University of Telecommunications and Post
Sofia, Bulgaria

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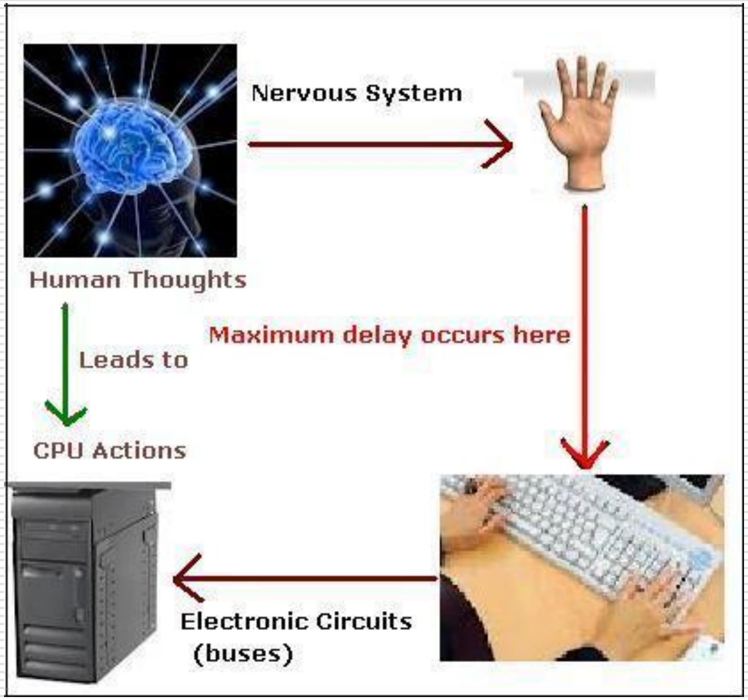
Brain-Computer Interface for Control and Communication with Smart Mobile Applications

Prof. Svetla Radeva, DSc, PhD

HUMAN - COMPUTER INTERACTION

The considered Human-Computer Interaction (HCI) system is based on Brain-Computer interface (BCI) which use measured Electroencephalography (EEG) activity or other electrophysiological measures of brain functions as new non-muscular channels for control and communication with smart devices and smart mobile applications for disabled persons. The research aims developing of technology for communication with smart mobile applications, based on processing of recorded electrophysiological signals at execution of different mental tasks.

HUMAN-COMPUTER INTERACTION



- Human brain decides the instruction for delivering to thinking activity;
- This decision, from human-brain, is transfer to human peripheral(s) by nervous system;
- From human peripheral(s), this decision is transferred to computer peripheral;
- From computer peripheral the decision, which is now computer command is transferred to CPU (computer brain);
- CPU executes the task.

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HUMAN - COMPUTER INTERFACE

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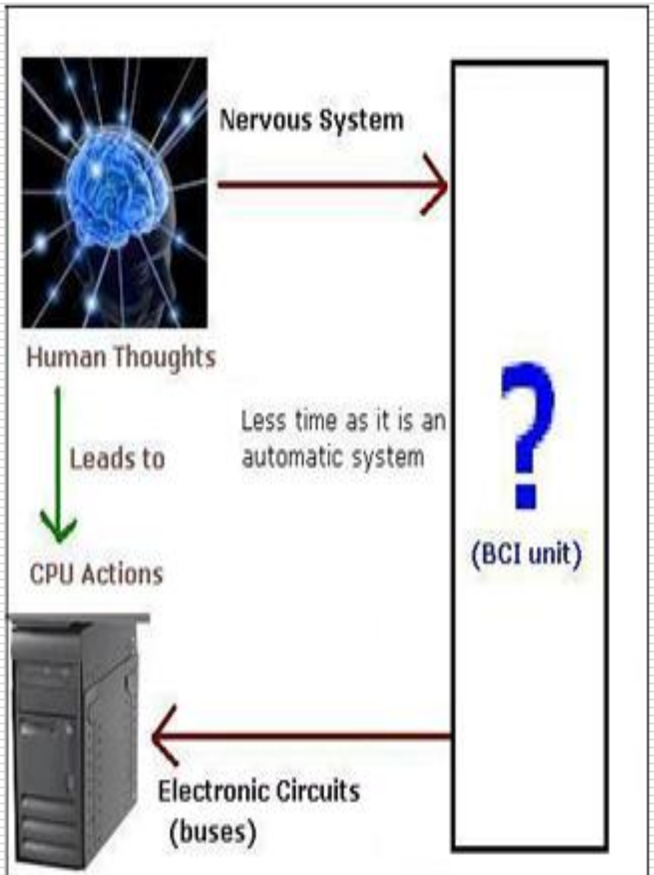

- The time taken by human brain to decide on the first step and CPU to execute the instruction on the last step is almost negligible . The rest steps are a medium which-just bridging a gap between human thinking process and CPU understanding process.

- If we can somehow bridge this gap via some automatic means, then a brain-computer interface will convert human brain thoughts directly into computer brain instructions or executing programs.

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BRAIN-COMPUTER INTERFACE

The interface between numan brain and computer, called Brain–Computer Interface (BCI) is a Human-Computer Interaction (HCI) technique where register brain signals directly convert into computer commands.

BCI implementation:

- computer games, which can be made more attractive, useful and effective with BCI;
- embedded systems;
- using BCI in operating machines;
- medical industry - biggest area of BCI application etc.

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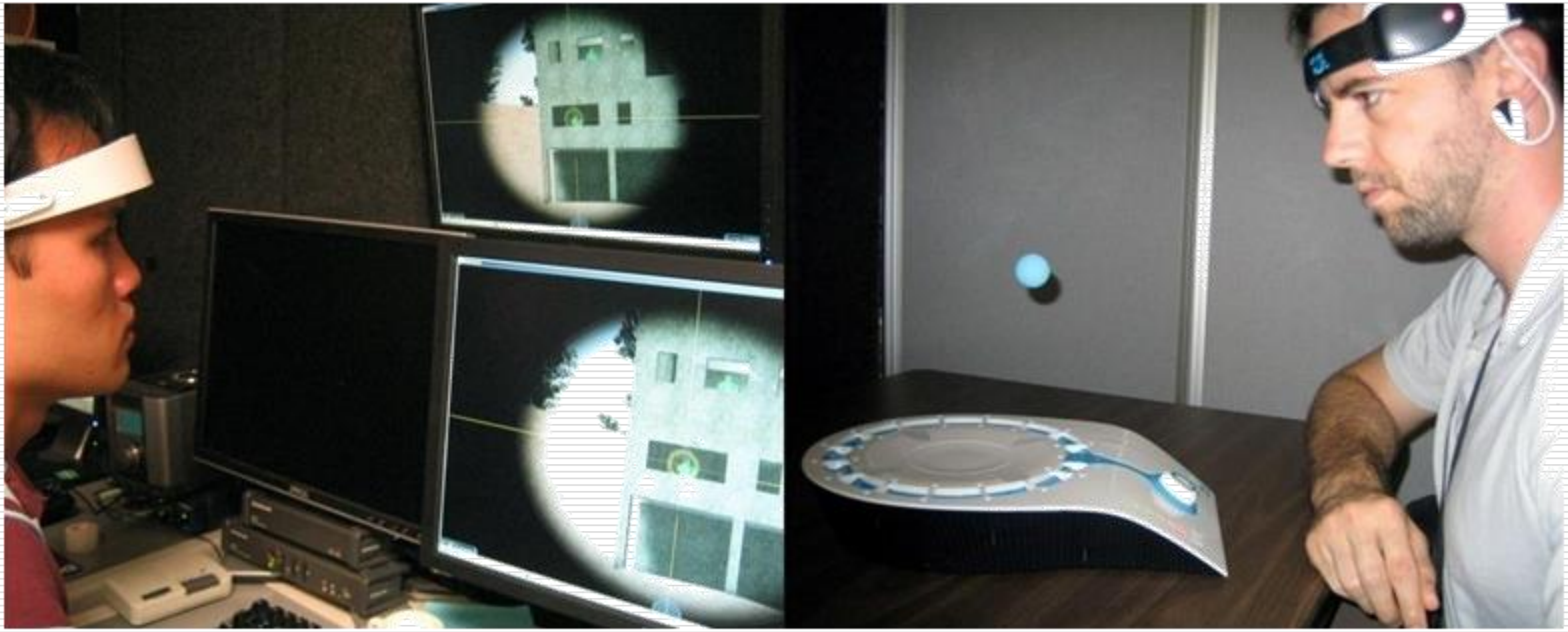
BRAIN-COMPUTER INTERFACE



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BRAIN-COMPUTER INTERFACE

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BCI system for communication with smart mobile applications

- **Step 1: *Thinking in Brain*** - when something is to be done a thought is developed into the brain which leads to development of a neuron potential pattern.
- **Step 2: *Reading Brain by EEG*** - when the developed potential pattern is read by EEG (or other similar techniques) to be transformed into an analyzable signal patterns. This is also known as EEG spectrum.
- **Step 3: *Analysis of EEG spectrum*** - the signal pattern developed by EEG equipment is analyzed using various pattern analysis techniques.

