Recognition of Motor Imagery Electroencephalography Using Independent Component Analysis and Machine Classifiers

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What is brain computer interface?

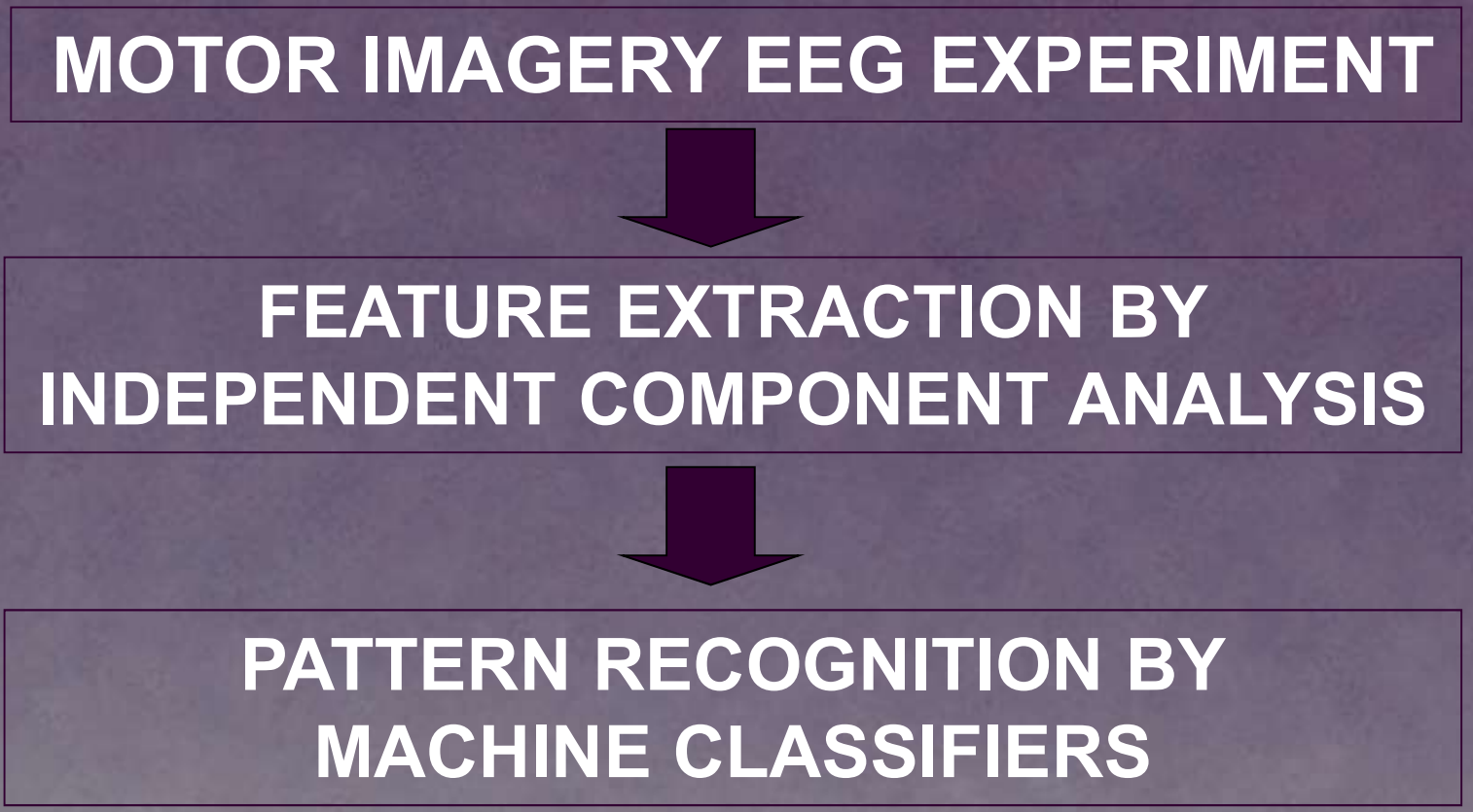
A technique in assisting people to communicate with external environments or trigger surrounding devices by means of their brain signals.

The **success** of BCI systems relies on two integral parts:

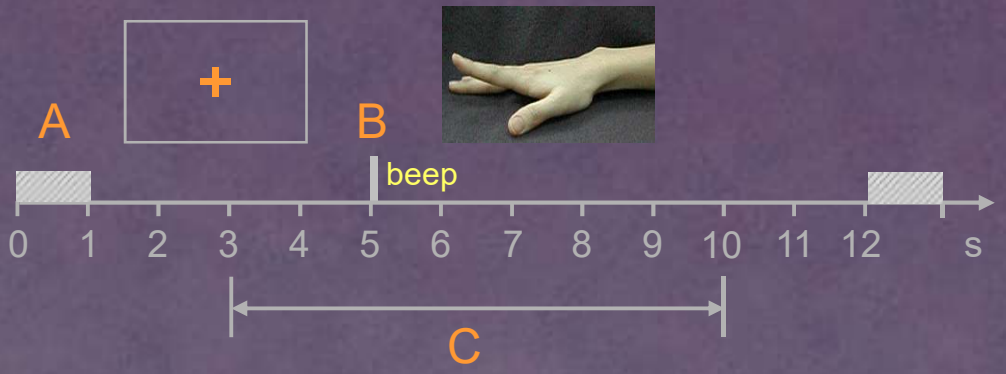
1. distinguishable neural patterns
2. effective classifiers.

AIM of this work :

1. extract reliably distinguishable feature from the motor imagery EEG using Independent Component Analysis (**ICA)**
2. employ **machine classifiers** to investigate the efficacy of extracted pattern

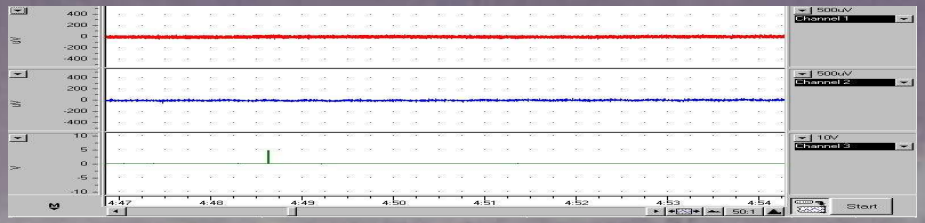

MOTOR IMAGERY EEG EXPERIMENT
FEATURE EXTRACTION BY INDEPENDENT COMPONENT ANALYSIS
PATTERN RECOGNITION BY MACHINE CLASSIFIERS

