Feature Selection for Classification of Motor Imagery Tasks Using Reinforcement Learning

Bio-Medical Computing Laboratory

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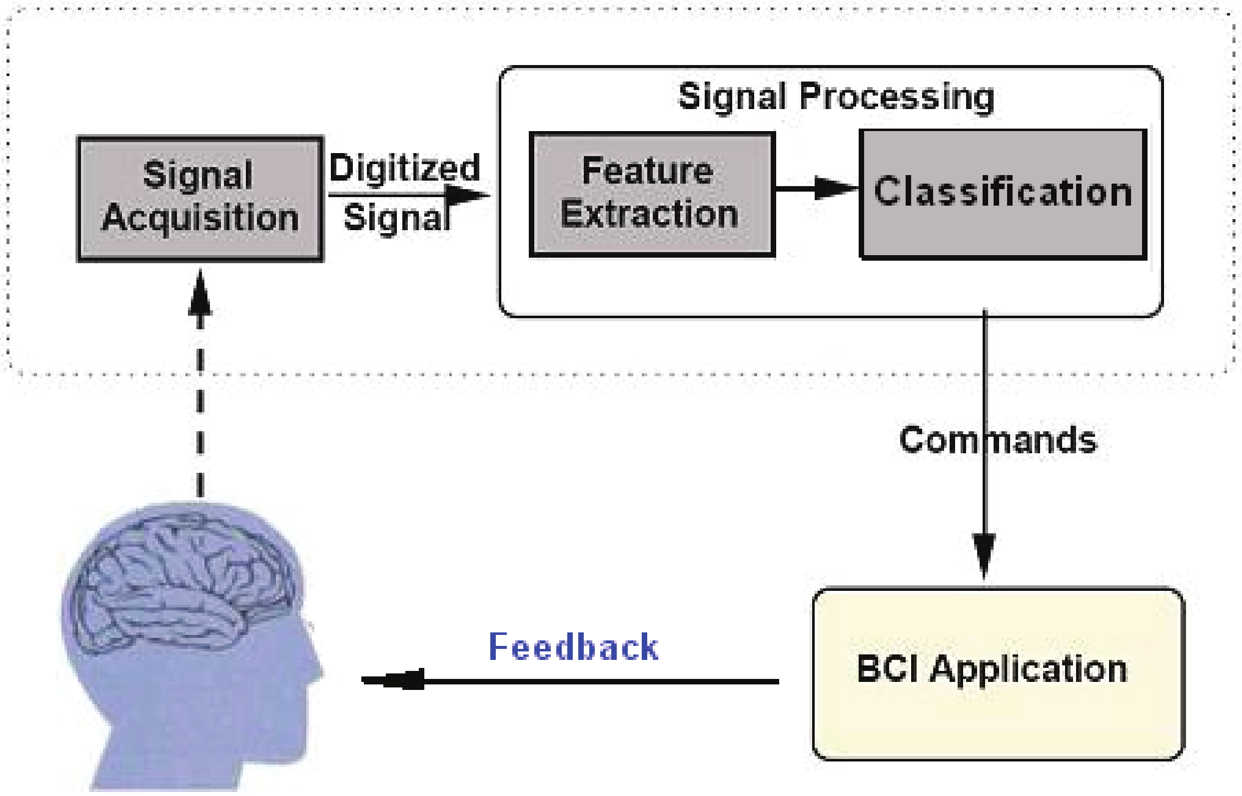
Index

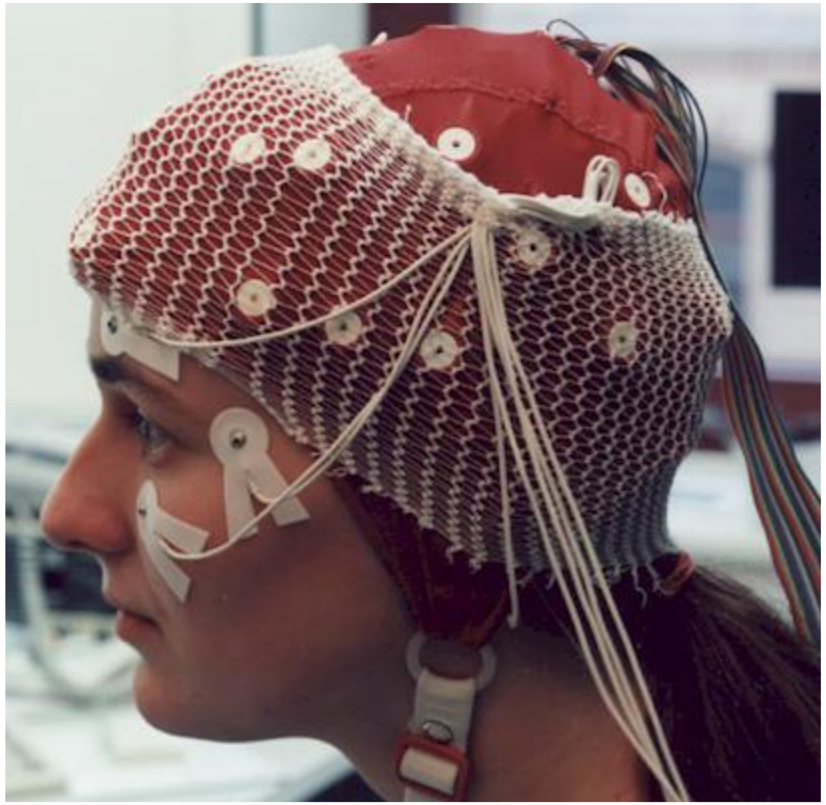
Introduction – Background

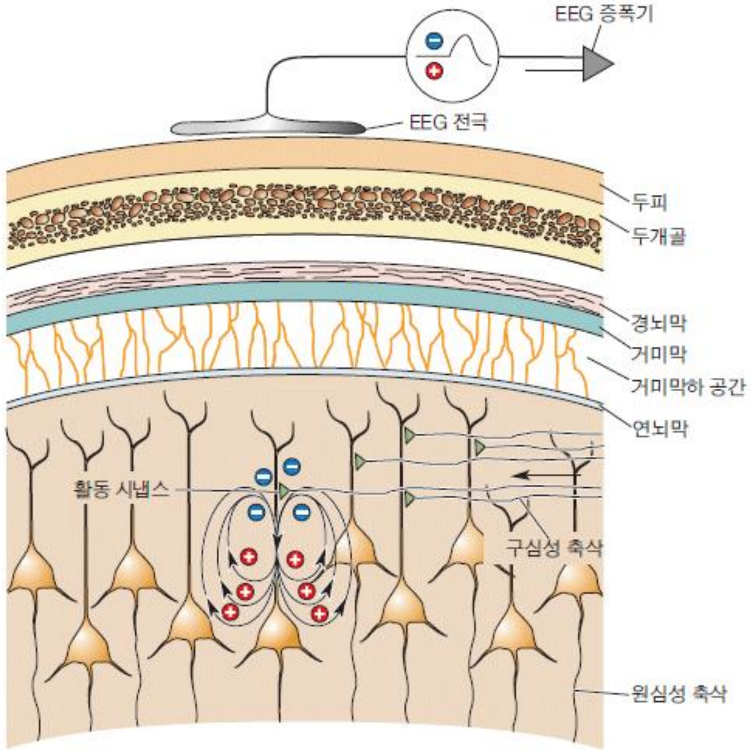
- Motor imagery (MI) is one of the Brain-Computer-Interface (BCI) paradigm based on EEG
- MI is based on Homunculus brain model



Introduction – Background

- What is the ElectroEncephaloGraphy (EEG)?





