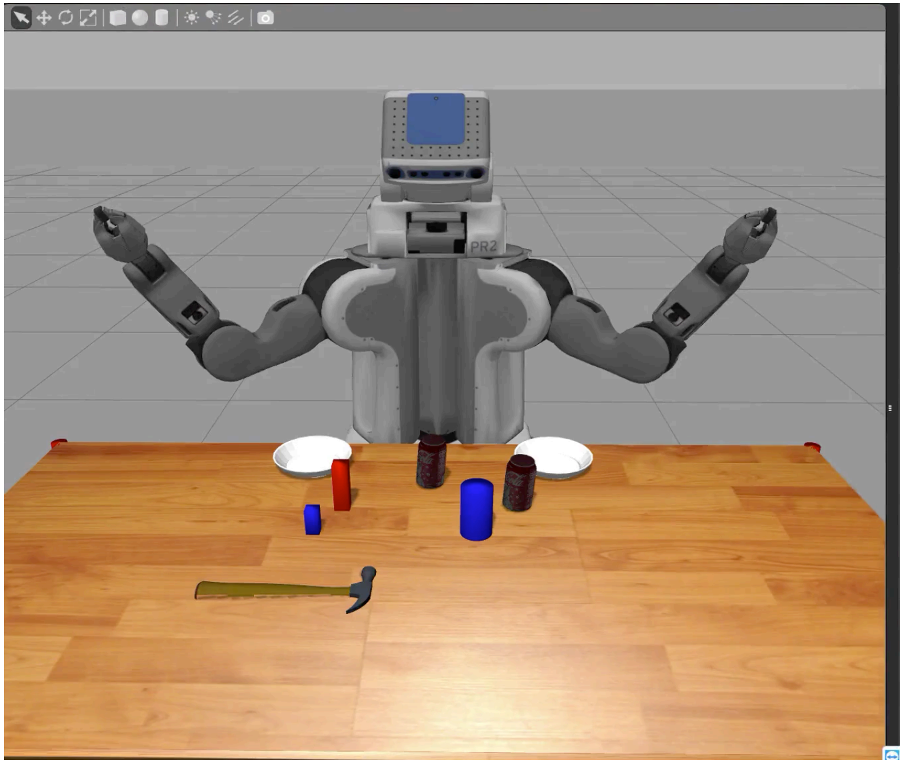
Sub	Case 1	Case 2
1	87.62%	85.35%
2	80.13%	82.77%
3	79.40%	80.01%
4	78.46%	83.28%
5	76.92%	78.59%
6	78.76%	76.46%

Schirrmeister, Robin Tibor, Jost Tobias Springenberg, Lukas Dominique Josef Fiederer, Martin Glasstetter, Katharina Eggensperger, Michael Tangermann, Frank Hutter, Wolfram Burgard, and Tonio Ball. "Deep learning with convolutional neural networks for EEG decoding and visualization." *Human brain mapping* 38, no. 11 (2017): 5391-5420.

Assistive robot + BCI

Trajectory Correction



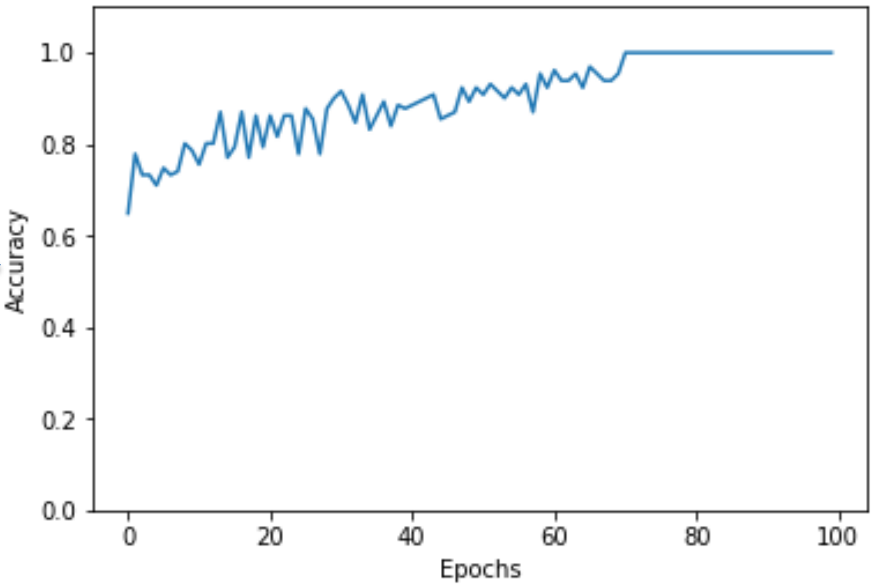


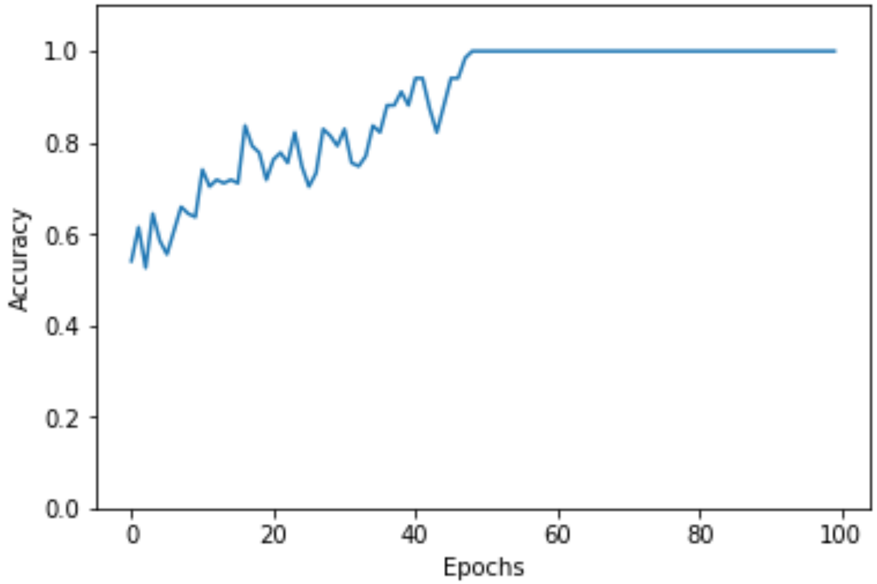
Trajectory Planning

Robot view

Self learning

Case 1





Case 2

Conclusions

- Developed a novel classifier to classify the normal EEG vs ErrPs using various deep learning techniques with classification rate of about 82%
- Demonstrated the applicability of error related potentials to robotic collaboration tasks
- Demonstrated the daily life tasks such as object sorting with the help of error related potentials as feedback for trajectory correction
- Developed a self learning algorithm that could learn on the go about the classification of objects in real time
- Demonstrated the adaptiveness of self learning algorithm with different user priorities

Acknowledgements

- Dr. James M. Conrad
- Dr. Andrew R. Willis
- Dr. Thomas P. Weldon
- Lab mates
- IEEE UNCC Student Chapter
- Friends and Well wishers


Thank you

Additional Slides

```
SGDClassifier(alpha=0.0001, average=False, class_weight=None, epsilon=0.1,
      eta0=0.0, fit_intercept=True, l1_ratio=0.15,
      learning_rate='optimal', loss='hinge', n_iter=5, n_jobs=1,
      penalty='l2', power_t=0.5, random_state=None, shuffle=True,
      verbose=0, warm_start=False)
```

Alpha = 0.0001

Learning rate
eta = 1.0 / (alpha * (t + t0))
where t0 is chosen by a heuristic proposed by Leon Bottou