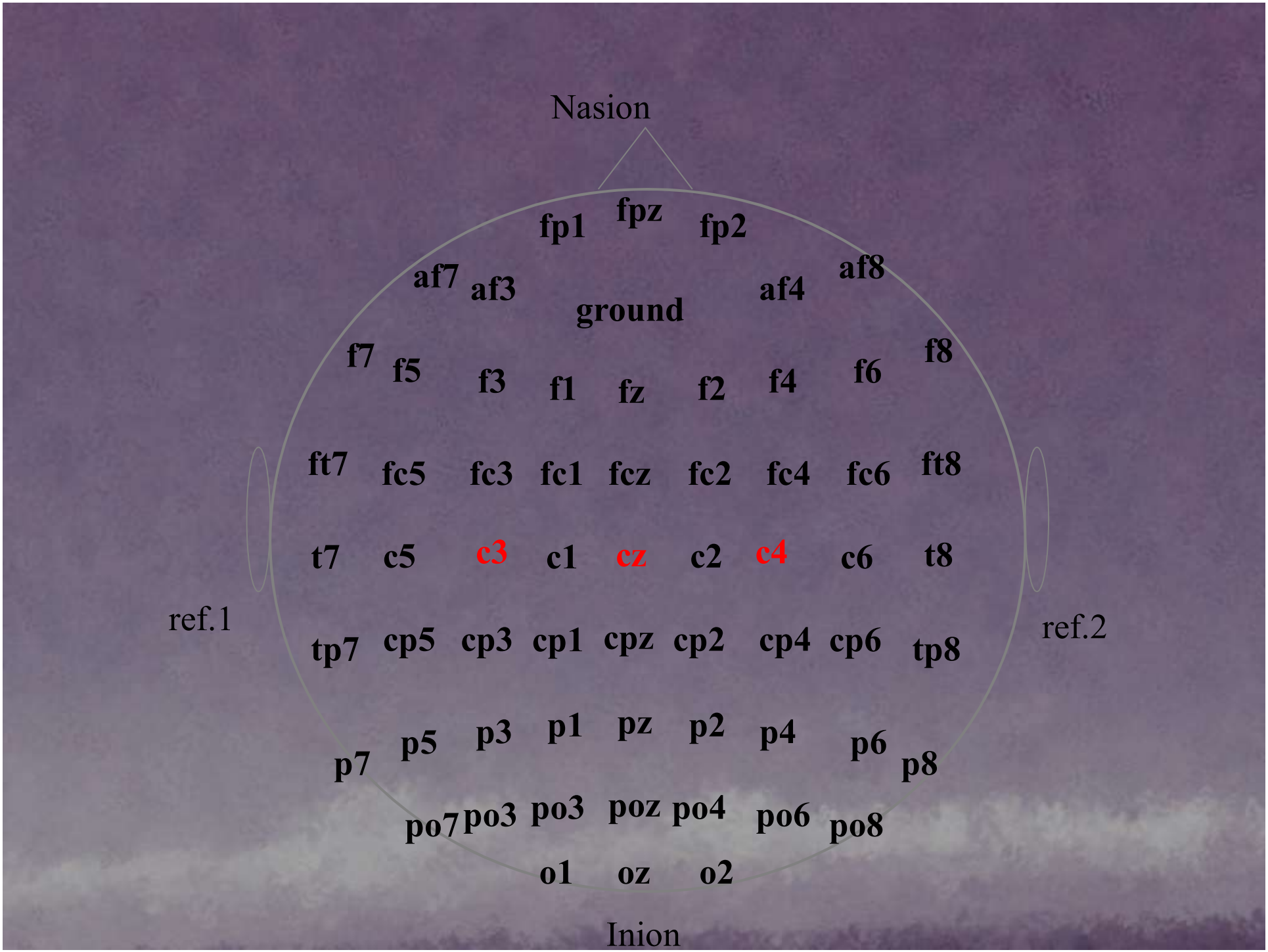
EEG Experiment Paradigm



A : Cue for eyes blinking
A-B : Eyes fixation
B : Cue for starting motor imagery
C : Time interval for data analysis

EMG Monitor




Nasion
fp1
fpz
fp2
af7
af3
af4
af8
ground
f7
f5
f3
f1
fz
f2
f4
f6
f8
ft7
fc5
fc3
fc1
fcz
fc2
fc4
fc6
ft8
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c3
c1
cz
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pz
p2
p4
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poz
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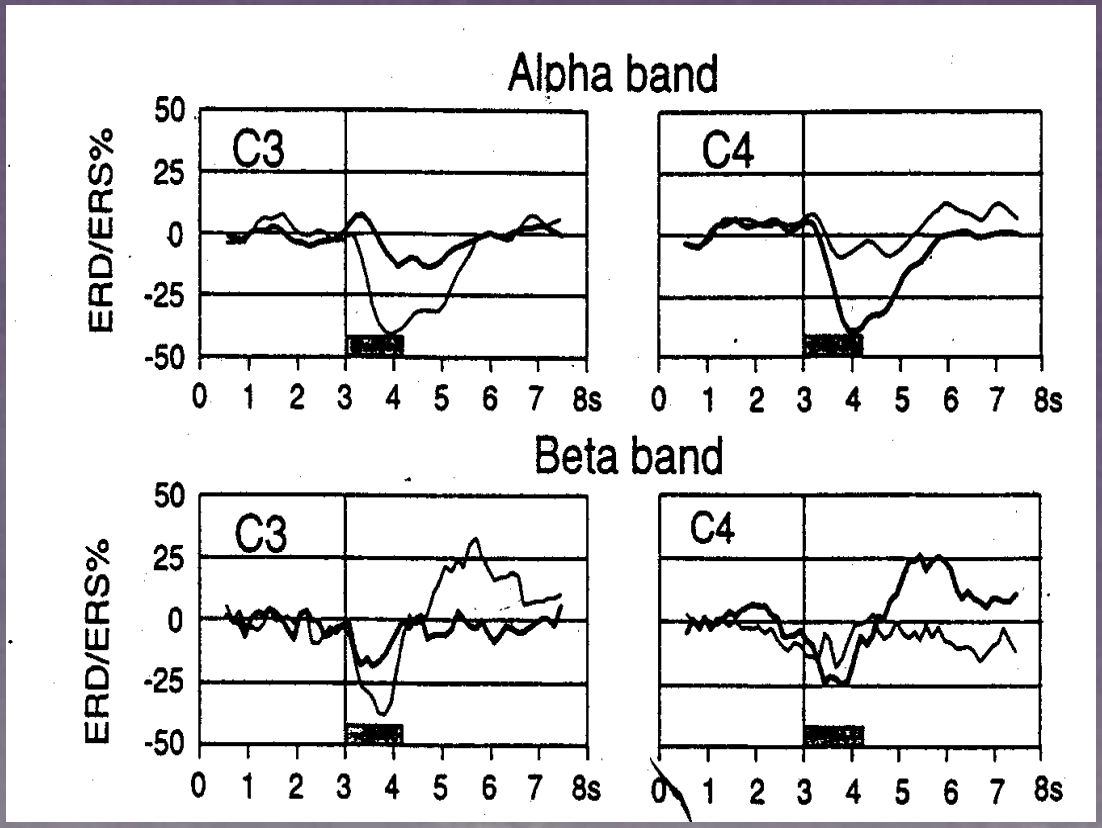
Inion