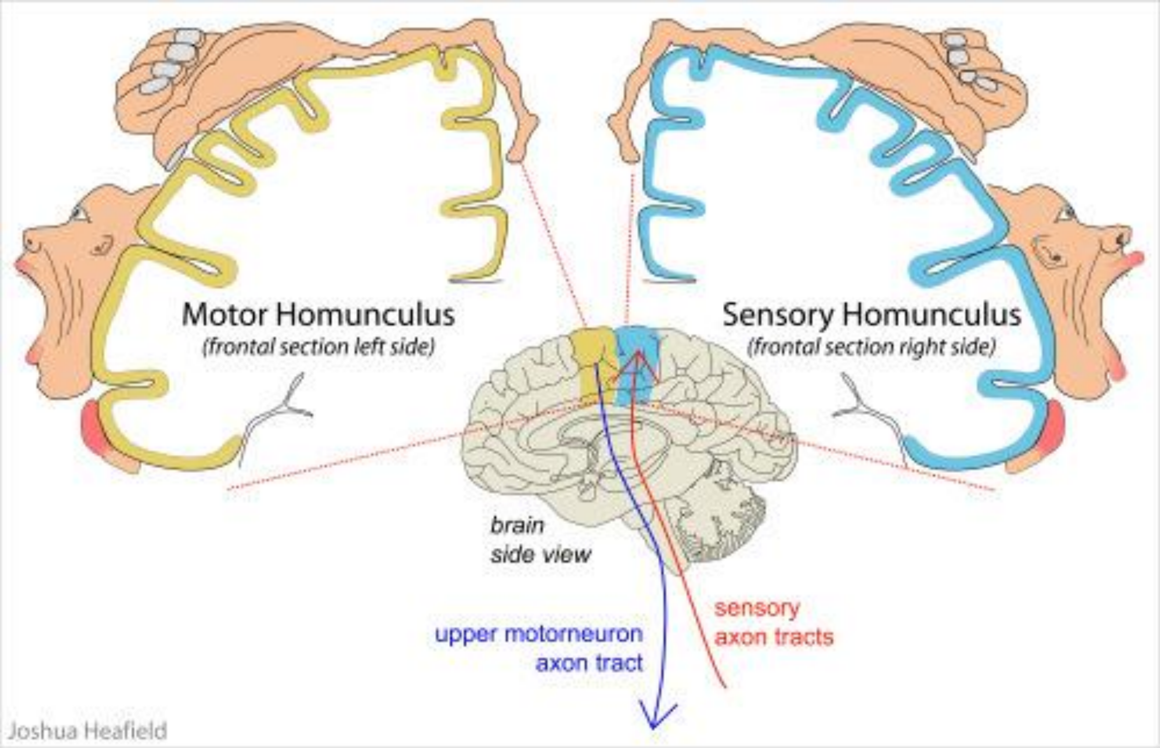
Introduction – Background

- How to measure brain signal

Invasive way

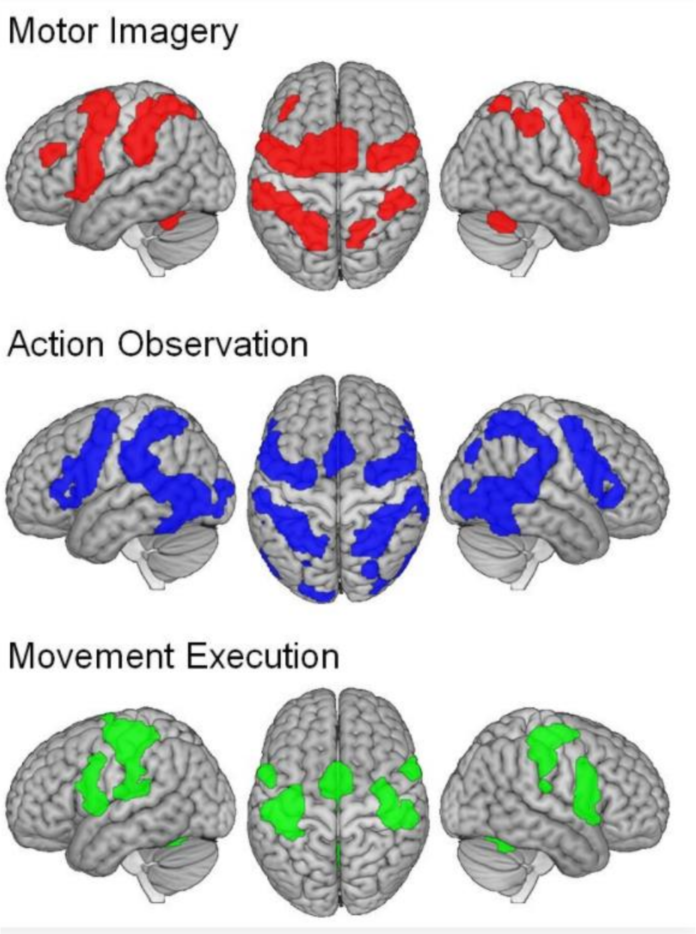
Non-invasive way

Introduction – Background

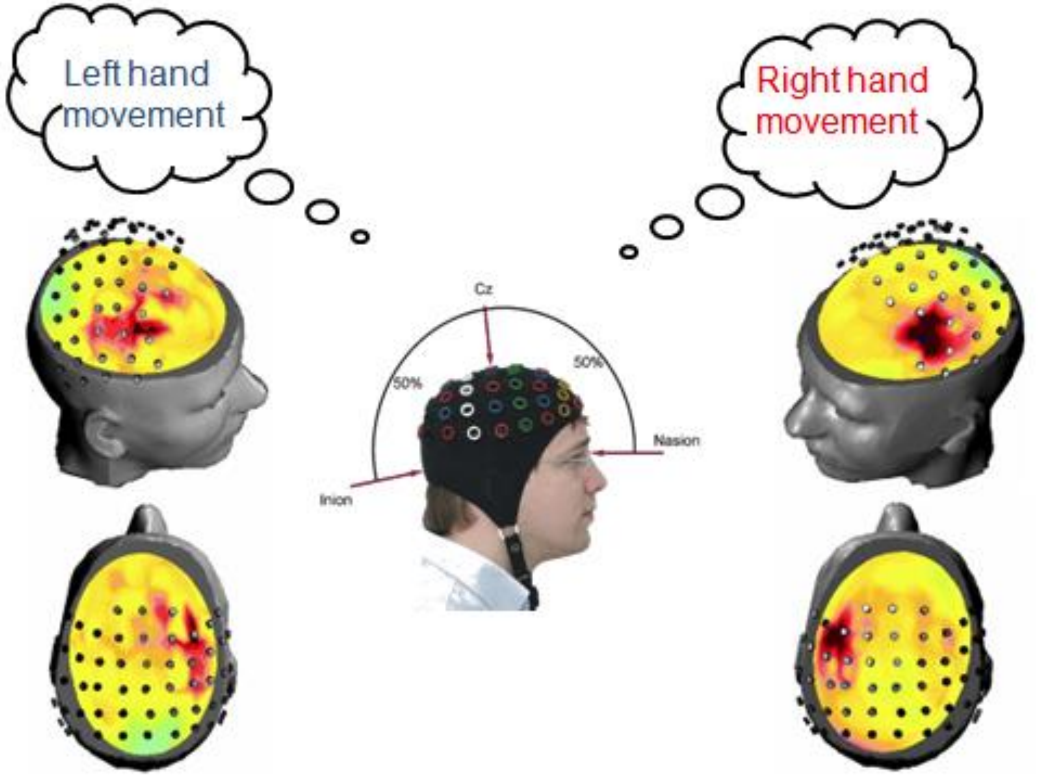


Homunculus Brain Model

Introduction – Background



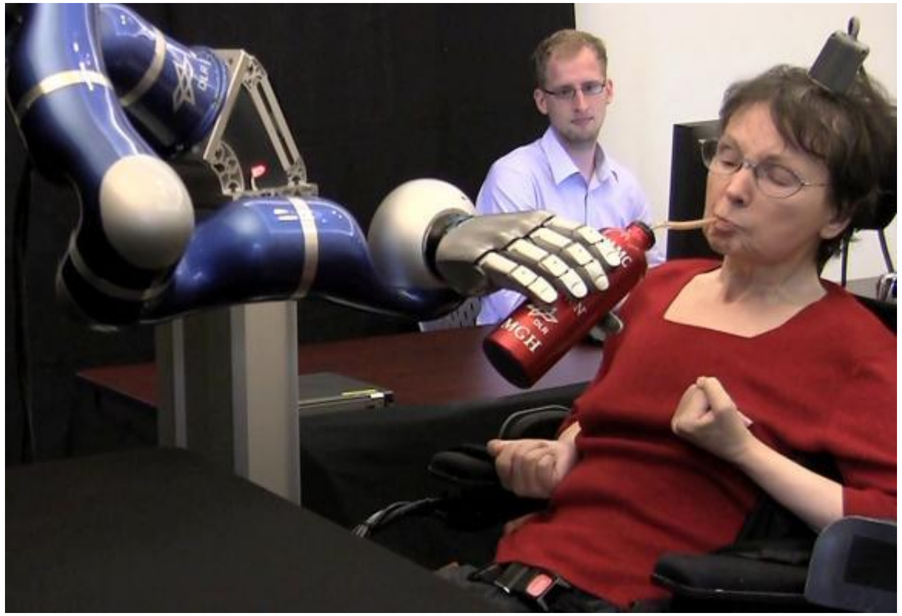
A Comparison Across Quantitative Meta-Analyses



Brain-Computer Interface for Motor Rehabilitation

Introduction – Background

- Currently, Motor imagery tasks can only be implemented in the laboratory scene
- The brain signals for motor imagery of most subjects are not easy to analyze.