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BRAIN-COMPUTER INTERFACE

- **Step 4: *Recognizing EEG spectrum*** - based on the signal analysis we recognize what task brain wants to get from computer or mobile device.
- **Step 5: *Converting into suitable computer signal*** - once we know the task to be done we can easily determine proper computer command (or sequence of command) to get the task from computer or mobile device.
- **Step 6: *Sending the signals to computer system*** - after discovering the required command or program, send the same to CPU which then execute the required task.

BRAIN-COMPUTER INTERFACE

- **Step 7: *Feedback to the user*** - after CPU accepts the input it carries out the operation and sends the feedback to user in various feedback-forms e.g. video, audio etc.
- As is seen, for realization of human-computer interaction with smart mobile applications it is necessary to provide:
    - ***filtering of register brain signals;***
    - ***pattern analysis techniques for clustering of neurons and pattern recognition***.

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SIGNAL PROCESSING AND CLUSTERING OF NEURONS

- At any moment the human brain generates wave for a particular thought, but at the same time generates also some waves corresponding to other unnecessary thoughts.
- These *additional waves act as noise* for original waves.
- For handling this problem it is necessary to develop some ***noise filtering mechanism*** that can detect the unrelated spectrum and filter them out from the useful spectrum.

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SIGNAL PROCESSING AND CLUSTERING OF NEURONS

- Another problem that have to be solved is connected with ***clustering of neurons***, where it is necessary to ***divide 80-120 billion brain-neurons into few clusters*** and the big question is – on what basis we should divide the neurons?
- For solving this problem is involved Artificial Intelligence and Artificial neural network.

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EXPERIMENTAL METHODS AND MEASUREMENTS

- The experimental BCI system includes 3D camera Panasonic HDC-Z0000, sender Spectrum DX9 DSMX, Sony GoPRO – GoPro HERO3, Nikon D902D smart TV Samsung UE-65HU8500 + LG60LA620S, ACER K11 Led projector, Linksys EA6900 AC1900 smart router, Pololu Zumo Shield, 8 core/32GB RAM/4TB HDD/3GB VGA computer for video processing that translate EEG signals into computer commands and two Electro-Caps (elastic electrode caps)

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EXPERIMENTAL METHODS AND MEASUREMENTS

- Two Electro-Caps (elastic electrode caps) was used to record each from positions C3, C4, P3, P4, O1, and O2, defined by the most popular 10-20 System of electrode placement at experimental setup.
- This system called 10-20 System is an international standard for EEG electrode placement locations on the human scalp.
- Based on results from pilot recordings, we selected the parietal (P3 and P4) regions as the locations of interest.

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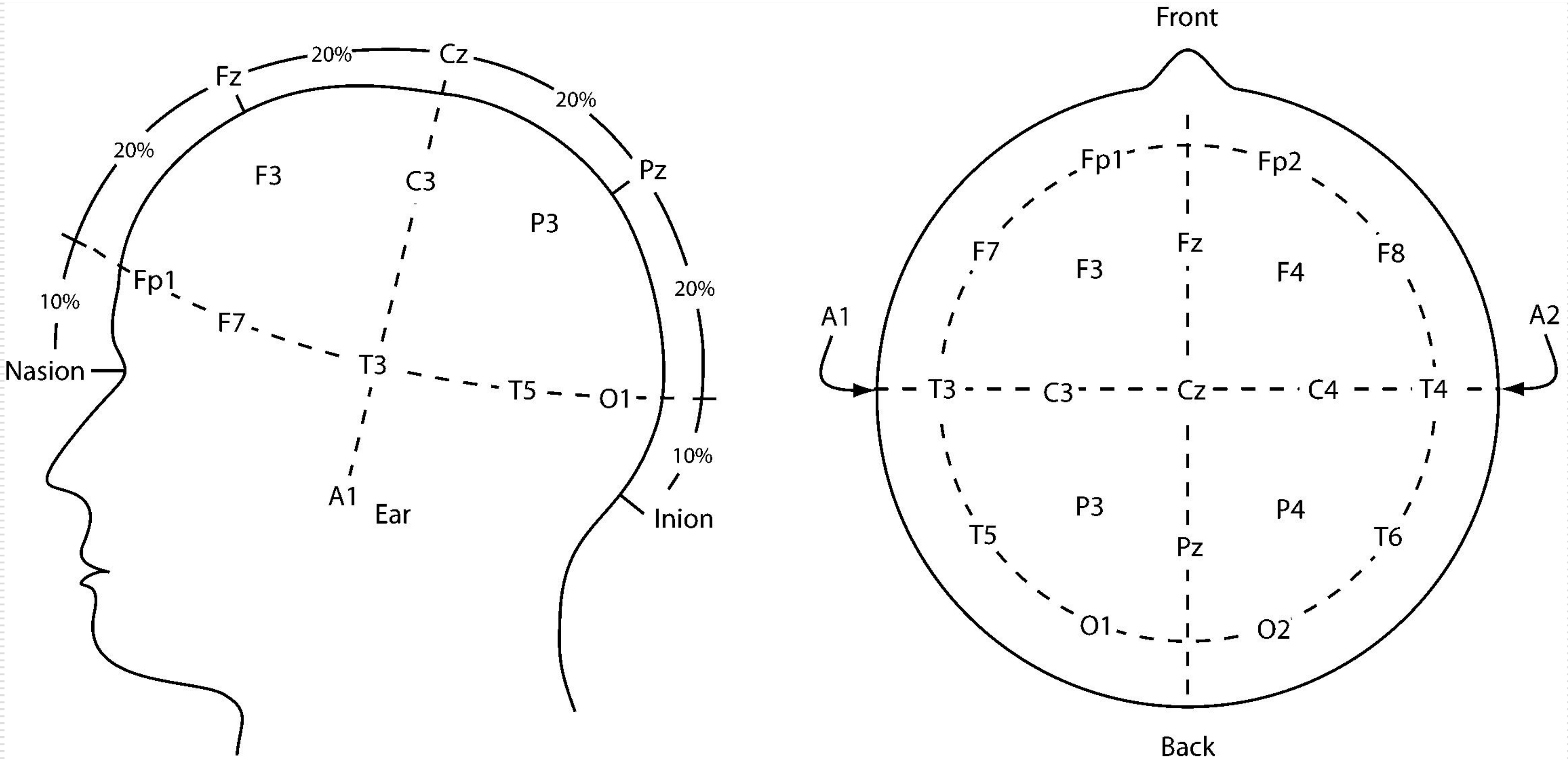
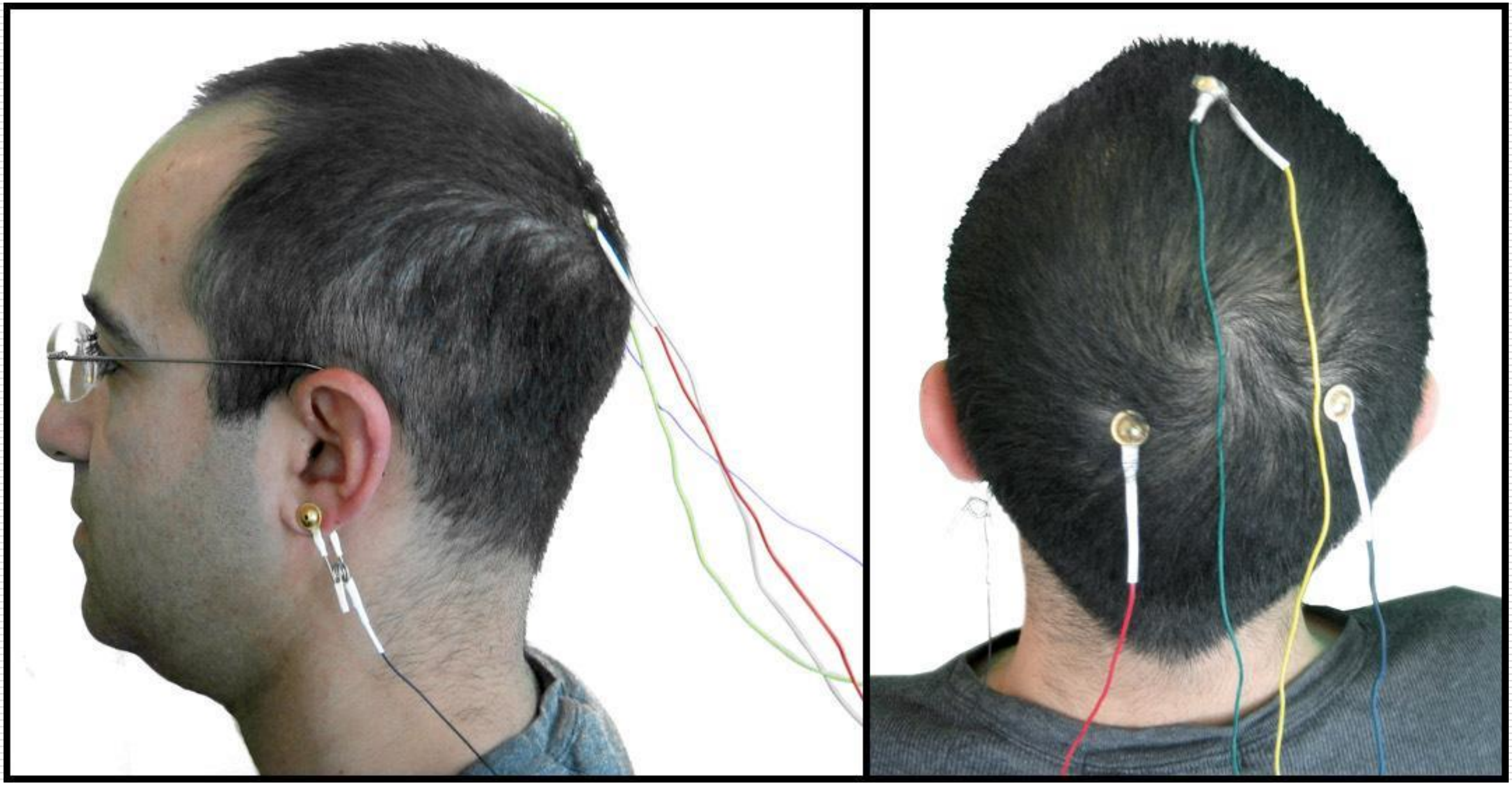
EXPERIMENTAL METHODS AND MEASUREMENTS