During imaged hand movement :



——Left motor imagery ——right motor imagery

Alpha band ERD was found over contralateral hemisphere, whereas the ipsilateral and central electrodes didn't show any significant band power changes.

Beta band ERS was only found over contralateral hand area following a beta ERD. No beta ERS was found at ipsilateral or medial locations.

G.Pfurtscheller, F.H. Lopes da Silva, Event-Related Dsynchronization, Ch 19

MOTOR IMAGERY EEG EXPERIMENT

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FEATURE EXTRACTION BY INDEPENDENT COMPONENT ANALYSIS

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PATTERN RECOGNITION BY MACHINE CLASSIFIERS

Independent Component Analysis

Channel 1: $x_1 = a_{11}s_1 + a_{12}s_2 + a_{13}s_3 + noise$

Channel 2: $x_2 = a_{21}s_1 + a_{22}s_2 + a_{23}s_3 + noise$

$\vdots$

Channel n: $x_n = a_{n1}s_1 + a_{n2}s_2 + a_{n3}s_3 + noise$

$$X = AS + N$$

Independent component analysis

$$S = WX$$

Hyvarinen A, Karhunen J, Oja E. Independent Component Analysis, John Wieley & Sons, Inc., New York, 2001

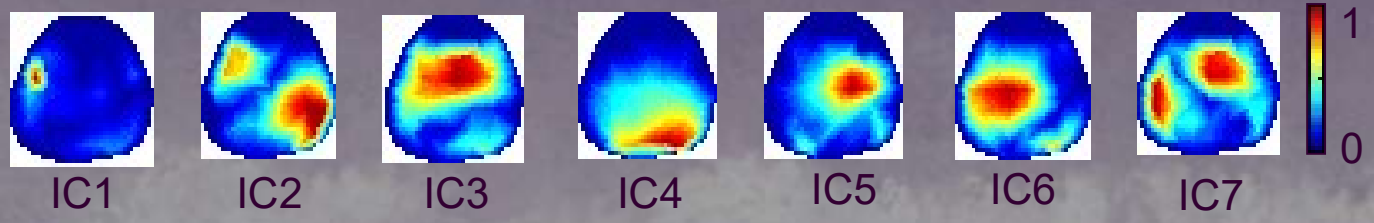
Feature Extraction with ICA

Step 1: Signal decomposition by using ICA.

a. Arranged each pre-processed epoch across *m* channels (*m*=62) and *n* sampled points (*n=1750*) into an matrix *X.*
ICA estimates an un-mixing matrix *W* and transform *X* into S :

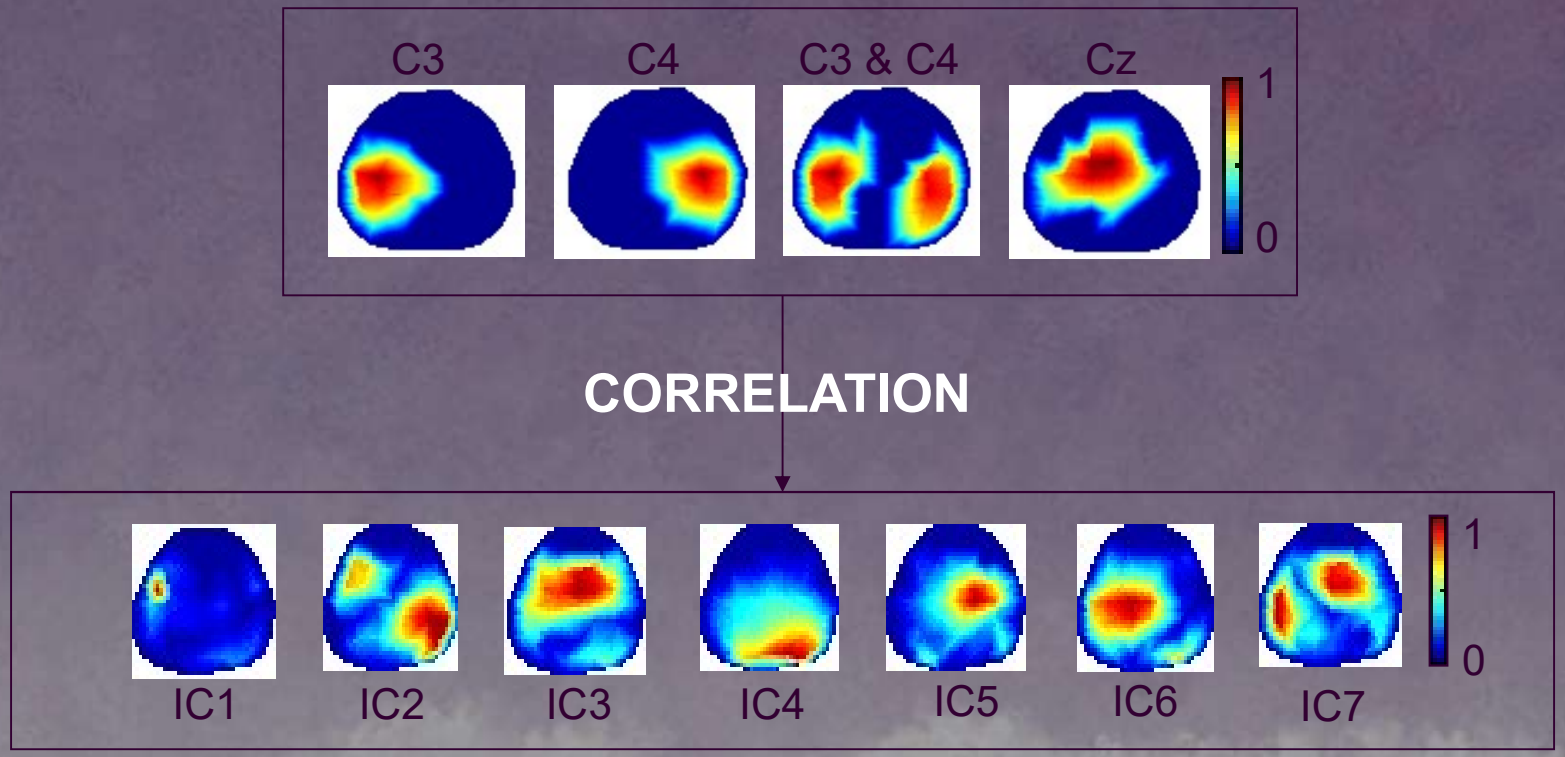
$$S = WX$$

the rows of *S* : independent sources
the columns of W^{-1} (mixing matrix) : spatial map (show as follows)



Feature Extraction with ICA

Step 2: Correlating the IC spatial maps with pre-defined spatial templates to select task-related components.