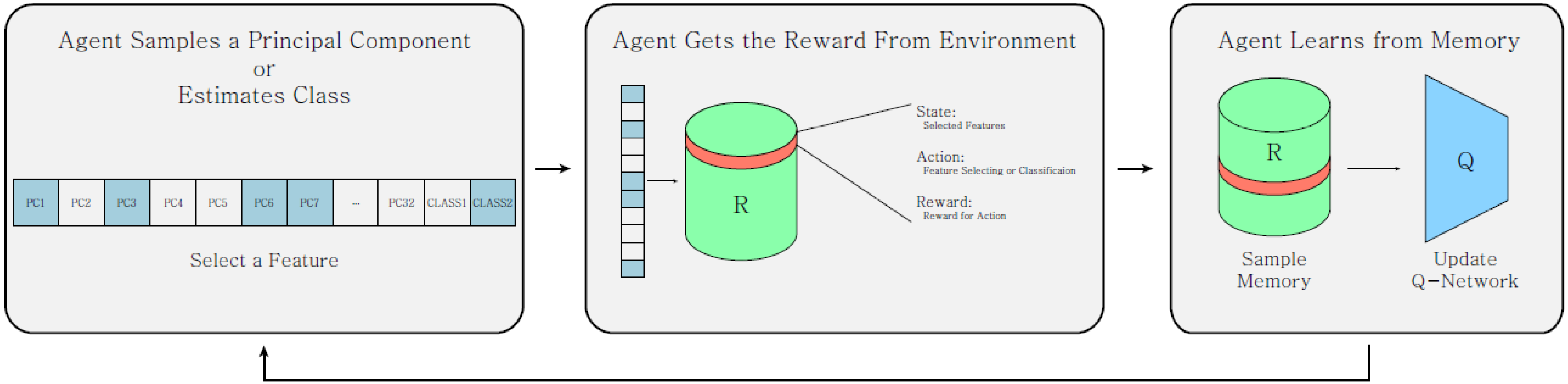


2008, Science & Technology: Monkey Uses Brain Power to Feed Itself With Robotic Arm

Introduction – Background

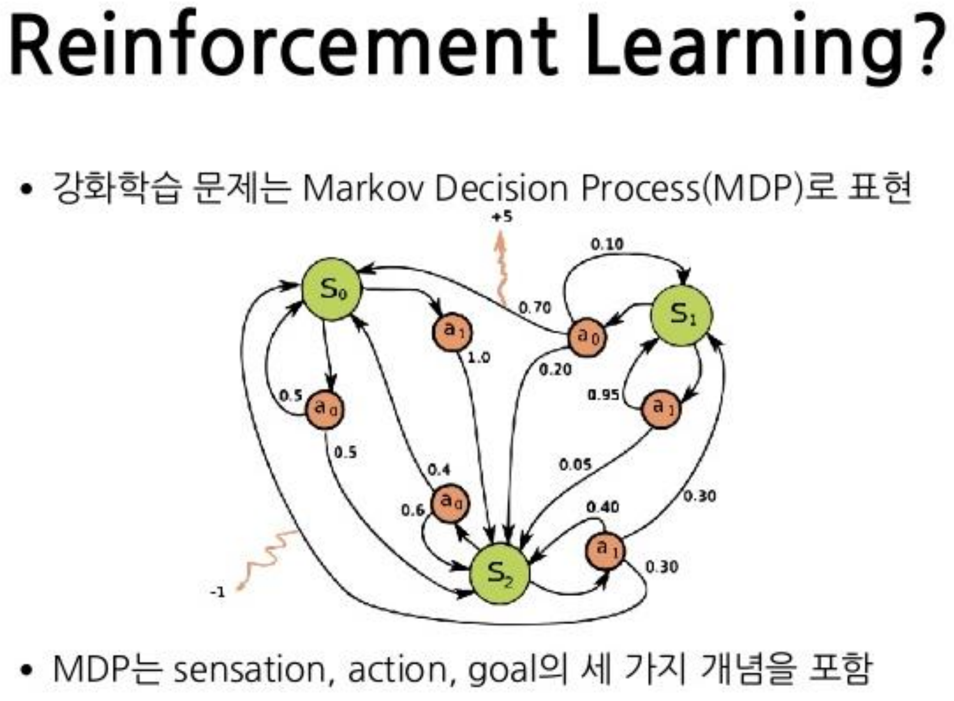
- For practical application…
  - need to reduce the amount of input data while increasing performance
  - Conventional method such as PCA, ICA, CSP employ eigenvalue for feaure reduction
  - Mutual Information feature reduction method use information entropy
  - Above those method could not guarantee maintaining good performance

    -> We apply reinforcement learning that directly approximates accuracy



Introduction – Background

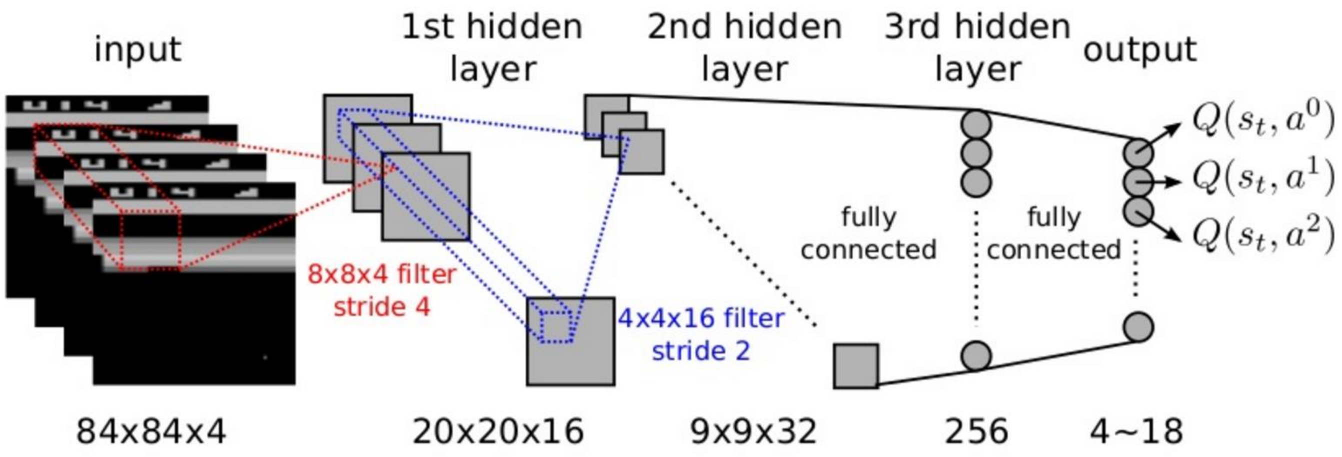
- Reinforcement Learning?
- Reinforcement learning problems can be expressed in Markov Decision Process (MDP)



- Sensation : Agent must be able to recognize the state of the environment
- Action : Agent decides action based on given state
- Goal : Must have a goal
  - The goal is to maximize rewards