EXPERIMENTAL METHODS AND MEASUREMENTS



EXPERIMENTAL METHODS AND MEASUREMENTS

- The subjects were asked to perform the following ***five mental tasks***:
  - baseline task - for any possible subjects relaxed and not thinking activity;
  - letter - emergency call -subjects dial up 122;
  - math task - imagined addition;
  - counting task - count edges or planes around an axis rotation of 3d graphics;
  - geometric figure rotation - subjects imagine rotation of shown figure.

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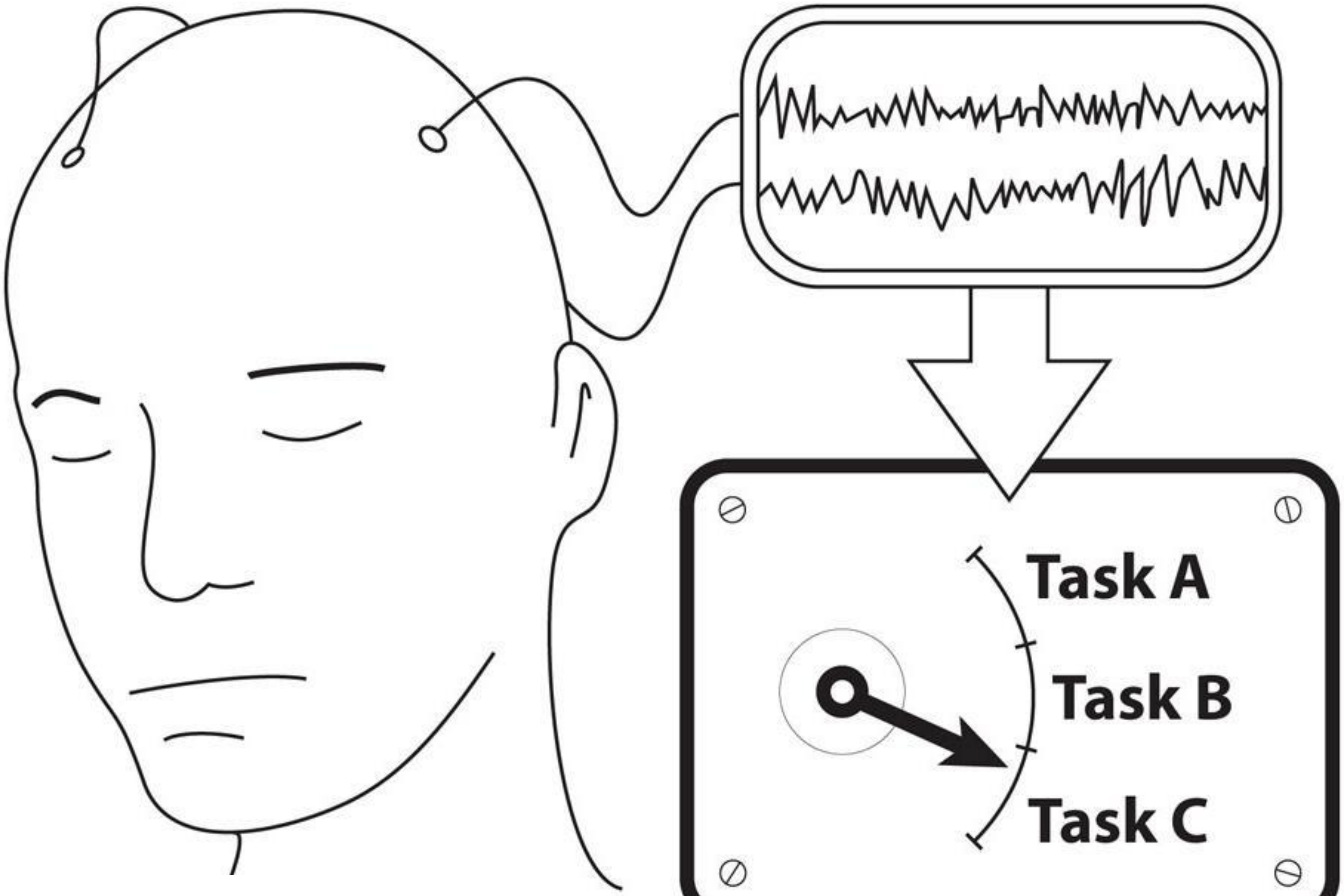
BRAIN-COMPUTER INTERFACE