Feature Extraction with ICA

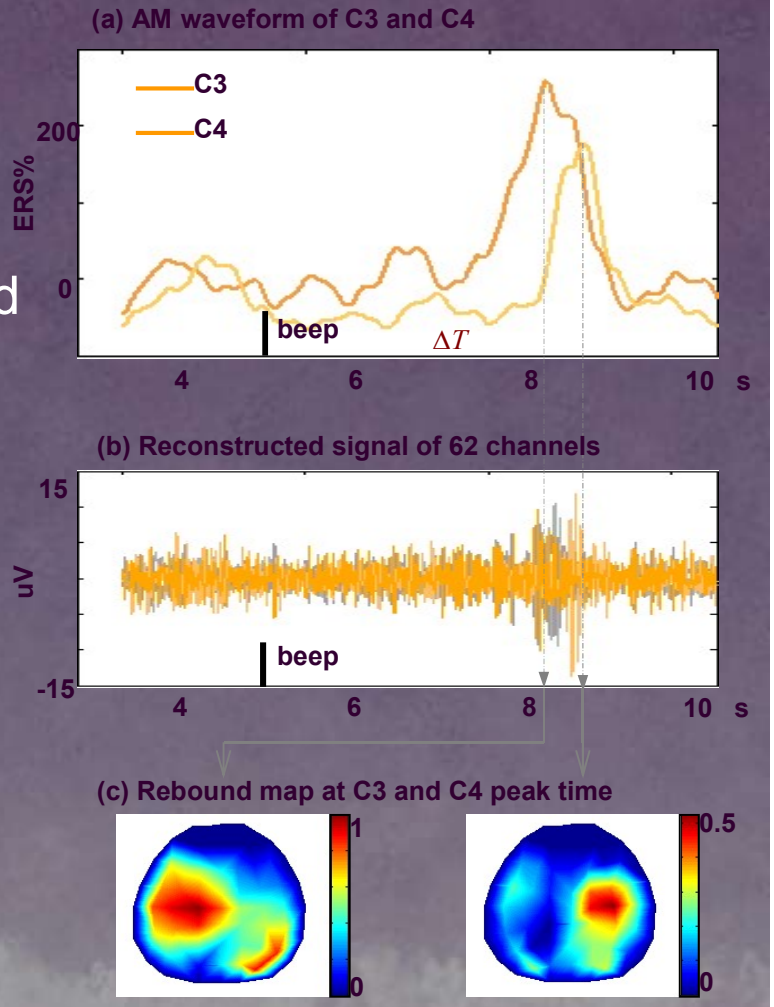
Step 3: Computing the envelopes of beta reactivity from reconstructed signals using the Amplitude Modulation method.(a)

$$m(t) = \sqrt{M_{BP}(t)^2 + H(M_{BP}(t))^2}$$

$M_{BP}(t)$: single-trial band-passed EEG signal

$H(M_{BP}(t))$: Hilbert transform of $M_{BP}(t)$

Step 4: Extracting the beta rebound maps. (c)



MOTOR IMAGERY EEG EXPERIMENT

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FEATURE EXTRACTION BY INDEPENDENT COMPONENT ANALYSIS

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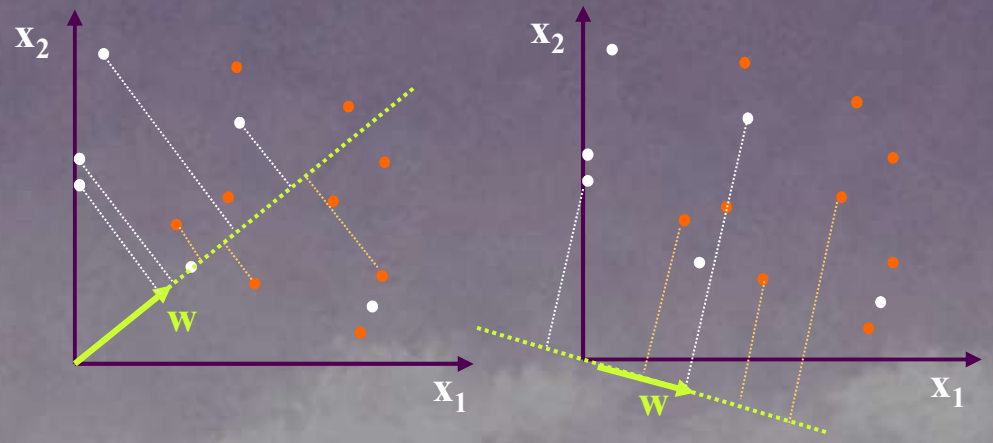
PATTERN RECOGNITION BY MACHINE CLASSIFIERS

1. LINEAR DISCRIMINANT ANALYSIS
2. BACK-PROPAGATION NEURAL NETWOR
3. RADIO-BASIS FUNCTION NEURAL NETWORK
4. SUPPORT VECTOR MACHINE

Linear Discriminant Analysis

For a given training sample set, determine a set of optimal projection axes such that the set of projective feature vectors of the training samples has the maximum between-class scatter and minimum within-class scatter simultaneously.