Introduction – Background

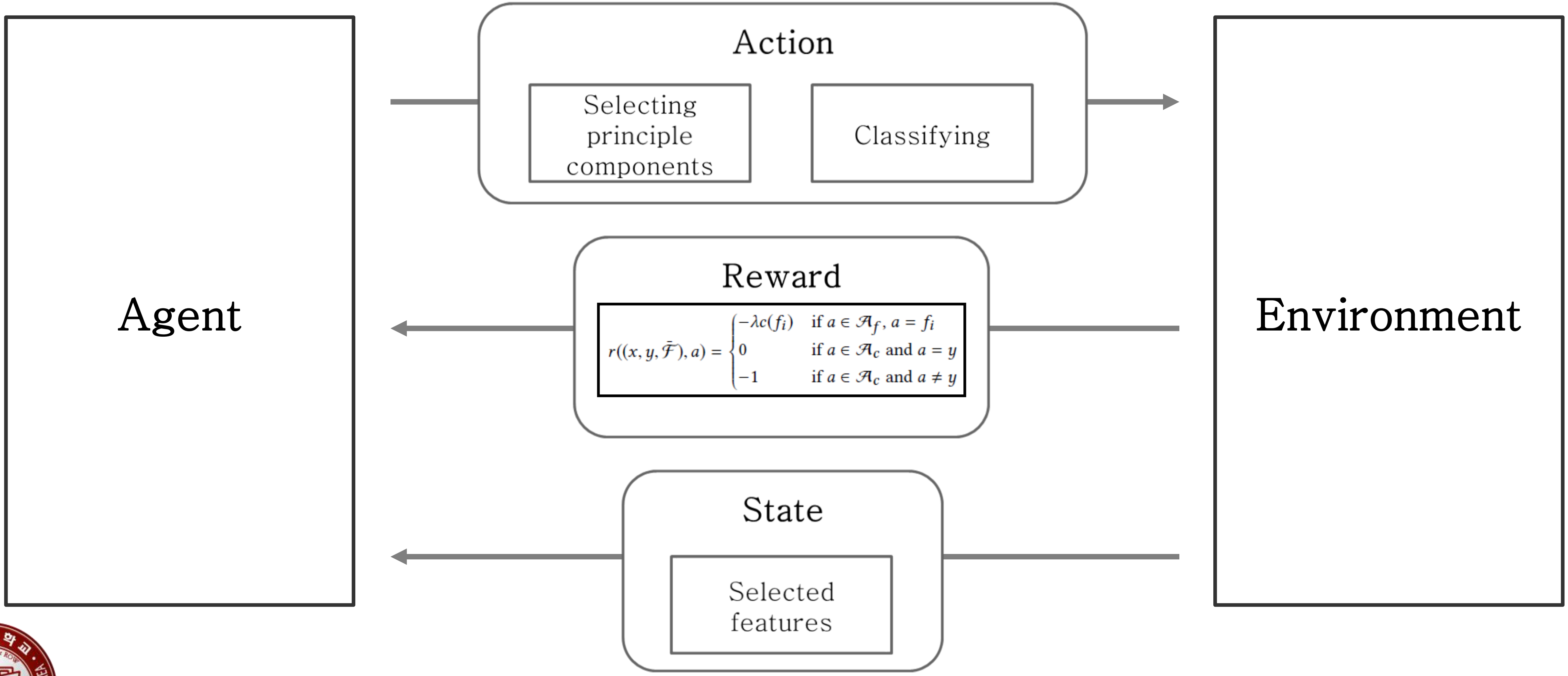
- Deep Q-Network (value-based reinforcement learning) [1]



$$q(s,a) = q(s,a) + \alpha(r + \gamma \max_{a'} q(s',a') - q(s,a))$$

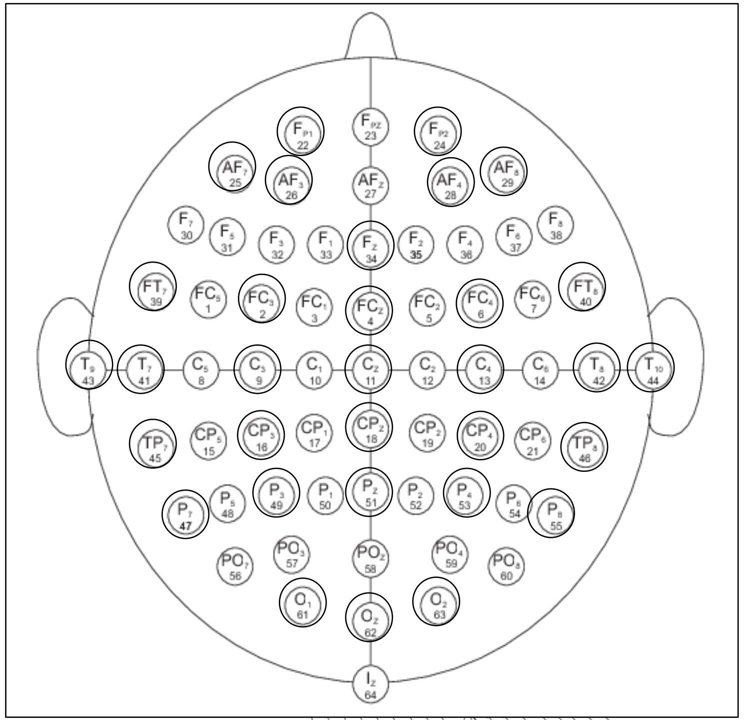
$$MSE = \left(r + \gamma \max_{a'} q_\theta(s',a') - q_\theta(s,a)\right)^2$$

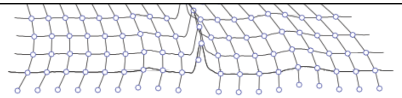
Introduction – Idea



Method - preprocessing

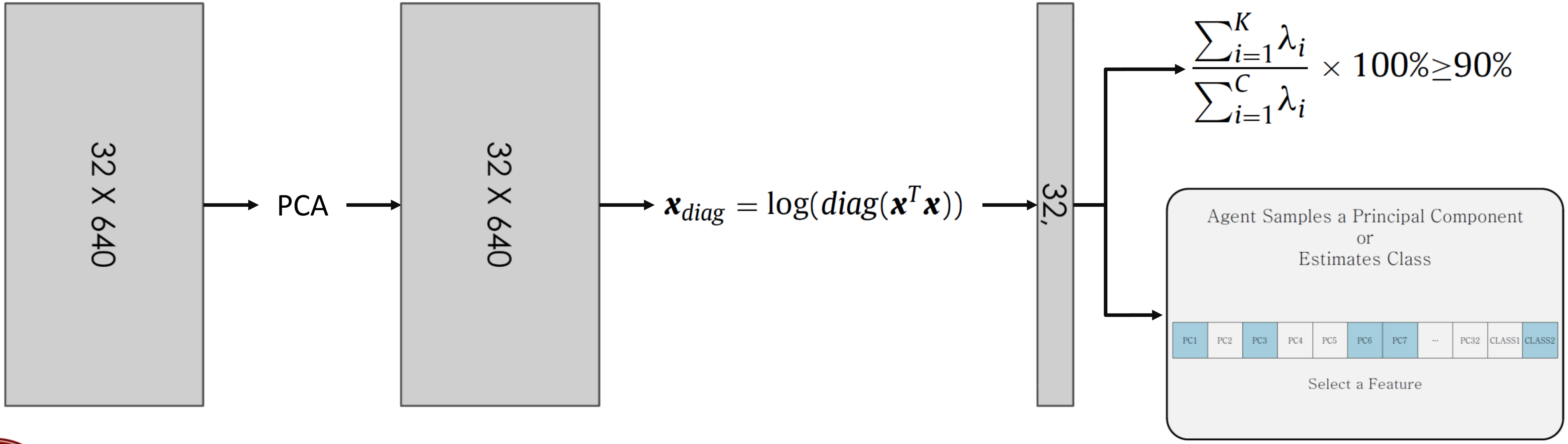
- Physiobank Motor/Mental Imagery (MMI) 109 subject database
- The EEGs were recorded from 64 electrodes according to the international 10-10 system
  - (Use the channels shown in the figure below)
- 45 trials for the left- and right-hand tasks
- sampling frequency of 160 Hz giving 640 samples (4 sec)