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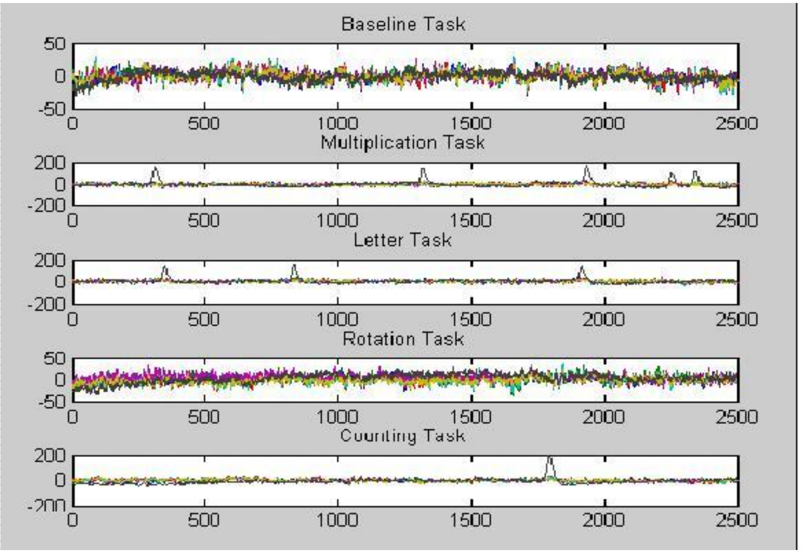
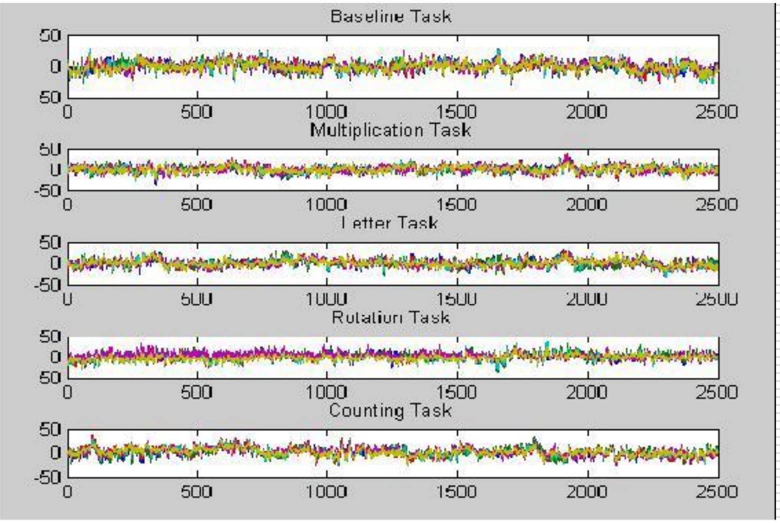
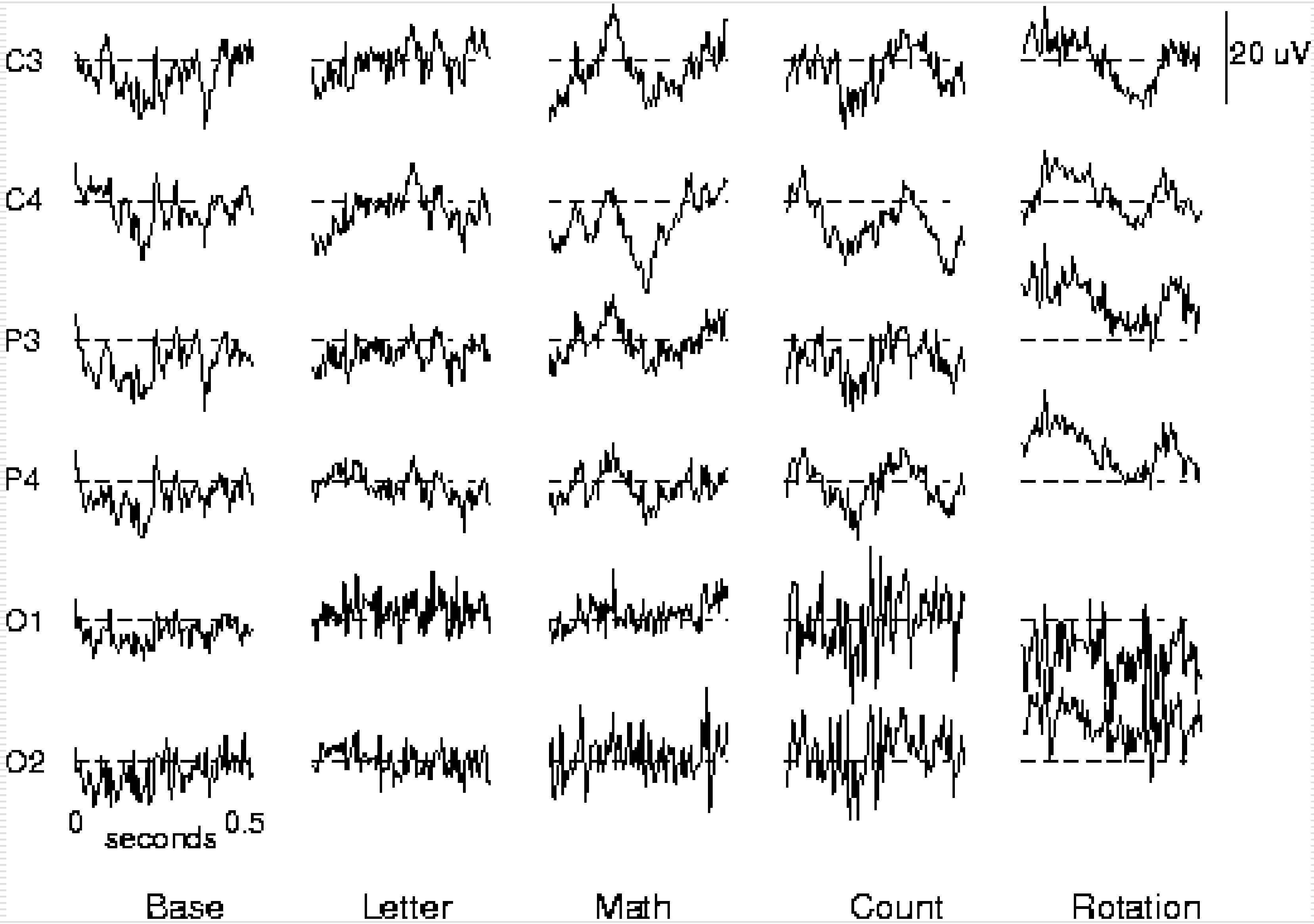
EXPERIMENTAL METHODS AND MEASUREMENTS

- The EEG data are segmented by rectangular windows. The length of each window is 1*s* (200 sampling points). Each mental task is repeated 20 times. Each time lasts 14 seconds. Each channel records 4000 sample data for each test.





EXPERIMENTAL METHODS AND MEASUREMENTS



EXPERIMENTAL METHODS AND MEASUREMENTS

- ***basic signal processing*** to transform the received time series data into a time independent data set;
- ***feature selection*** was processed to prune the feature set, keeping only those that added the most useful information to the classifier and to prevent overfitting;
- Selected features were used to ***train a Bayesian Network and perform the classification***.

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EXPERIMENTAL METHODS AND MEASUREMENTS

- ***spectral power of the signal*** in a set of six standard frequency bands: 4*Hz* (delta), 4-8*Hz* (theta), 8-12*Hz* (alpha), 12-20*Hz* (beta-low), 20-30*Hz* (beta-high), and 30-50*Hz* (gamma).
- In this work was used 18-fold cross validation, instead of standard 10-fold cross validation, to control the block design of the data collection procedure. For each fold, the model trained on 9 of the 10 available trials and reserved one trial for testing. A trial contains 13 contiguous windows for each task.

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EXPERIMENTAL METHODS AND MEASUREMENTS

- 18-fold cross validation, instead of standard 10-fold cross validation, to control the block design of the data collection procedure;
- For each fold, the model trained on 9 of the 10 available trials and reserved one trial for testing;
- A trial contains 13 contiguous windows for each task. Each of reported results is the mean classification accuracy after repeating this process 10 times using a different test trial for each fold.

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EXPERIMENTAL METHODS AND MEASUREMENTS

- Each of reported results is the mean classification accuracy after repeating this process 10 times using a different test trial for each fold.

Subject number	Mental Tasks				
	Base	*Letter*	*Math*	*Count*	*Rotate*
1	91.3%	63.4%	75.7%	69.4%	74.5%
2	92.4%	72.5%	78.3%	79.9%	67.2%
3	87.8%	78.8%	64.2%	78.6%	80.1%
4	90.2%	69.6%	69.7%	69.4%	78.2%
5	93.7%	67.5%	78.9%	76.4%	63.4%
6	89.3%	62.7%	80.2%	73.8%	78.1%
Mean	90.8%	69.08%	74.5%	74.58%	73.6%

- classification accuracies with Bayesian Network classifiers for five mental tasks