$$J(w) = \frac{w^t S_b w}{w^t S_w w}$$

Sb : between-class scatter matrix
Sw : within-class scatter matrix

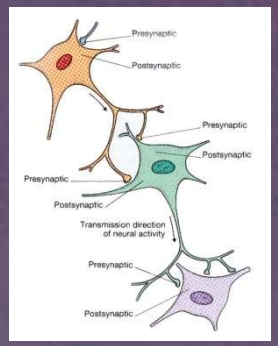
Back Propagation Neural Network

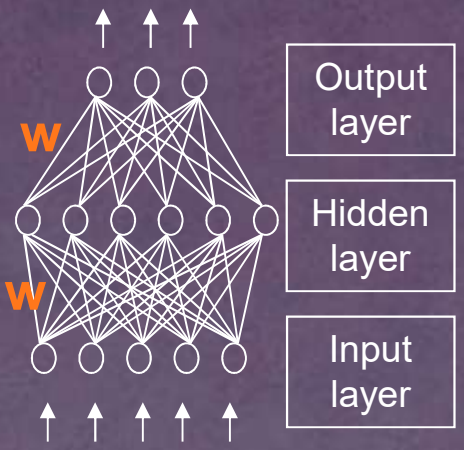
*** Forward pass:**

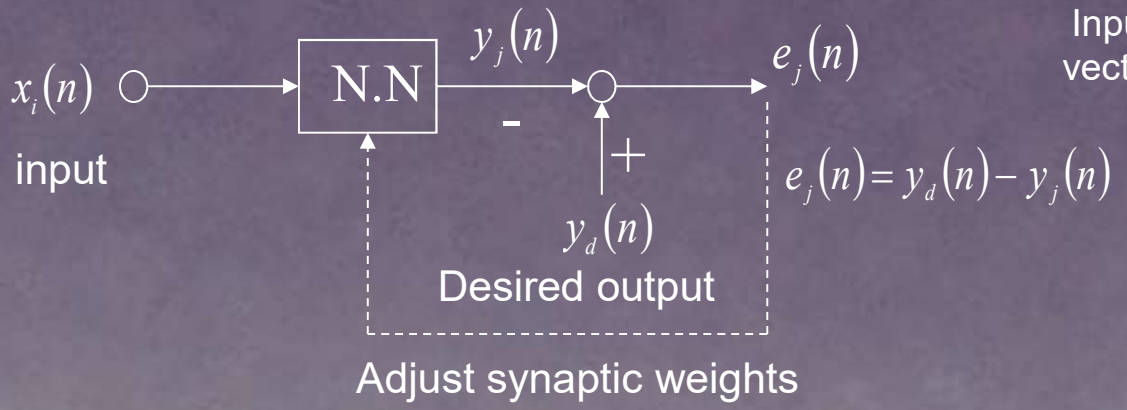
$$e_j(n) = y_d(n) - y_j(n)$$

*** Backward pass**

$$\Delta w_{kj}(n)$$



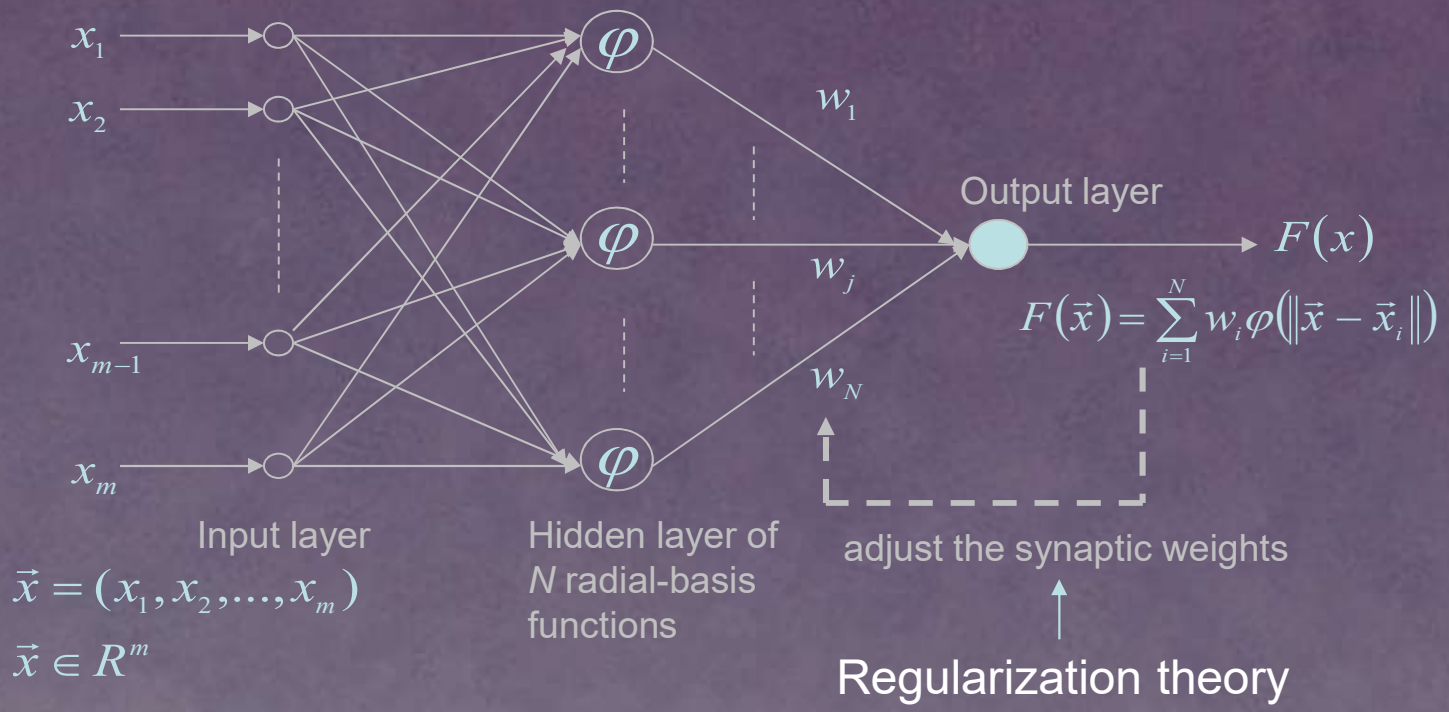




Parameters -- **Hidden layer : 1**

Neurons : 10

Radial Basis Function Neural Network

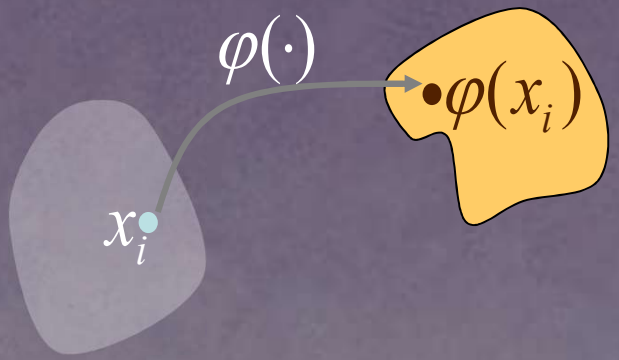