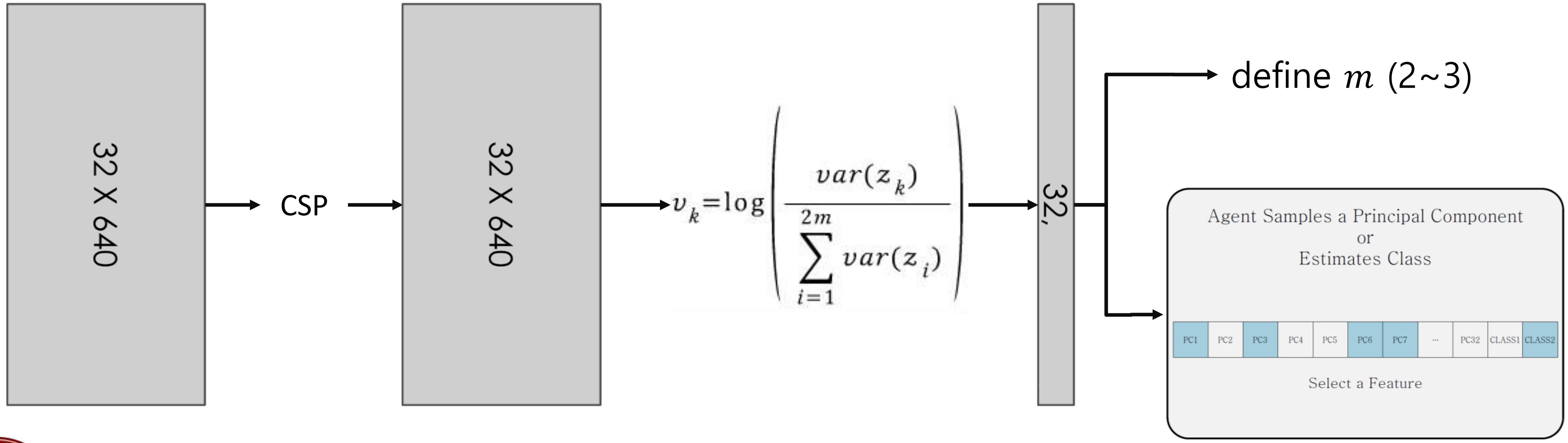
Comparison with Conventional Method

- To leave alpha and beta waves, 8-25 Hz 5th order Butterworth IIR filtering
- Feature extraction method
  - Principal Component Analysis

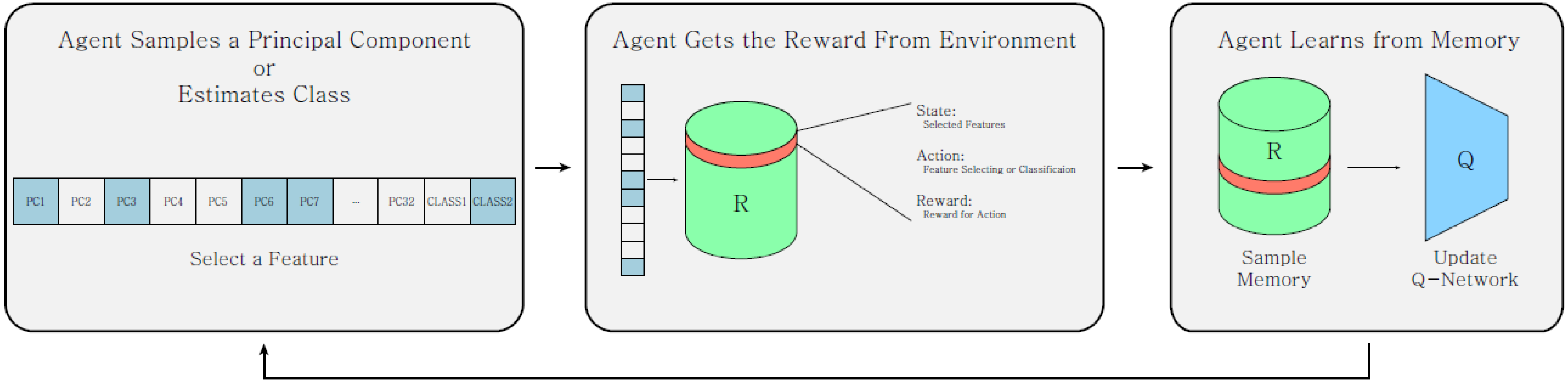


Comparison with Conventional Method

- Feature extraction method
  - Common Spatial Pattern

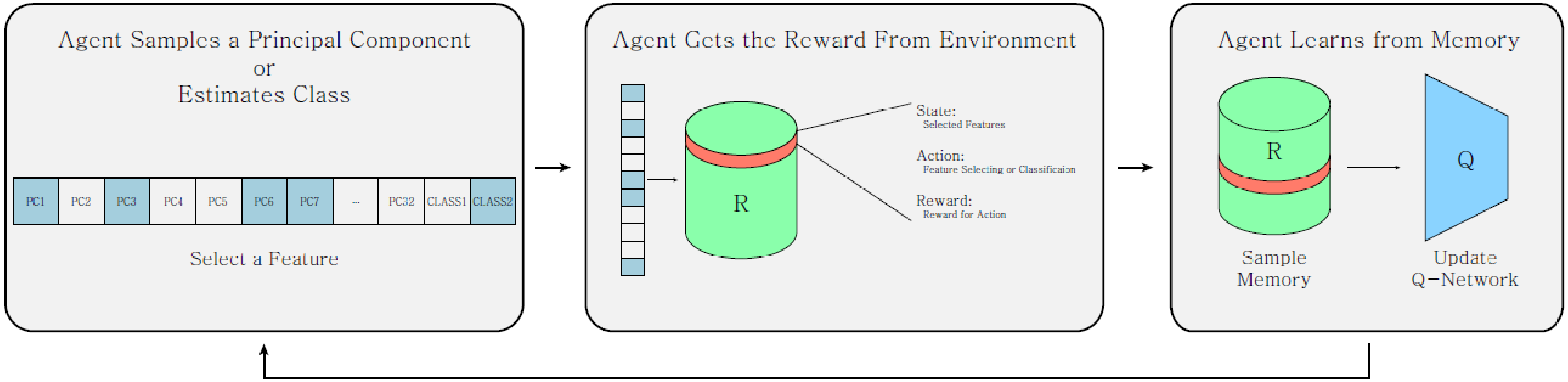


Proposed Method – Structure



- DQN (DDQN + Dueling DQN) [2][3]
  - DDQN - overestimation을 방지하기 위해 두 개의 Q-value를 사용
  - State Q-value와 State-Action Q-value를 분리 하여 사용
- Action에 따른 state의 변화와 reward를 Experience Replay Memory에 저장
  - Bootstraping 하여 랜덤하게 update
- Agent가 feature를 하나씩 선택하는 방식으로 episode를 진행
  - Feature를 선택하다가 Classifying 할 경우, episode 종료

Proposed Method – Structure



- ε-greedy 정책에 따라 각 feature와 class를 선택
- feature를 많이 선택할 수록, 틀릴 수록 누적보상이 적어진다.