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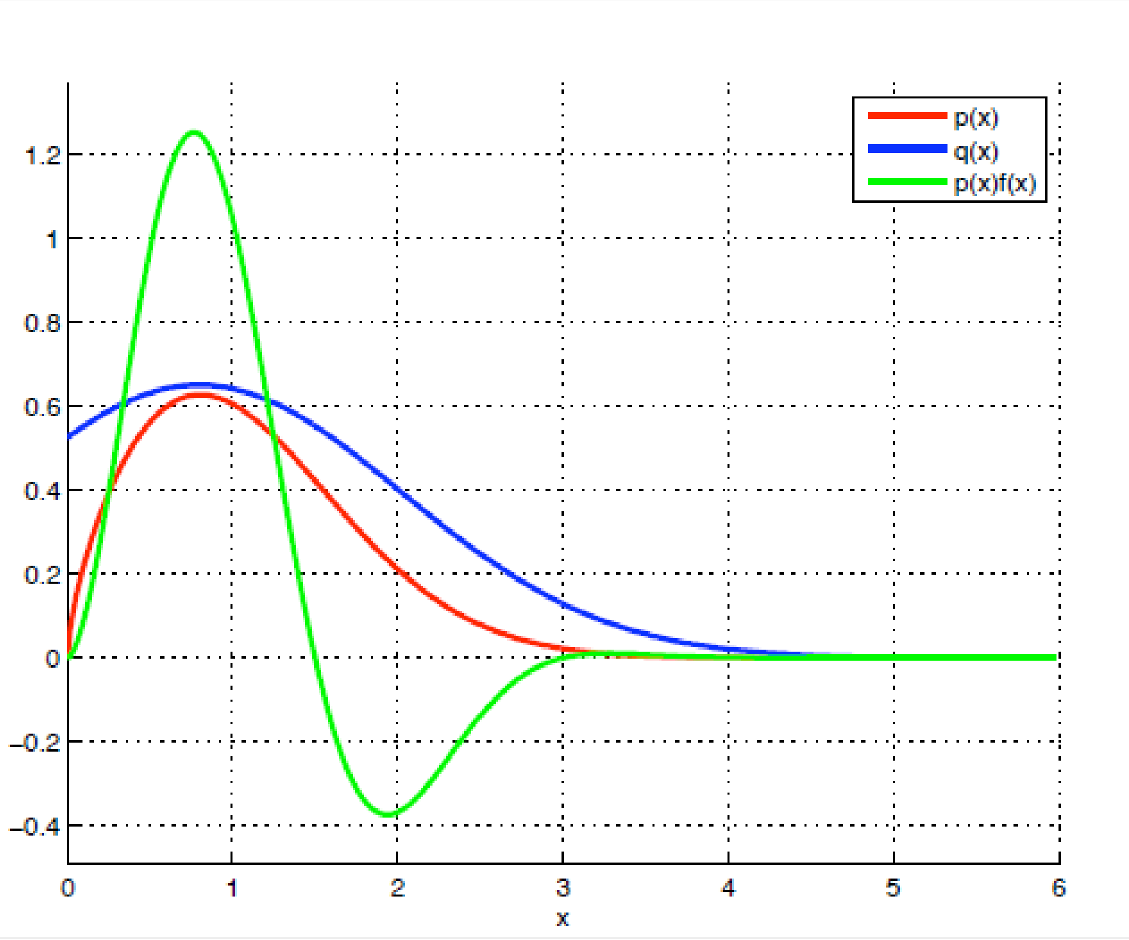
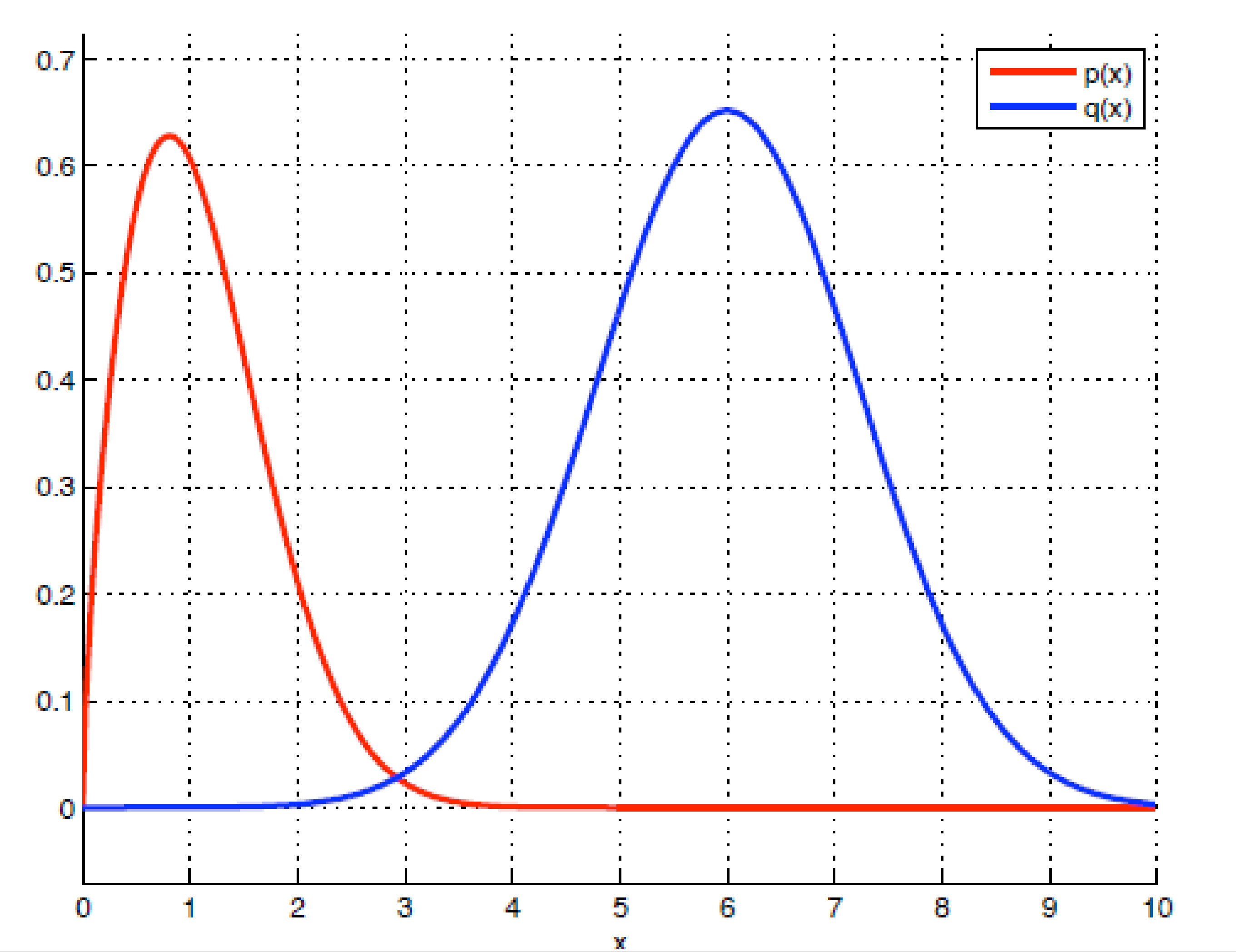
EXPERIMENTAL METHODS AND MEASUREMENTS

- Comparison between received results with Bayesian Network classifiers and pair-wise classifier



- shifting the mean of the sampling distribution



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Conclusions

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- An approach for HCI with classification of recorded electrophysiological signals at different mental tasks for connection via BCI with smart mobile applications is suggested;
- With considered experimental setup of brain-computer interface were provided experiments with six subjects for execution of five mental tasks.
- The measured outputs after noise filtering were classified with Bayesian Network classifier and with of pair-wise classifier.

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Thank you

Machine Learning Techniques for EEG-based Brain Imaging

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Prof. Svetla Radeva, DSc, PhD

This talk

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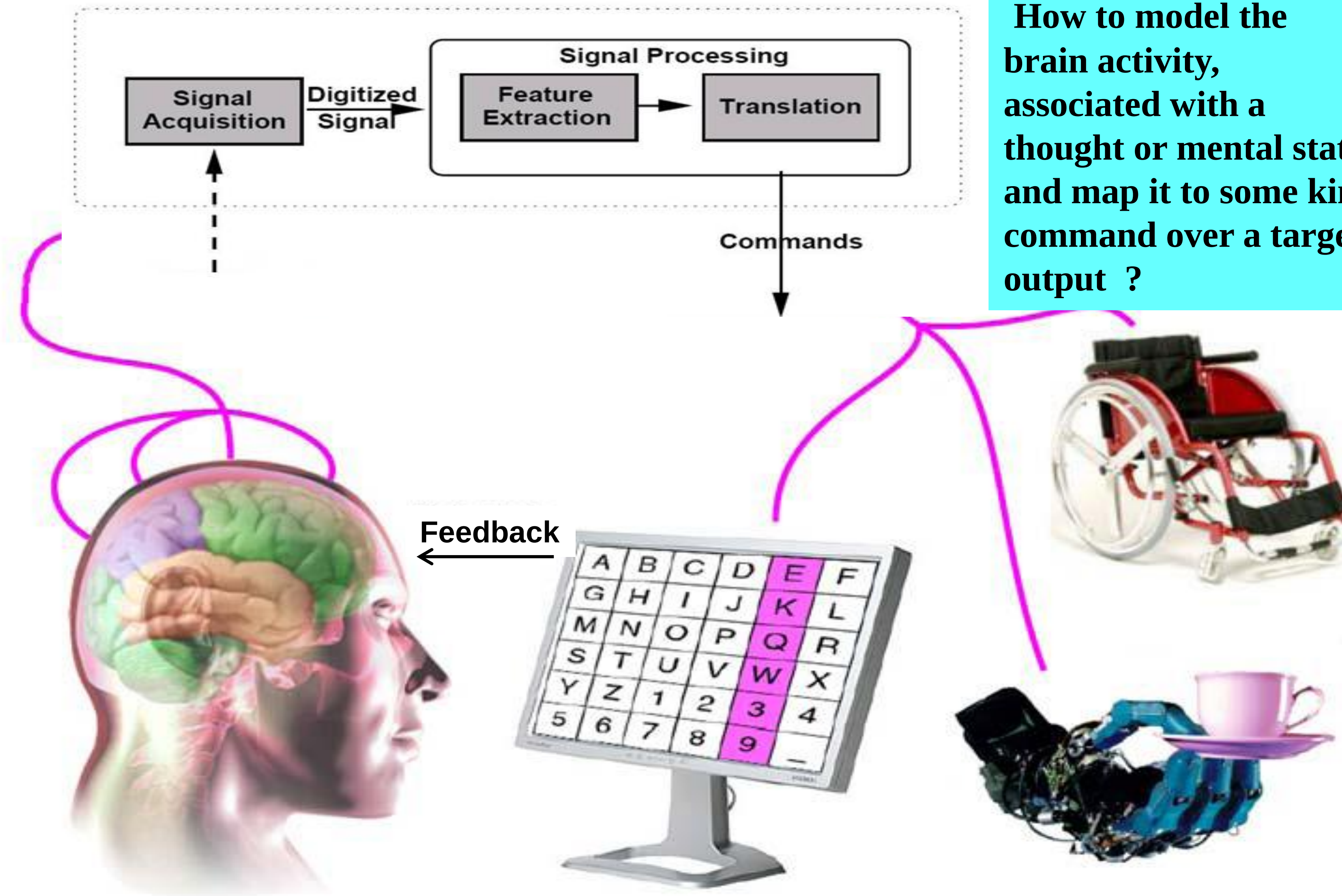
- Motivation – Brain Computer Interface (BCI)
- Motor Imagery EEG -based BCI
- Reconstruction of brain active zones based on EEG
- Learning to decode human emotions with Echo State Networks (ESN)
- Real data results