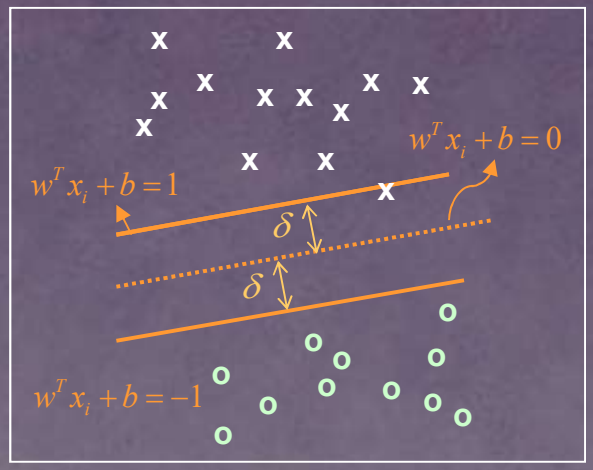
Parameters -- **Hidden layer : 1**
Neurons : the same as training data set

Support Vector Machine

1. **Nonlinear mapping** of an input vector into a **high-dimensional feature space** that is hidden from both the input and output.

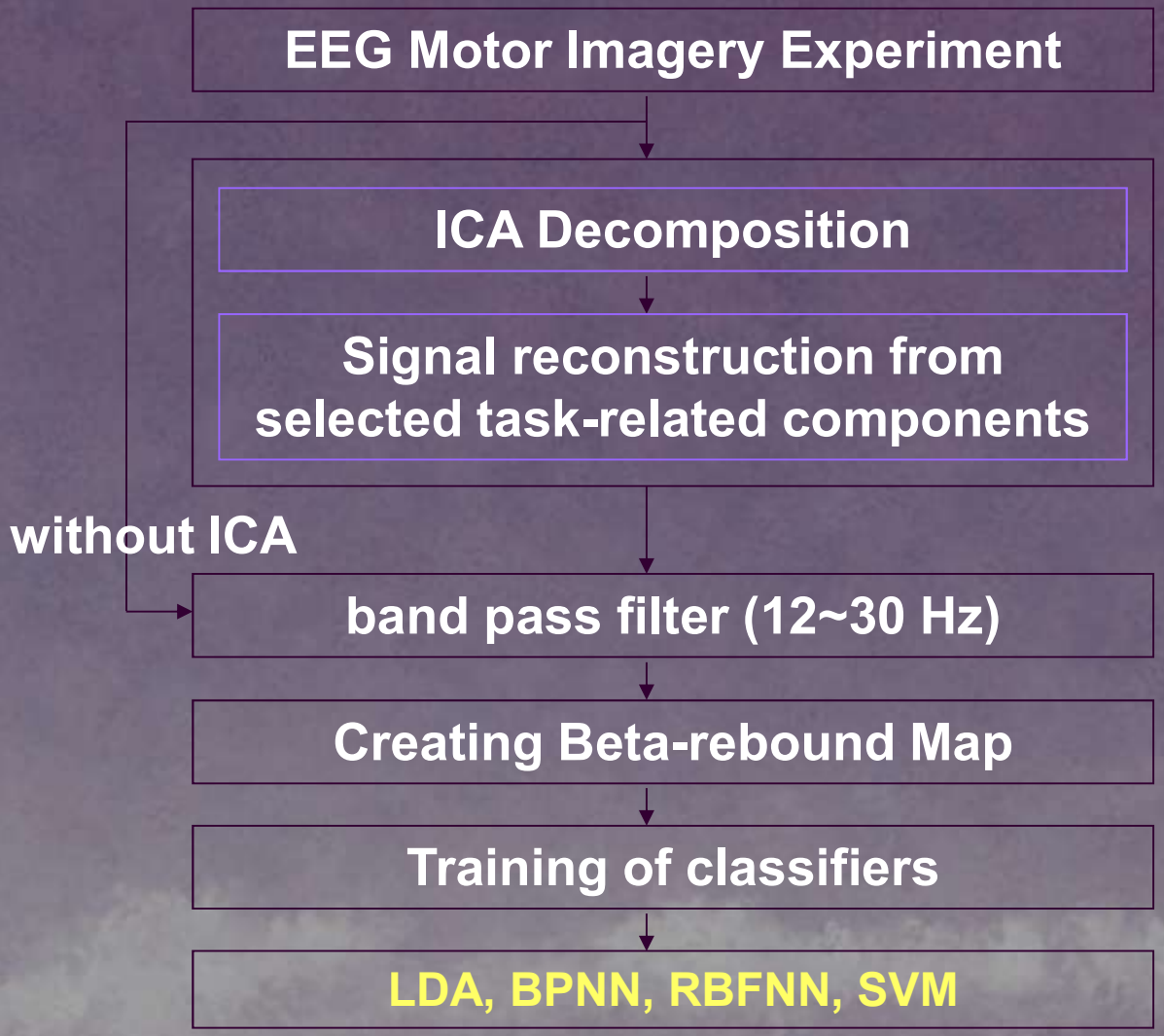
2. Construction of an **optimal hyperplane** for separating the features discovered in step1.





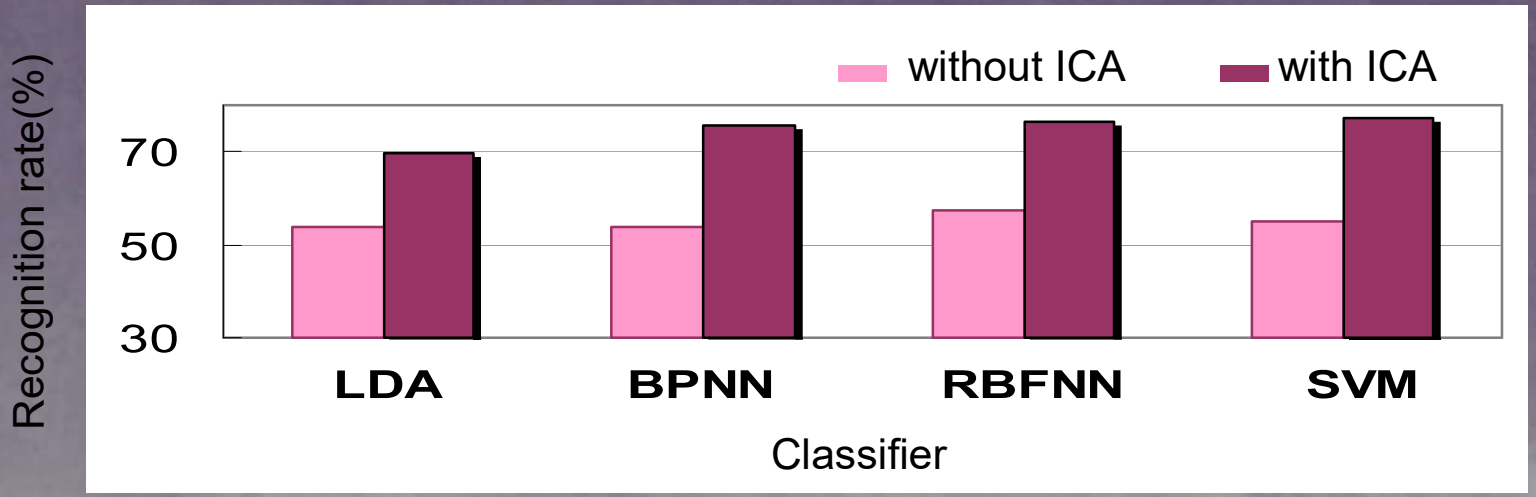
Parameters – **nonlinear mapping : radio-basis function**