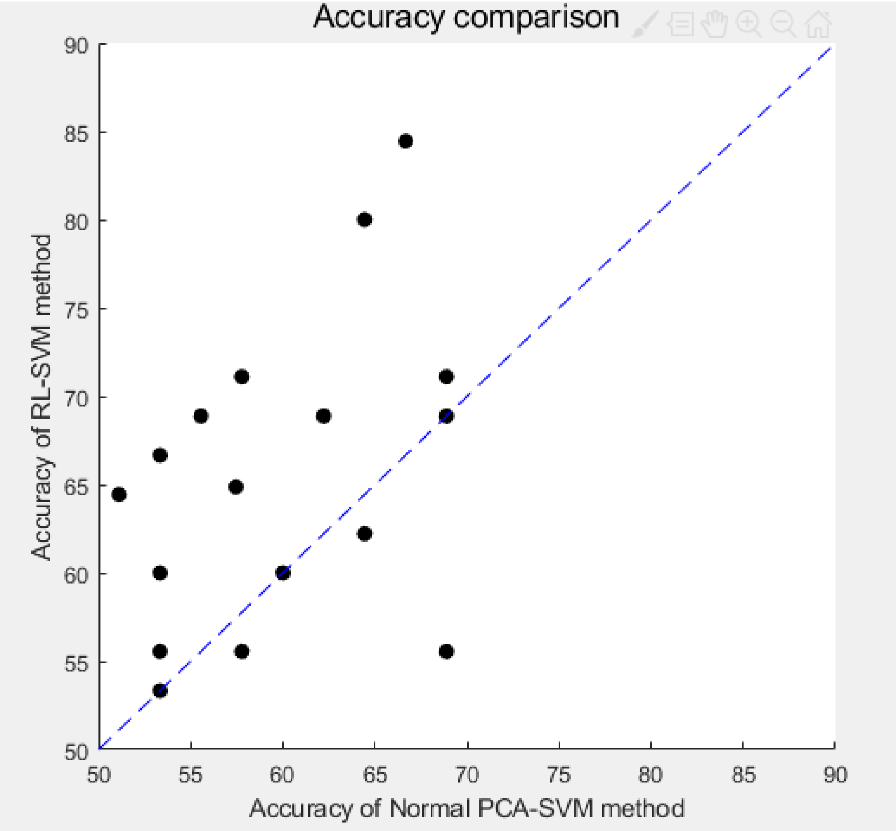
λ의 값에 따라 feature선택의 Cost를 정할 수 있다.

$$r((x, y, \bar{\mathcal{F}}), a) = \begin{cases} -\lambda c(f_i) & \text{if } a \in \mathcal{A}_f,\ a = f_i \\ 0 & \text{if } a \in \mathcal{A}_c \text{ and } a = y \\ -1 & \text{if } a \in \mathcal{A}_c \text{ and } a \neq y \end{cases}$$

Proposed Method – Evaluation

- Use features found through reinforcement learning algorithm as input data of classifier
  - Random Forest
  - Support Vector Machine
- Compare with other Feature Reduction algorithms for performance check of reinforcement learning algorithm
  - Mutual Information (MI)
  - eigenvalue-based Principal Component analysis (PCA)
  - eigenvalue-based Common Spatial Pattern (CSP)
- Leave-one-out cross validation (LOOCV) – intra subject test