What is Brain Computer Interface?

How to model the brain activity, associated with a thought or mental state, and map it to some kind command over a target output ?



EEG segmentation

EEG signals - waves inside 0-60 Hz. Different brain activities :

- **Delta band** (below 4 Hz) - corresponds to a deep sleep
- **Theta band** (4-8 Hz) - typical for dreamlike state, old memories
- **Alpha band** (8-13 Hz) - relaxed state (occipital brain zone)
- **Mu rhythm** (8-13Hz) – movement intention and preparation, imagery movement (sensory- motor cortex)
- **Beta band** (13-30 Hz) - related with concentration and attention
- **Gamma band** (30-50 Hz) - mental activities as perception, problem solving, creativity

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EEG BCI Paradigms

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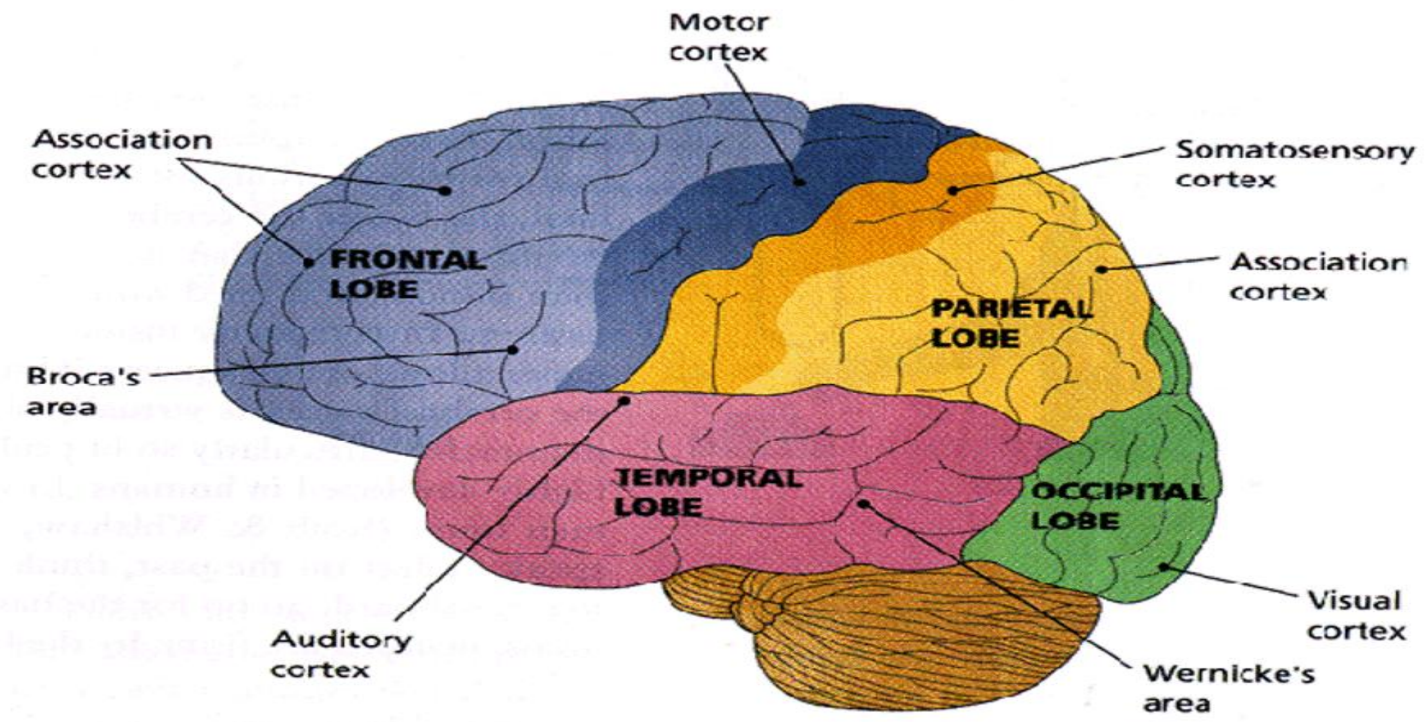


- **Motor imagery tasks** : changes in mu rhythms in sensory motor cortex

•**Visual/Auditory Evoked Potentials** (EP): changes generated in response to visual/auditory stimulus (ex. VEP P300)

Motor Imagery BCI Paradigm

- A second before a subject initiates voluntary movement, the mu rhythms over the hemisphere contralateral to the movement direction in the sensory-motor cortex decrease in amplitude.

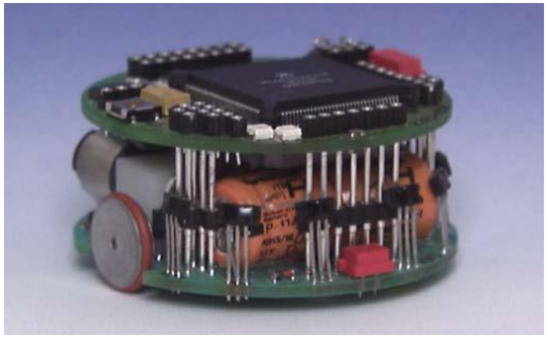
- Mu rhythms returns to the baseline within a second after movement is initiated .

- These activity-dependent changes in mu-rhythms are termed ***Event Related Desynchronization*** (ERD) and ***Event Related Synchronization*** (ERS).

- The objective is to detect ERD and ERS.