Training Stage of Machine Classifiers

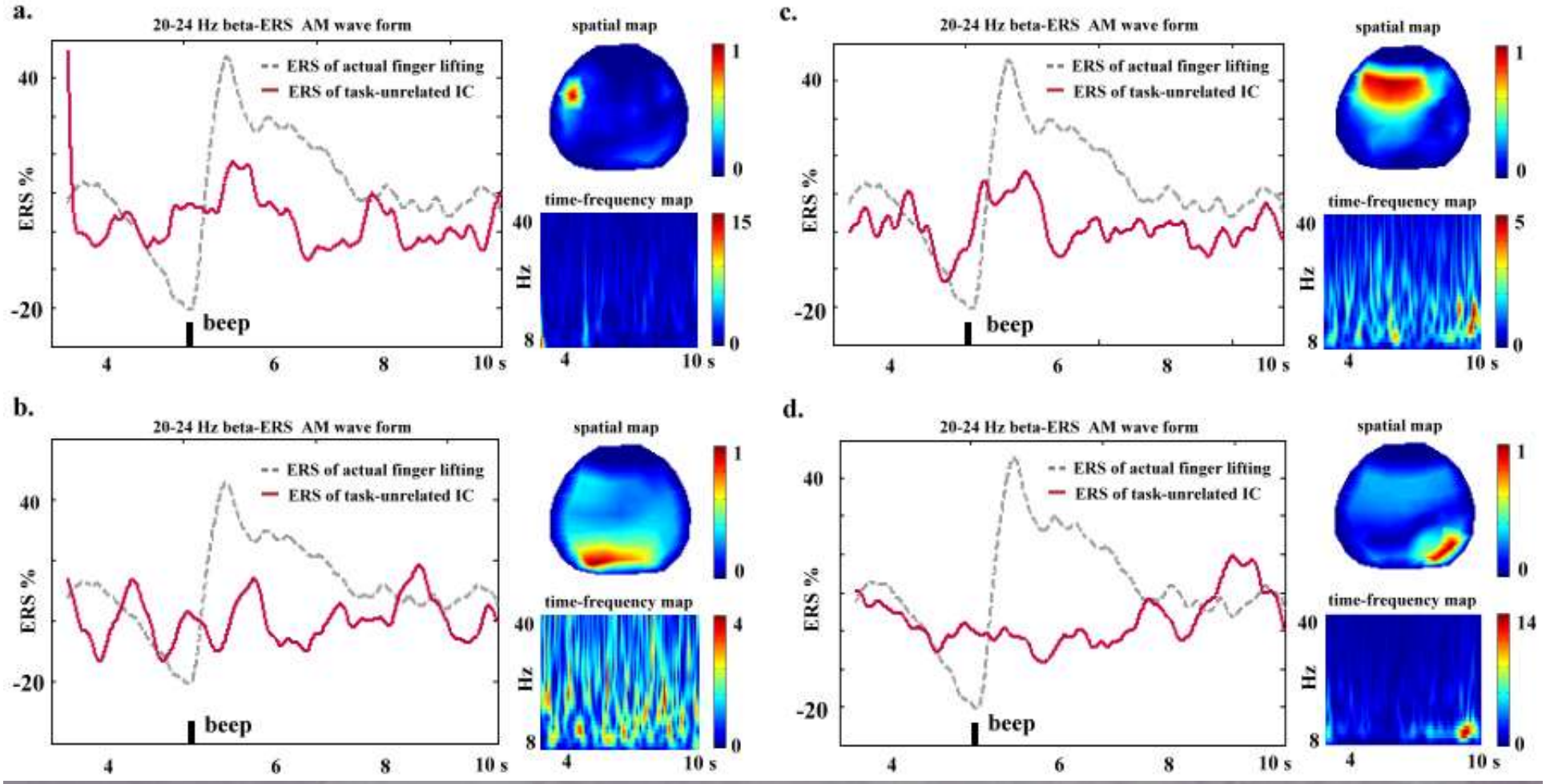


*AVERAGE RECOGNITION RATE OVER 4 SUBJECTS

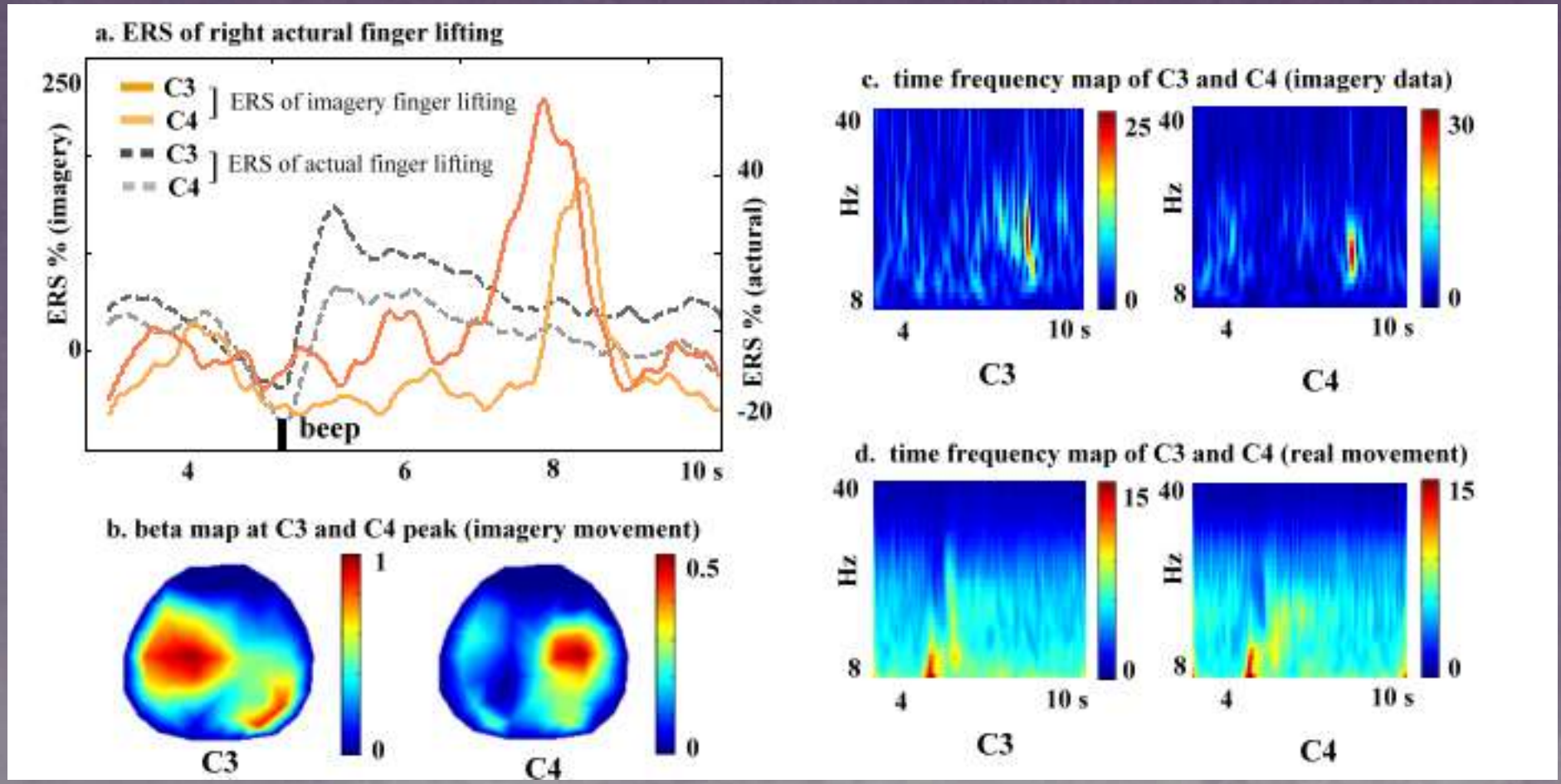
Classification Accuracy(%)	Classifier			
	LDA	BPNN	RBFNN	SVM
without	54	54	57.3	55
with ICA	69.8	75.5	76.5	77.3



The Features of Task-unrelated Components

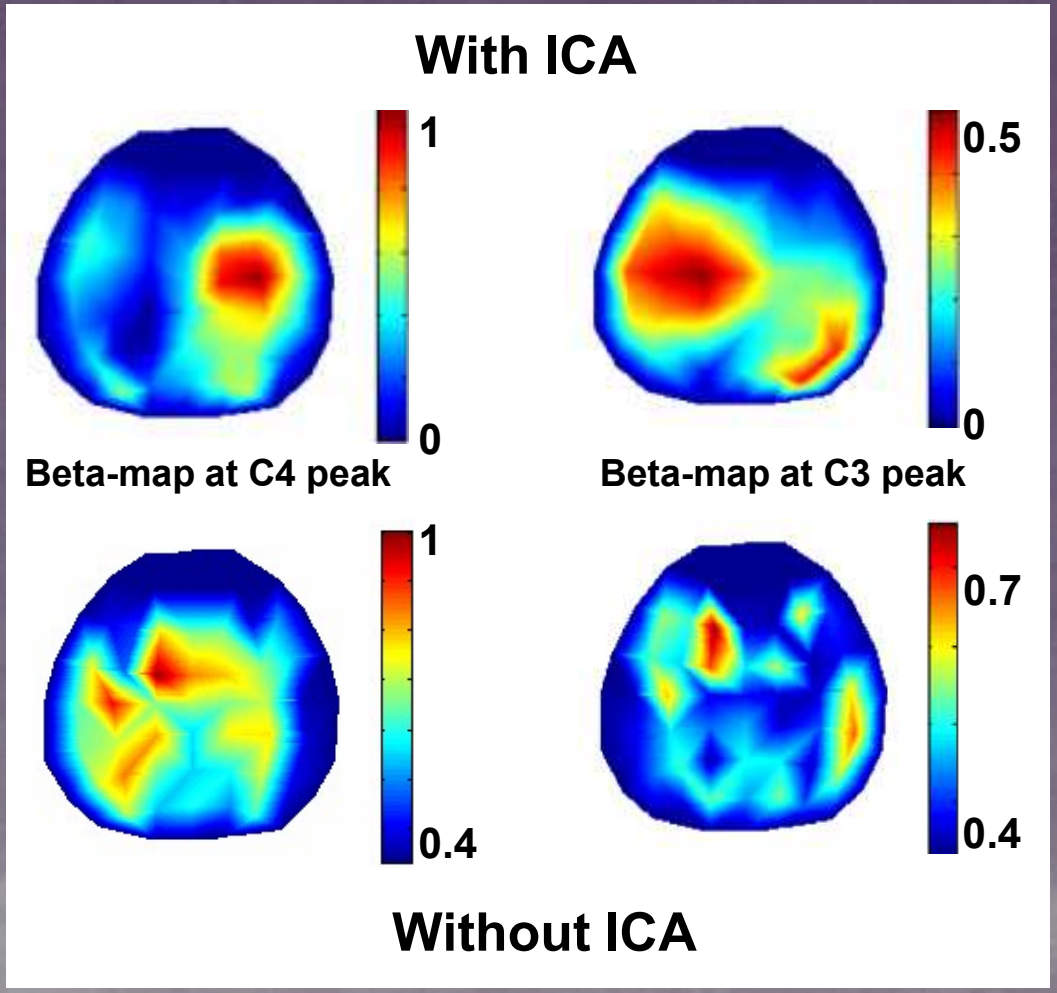


The Single-trial EEG with Feature Extraction by ICA



Comparison of Single-trial EEG with and without ICA

Imagery right index finger lifting



CONCLUSIONS

•We have developed an ICA-based method in extracting the beta rebound map as a reliable feature from motor imagery EEG.

•With a minimum training for each subject (20 minutes only), satisfactory classification rates (70%) from four classifiers have been achieved.