Result


Accuracy comparison
Accuracy of RL-SVM method
Accuracy of Normal PCA-SVM method
50
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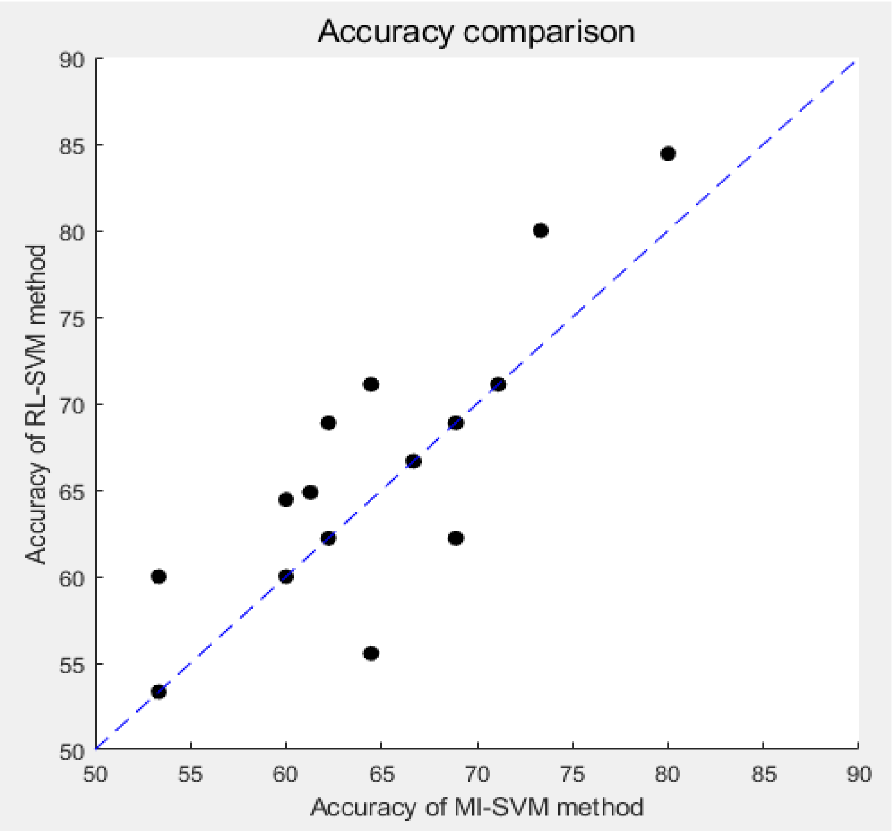
90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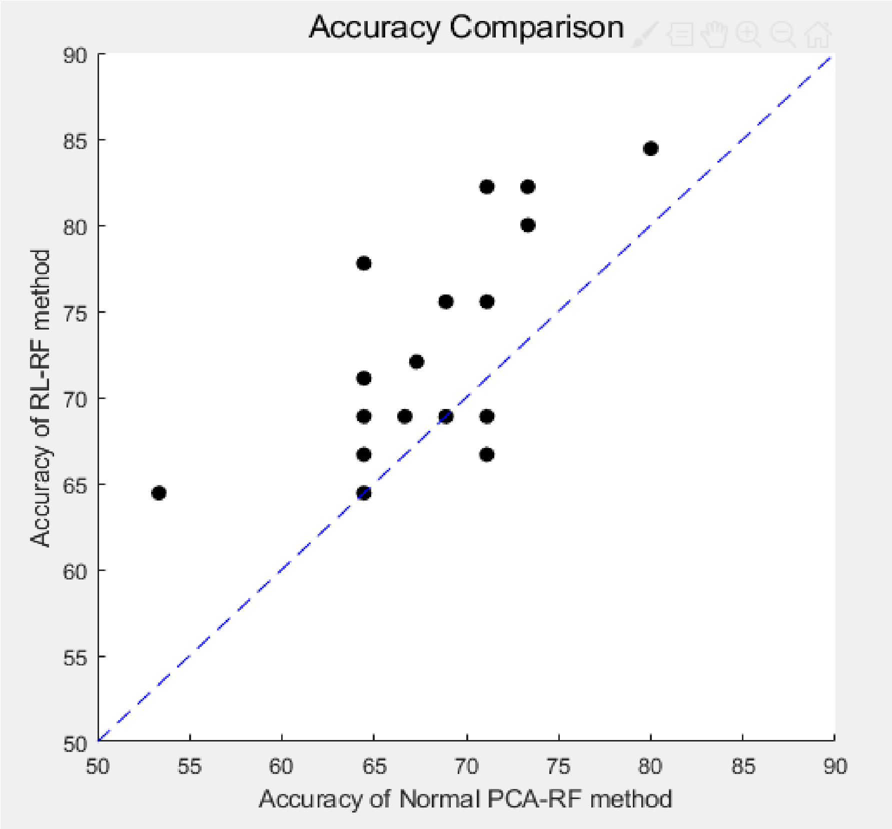
Accuracy Comparison
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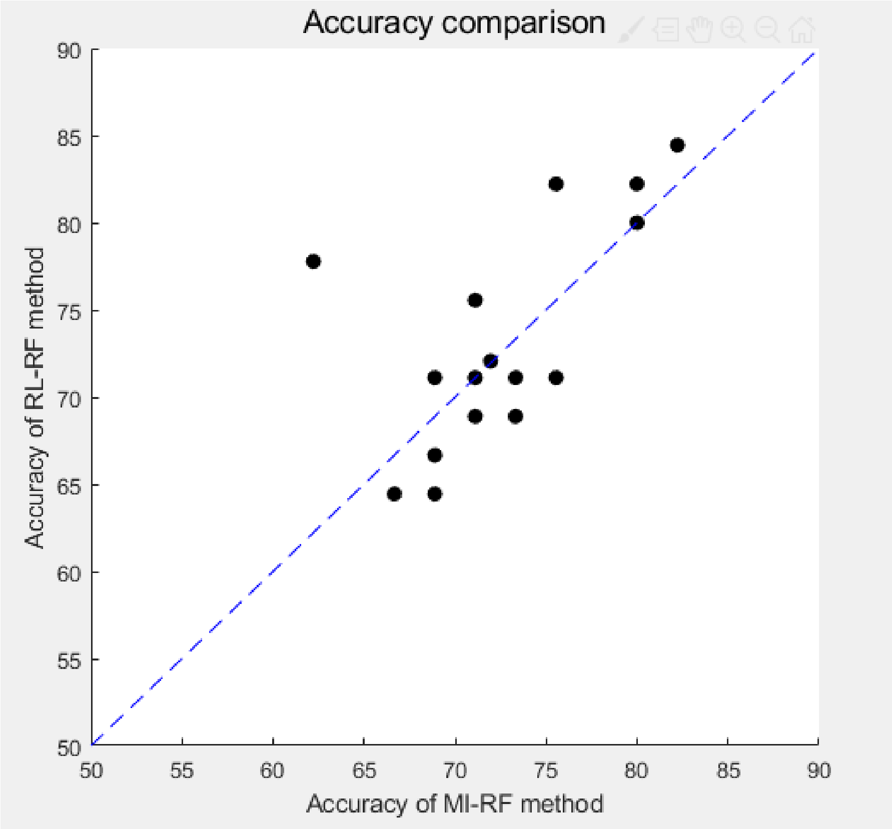
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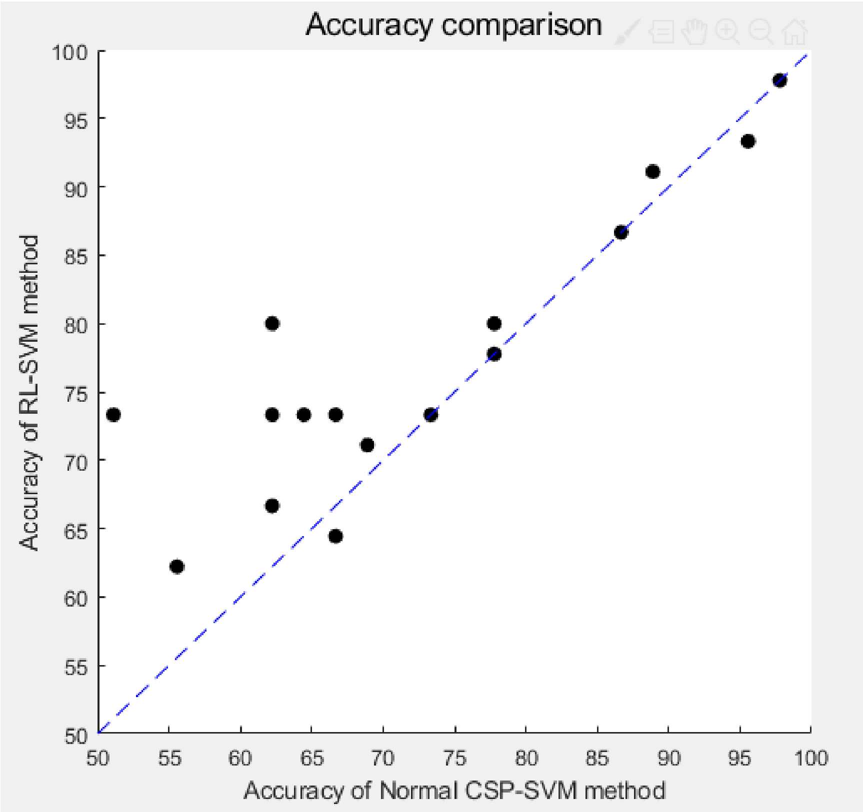
Accuracy comparison
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Accuracy of Normal CSP-SVM method
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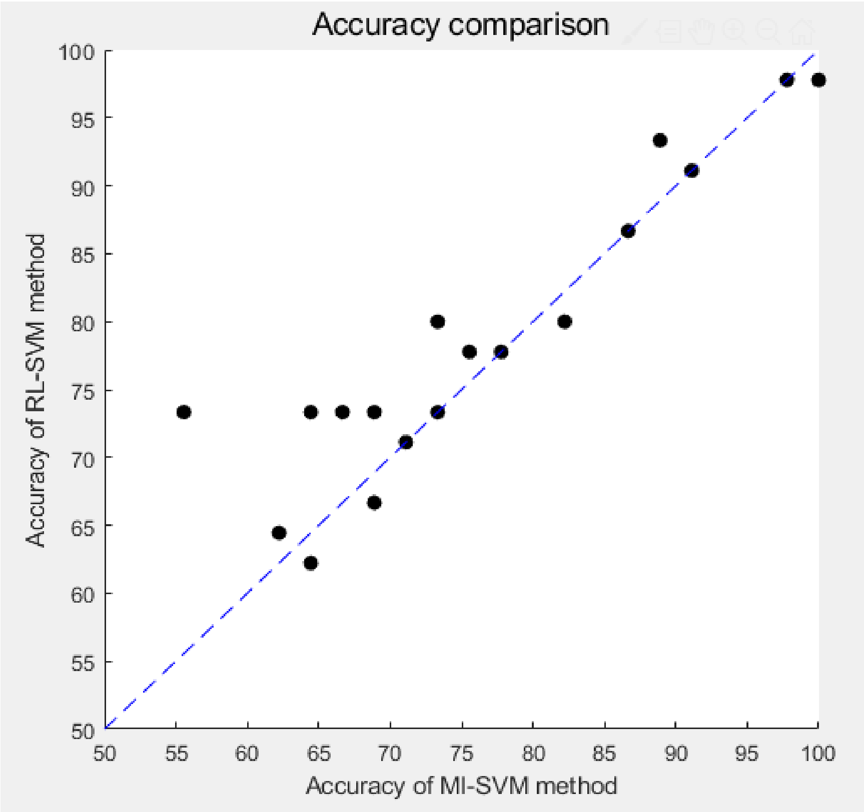
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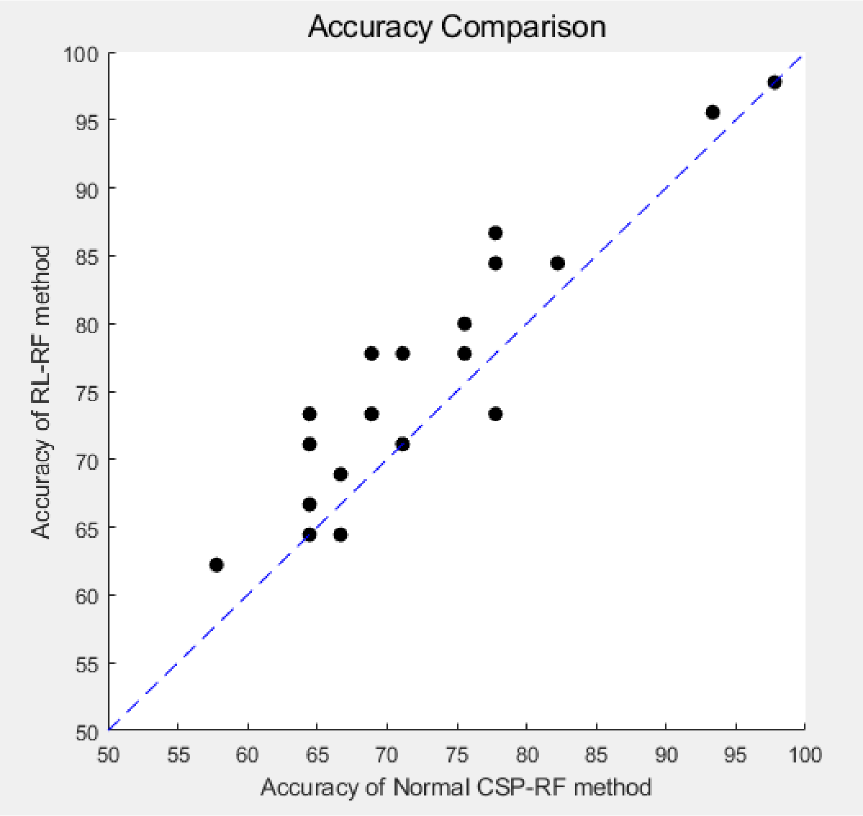
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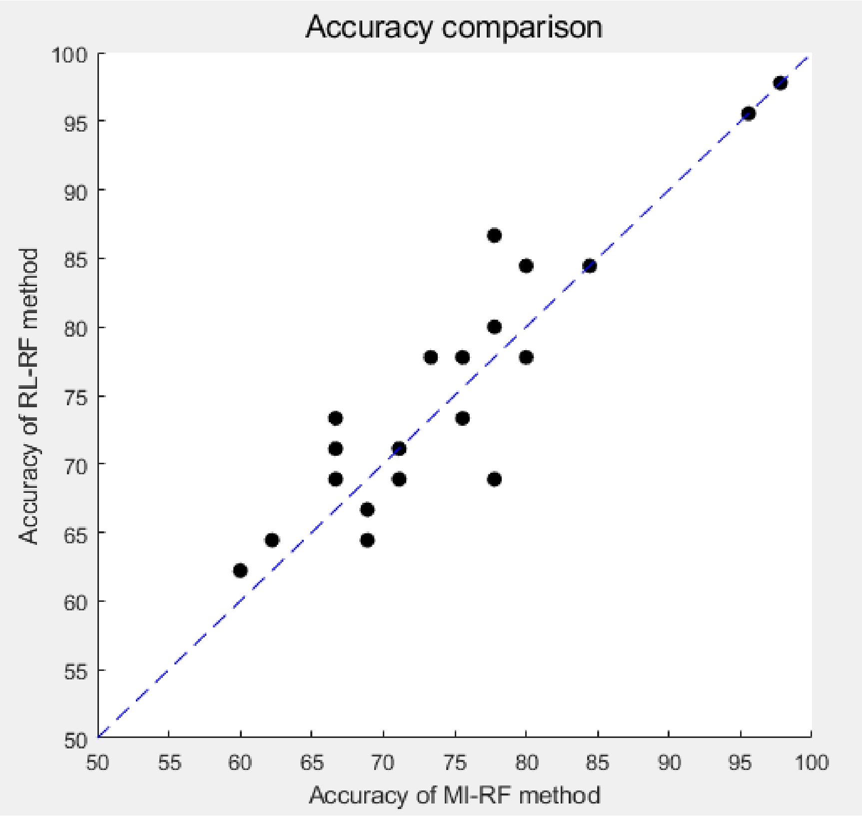
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100