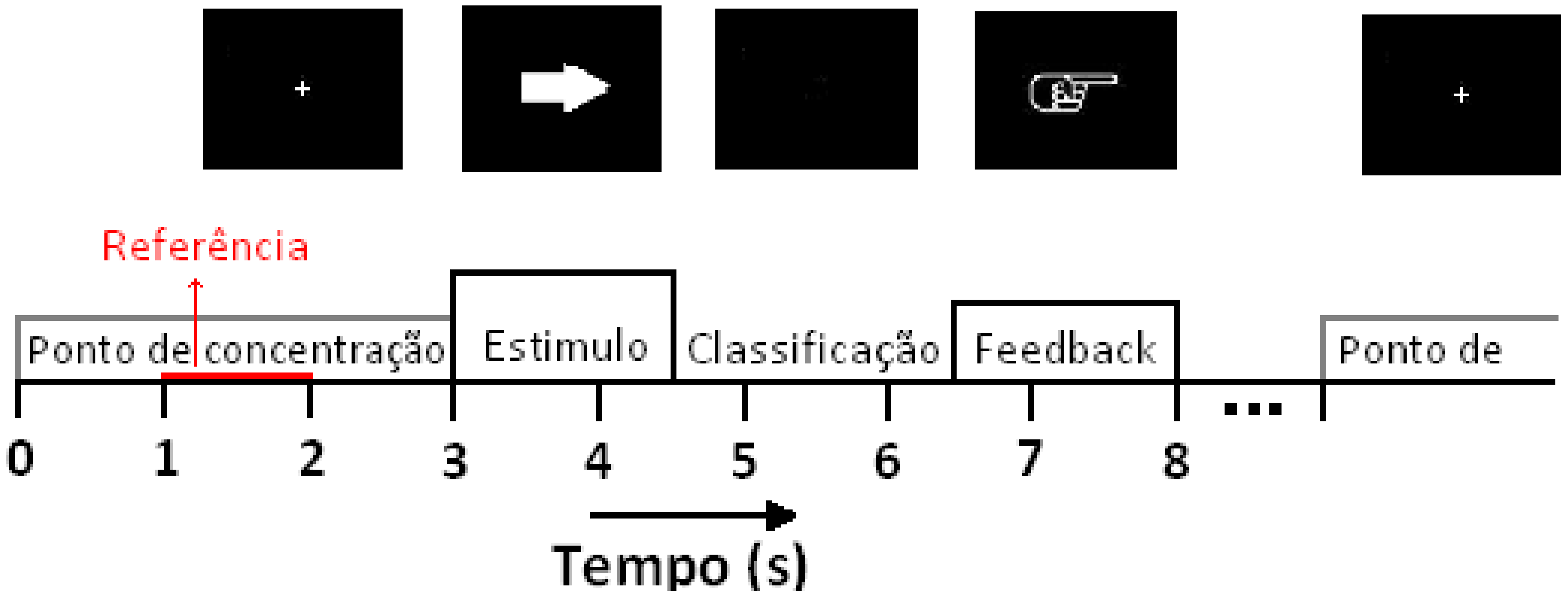
BCI Prototype with mini-robot

Modulation of mu rhythms (during motor imagery tasks) to control a mini robot on an improvised motorway



Subject training

Training stage - The user learns to modulate its mu-rhythms with the help of visual feedback



Real-time BCI – control of a mobile robot

EEG signal processing

- Standard pass-band (1-40Hz) digital filter

- One equivalent canal for each hemisphere (Spatial Surface Laplacian Filter)

C_LH = C3 – 1/3*(F3+P3+Cz) (left hemisphere)
C_RH = C4 – 1/3*(F4+P4+Cz) (right hemisphere)

- Extract mu rhythms (8-13 Hz) from sensory motor cortex channels

- Signal divided in blocks of 128 Samples (0.5 s)

- Feature extraction - Energy (P) per block for each hemisphere

BCI motor commands

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$$ERD\% = \frac{P - B}{B} 100$$

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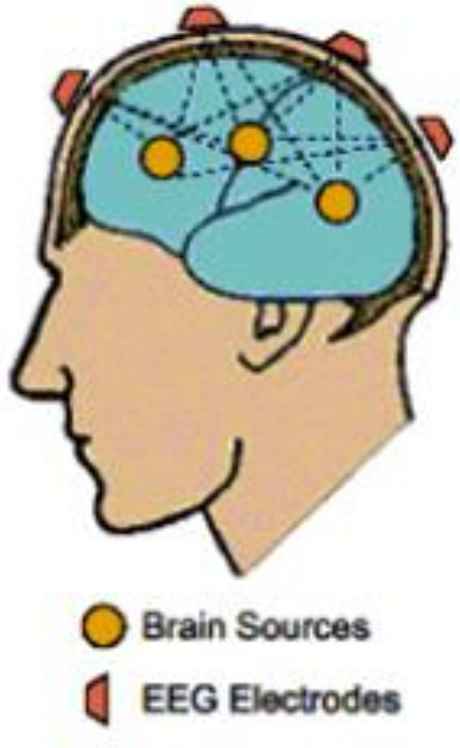
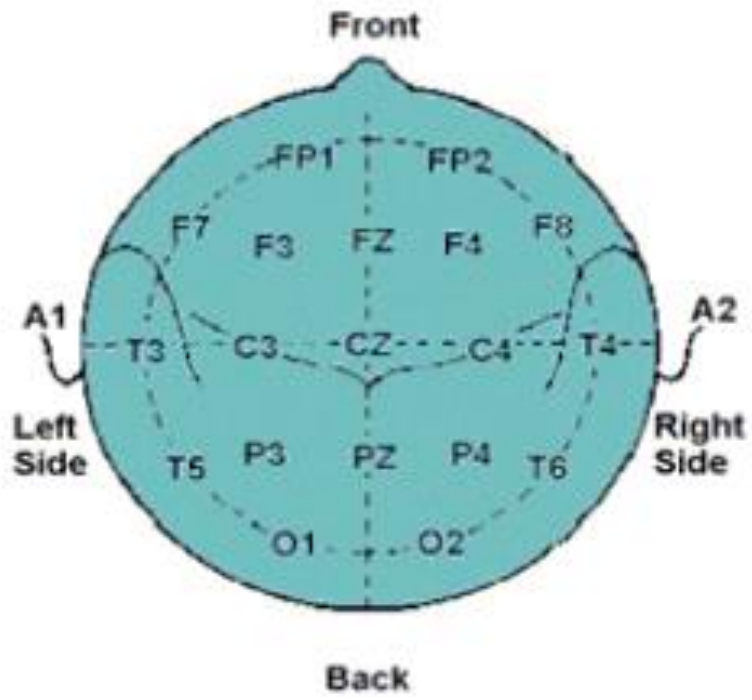
RULES:

- if only the C_RH verifies ERD - “move LEFT”;
- if only the C_LH verifies ERD - “move RIGHT”;
- if both C_RH & C_LH verify ERD - “move FORWARD”;
- if neither of the channels verify ERD - “STOP”

Source-based noninvasive BCI





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Reconstruction of dynamic brain dipoles based only on EEG

1) **Estimate the number of the few most active brain zones (dipoles) .**

2) **Statistical (Particle Filter) approach to estimate:**

   a) **Moving (over time) dipole locations in the head geometry (x,y,z coordinates);**

   b) **Oscillations at the estimated locations (dipole moments).**

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Forward EEG model

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$$z_k = L(d_k)s_k + v_k \quad z_k = \begin{bmatrix} EEG\_\text{channel1} \\ \vdots \\ EEG\_\text{channelN} \end{bmatrix}_k$$

- Space location (x,y,z) of M brain dipoles

$$\Rightarrow d_k = [d_k(1),\ldots\ldots d_k(M)]^T \in R^{3M\times 1}$$

- Brain dipole oscillations (amplitude and orientation)

$$\Rightarrow s_k = [s_k(1),\ldots\ldots s_k(M)]^T \in R^{3M\times 1}$$

- Lead-field matrix (function of dipole location, EEG electrode positions, head geometry, electric conductivity)

$$L(d_k) = [L_1(d_k(1)),\ldots\ldots L_M(d_k(M))]^T \in R^{n_z\times 3M}$$

EEG source reconstruction – inverse problem

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$$z_k = L(d_k)s_k + v_k \quad \Rightarrow \quad \{s_k, d_k\} = ?$$

Deterministic methods (ONLY <u>static dipoles</u>)

- Multiple Signal Classification (MUSIC)
- Spatial Filters (ex. Beamforming)
- Blind Source Separation

Assumptions:

-Brain source location is fixed and known

or

-Make an exhaustive search of the total head volume

-Given source space locations, estimate amplitude and directions of the source oscillations

Bayesian state estimation problem

- **State model (*f* – state transition function)**

$$x_k = f\left(x_{k-1}, w_k\right)$$

- **Measurement (observation) model**

$$z_k = h\left(x_k, v_k\right)$$

- Kalman Filter (linear *f* and *h* and Gaussian *w* and *v*)

- Extended KF (requires linearization around predicted values)

- Nonparametric (numerical, discrete) methods -
  <u>no constrains on *f* , *h* , w, v</u>

EEG source estimation – Bayesian approach

- **Observation model**

$$z_k = L(d_k)s_k + v_k \quad \Rightarrow \quad \{d_k, s_k\} = ?$$

- **State model** $x_k = ax_{k-1} + w_k, \quad x_k = [d_k, s_k]$

Brain source state model (random walk in the source space)

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Particle Filter (PF)

,

- Generate N samples according to a chosen distribution

$$x_0^{(l)} \sim p(x_0), l = 1....N, \quad w_0^{(l)} = 1/N$$

- The prediction of the state given previous measurements is approximated by a set of weighted particles:

$$p(x_k \mid z_{1:k}) \approx \sum_{l=1}^{N} \pi_k^{(l)} \delta\left(x_k - x_k^{(l)}\right) \qquad \pi_k^{(l)} = \frac{w_k^{(l)}}{\sum_{l=1}^{N} w_k^{(l)}}$$

- When a new measurement comes the weights are updated

$$w_k^{(l)} = w_{k-1}^{(l)} p(z_k \mid x_k^{(l)})$$

- State estimation

$$\hat{x}_k = \sum_{l=1}^{N} \pi_k^{(l)} x_k^l$$

Information theoretic criterion (IC)