Result

Classifier	Feature Selection Method	Accuracy	Precision	Recall
RF	Normal PCA	67.30/5.36	69.09/6.00	72.06/6.19
RF	MI	71.96/4.69	73.64/6.07	68.78/7.99
RF	**RL**	**72.06/6.19**	73.35/8.06	70.67/8.76
SVM	Normal PCA	57.46/8.29	49.22/22.28	55.61/29.23
SVM	MI	62.27/9.85	52.95/27.69	52.36/30.41
SVM	**RL**	**64.87/8.18**	**63.51/16.85**	**60.48/22.44**
RF	Normal CSP	72.83/9.77	75.62/11.20	69.90/12.36
RF	MI	74.95/9.68	75.68/10.47	70.82/12.45
RF	**RL**	**76.06/9.70**	73.28/10.50	64.12/14.53
SVM	Normal CSP	74.24/13.52	74.15/13.91	75.06/14.02
SVM	MI	75.96/11.87	75.53/12.61	76.71/13.05
SVM	**RL**	**78.38/10.01**	**78.63/10.81**	**78.71/11.14**

Result

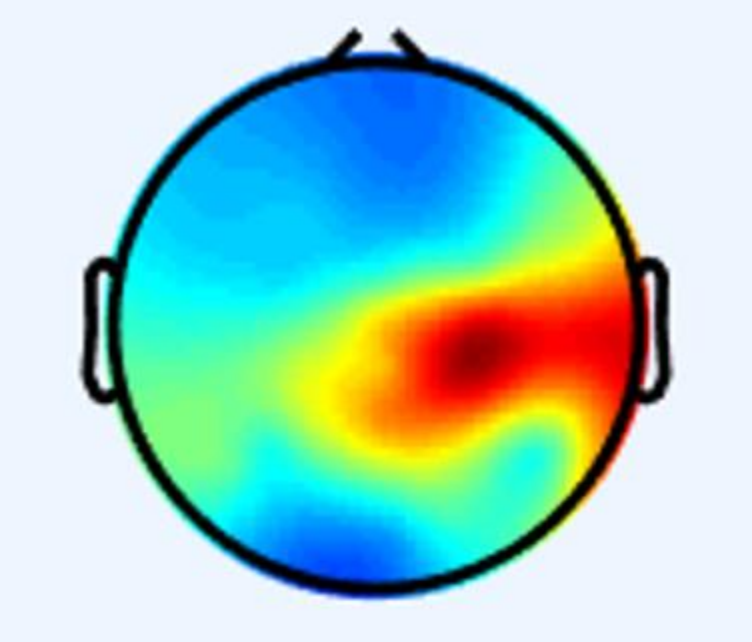
- One-tailed paired t-test

Normal PCA method	RF	$p < 0.001$
	SVM	$p < 0.005$
Mutual information method	RF	-
	SVM	$p < 0.05$

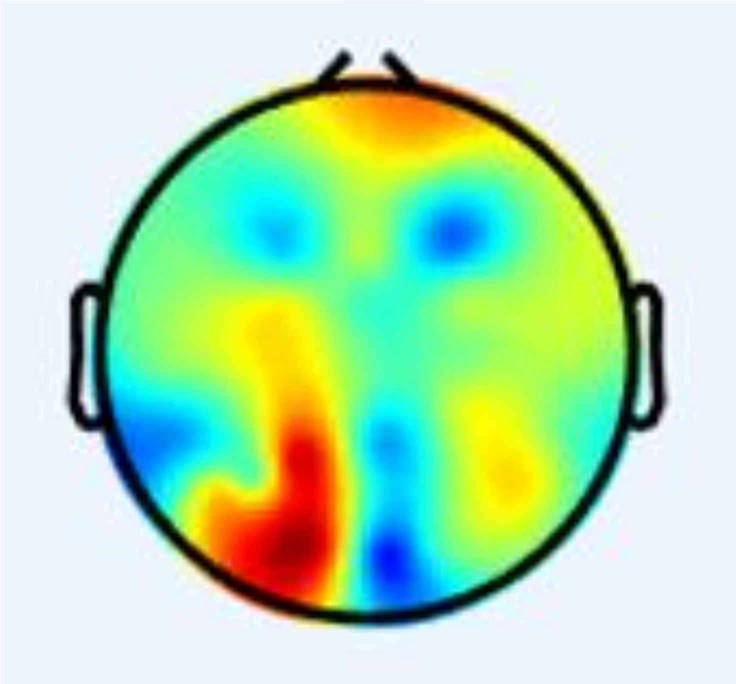
Normal CSP method	RF	$p < 0.005$
	SVM	$p < 0.01$
Mutual information method	RF	-
	SVM	$p < 0.05$

Conclusion

- 29^{th} subject's best eigenvector (spatial filter)



PCA



CSP

Conclusion

- Proposed algorithm have better performance compared to the other feature reduction algorithm such as PCA, CSP, MI
  - Because it approximates directly performance, not eigenvalue or information entropy
- The selected eigenvectors well reflect the characteristics of the motor imagery potential, which is divided left and right.
- The algorithm does not contain a classifer, so the complexity is not relatively high
  - If classifier is installed, performance can be increased but complexity is also greatly increased.

Future work

- 현재 연구되고 있는 강화학습 기반 AutoML 알고리즘들은 고정된 Neural Network 에 대해서 Optimal Hyperparameter를 찾고 있음 [4][5]
  - 본 연구와 결합하여, Neural Network 의 크기가 조정 가능한 AutoML 알고리즘을 개발할 수 있음
- Empirical Mode Decomposition (EMD) 의 IMF 성분들은 입력데이터로써 좋은 성능을 가지고 있으나, 중요한 성분을 자동으로 찾아내기 어려움 [6]
  - 본 연구와 결합하여, 필요한 IMF 성분들을 효율적으로 추출해낼 수 있음

Reference

- [1] Volodymyr Mnih. 2015. Human-level control through deep reinforcement learning. *Nature* volume518. pages529–533
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