’

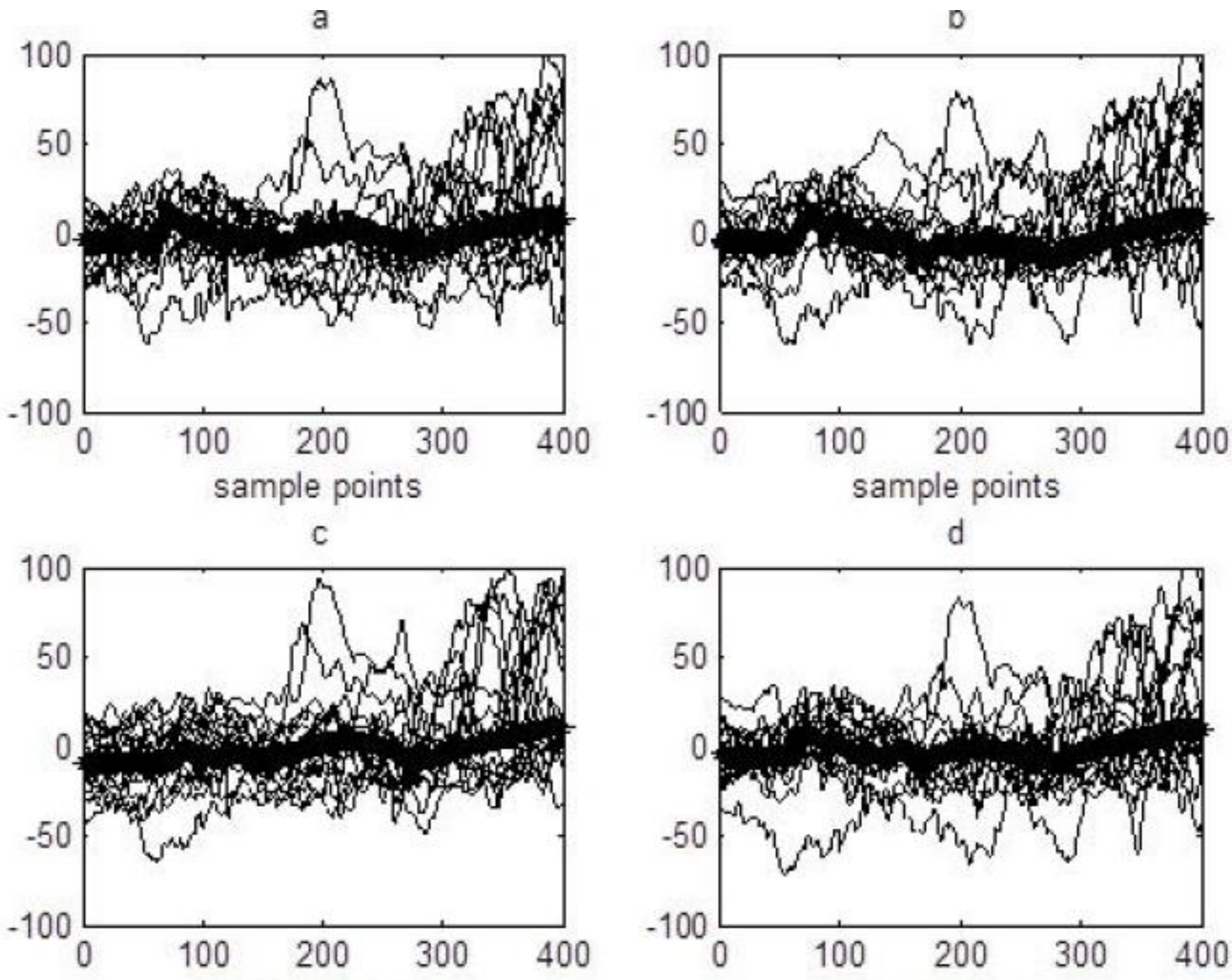
$$IC(m) = T(n_z - m)\log\left[\frac{1}{n_z - m}\sum_{i=m+1}^{n_z}\lambda_i\right] -$$

$$T\sum_{i=m+1}^{n_z}\log(\lambda_i) + 2m(2n_z - m + 1)\log(T)$$

m **- the number of the independent active dipoles**
n_*z* **- the number of EEG channels.**
T**- the number of sample points**
λ_i **- the eigenvalues of the covariance matrix of EEG observ.**

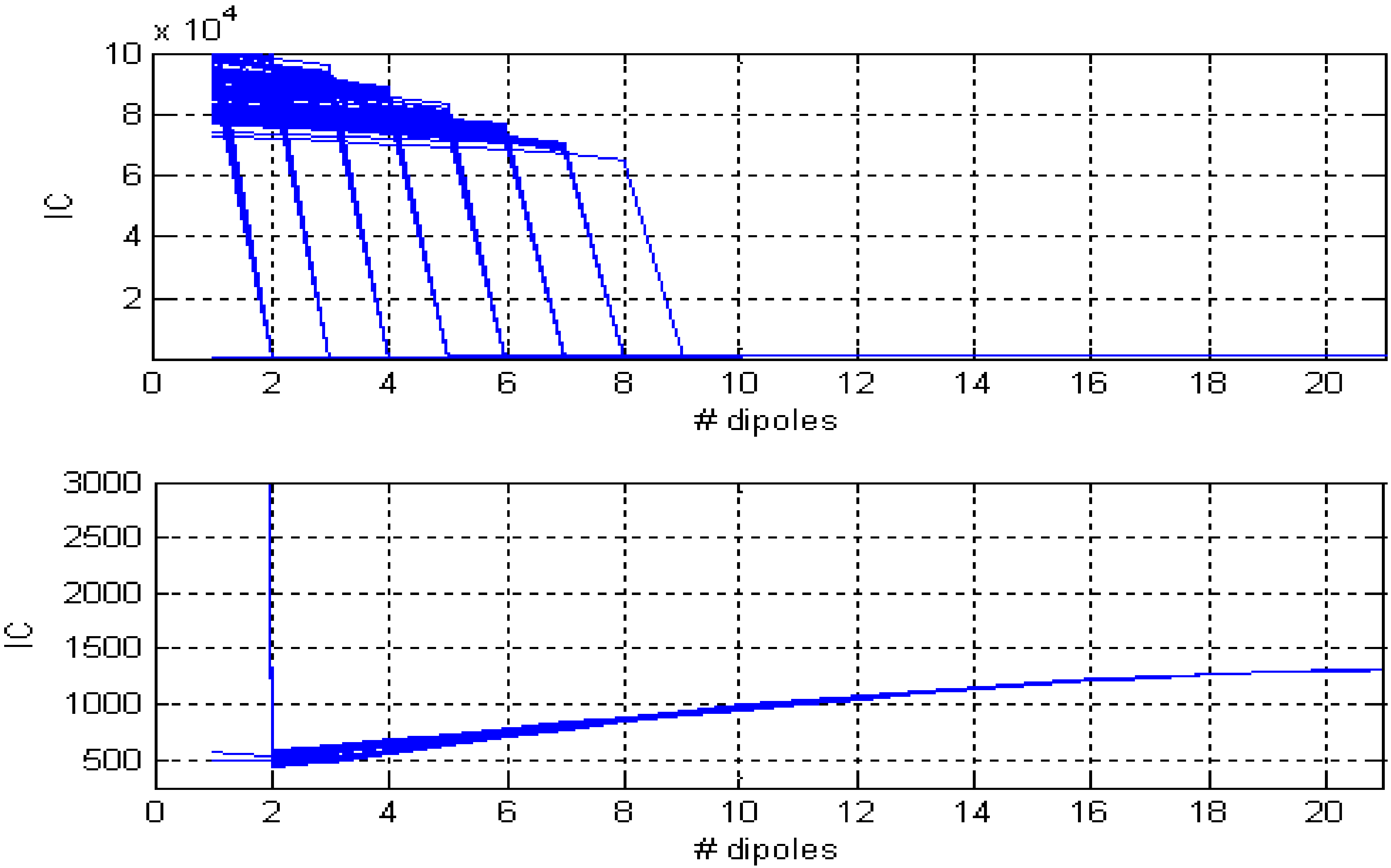
<u>The number of active dipoles is the *m* for which C has minimum</u>

Real EEG – Visually Evoked Potentials (VEP)



Superposition of 148 VEP (electrodes Pz, P2, P3,P4)

Real EEG – Visually Evoked Potentials (VEP)



Estimation of the # of active dipoles by IC for real EEG data:

Top: 148 trials, min IC for 2 to 9 dipoles

Bottom: 18 trials, min IC for 2 dipoles

Recovered position and oscillations - subject 1

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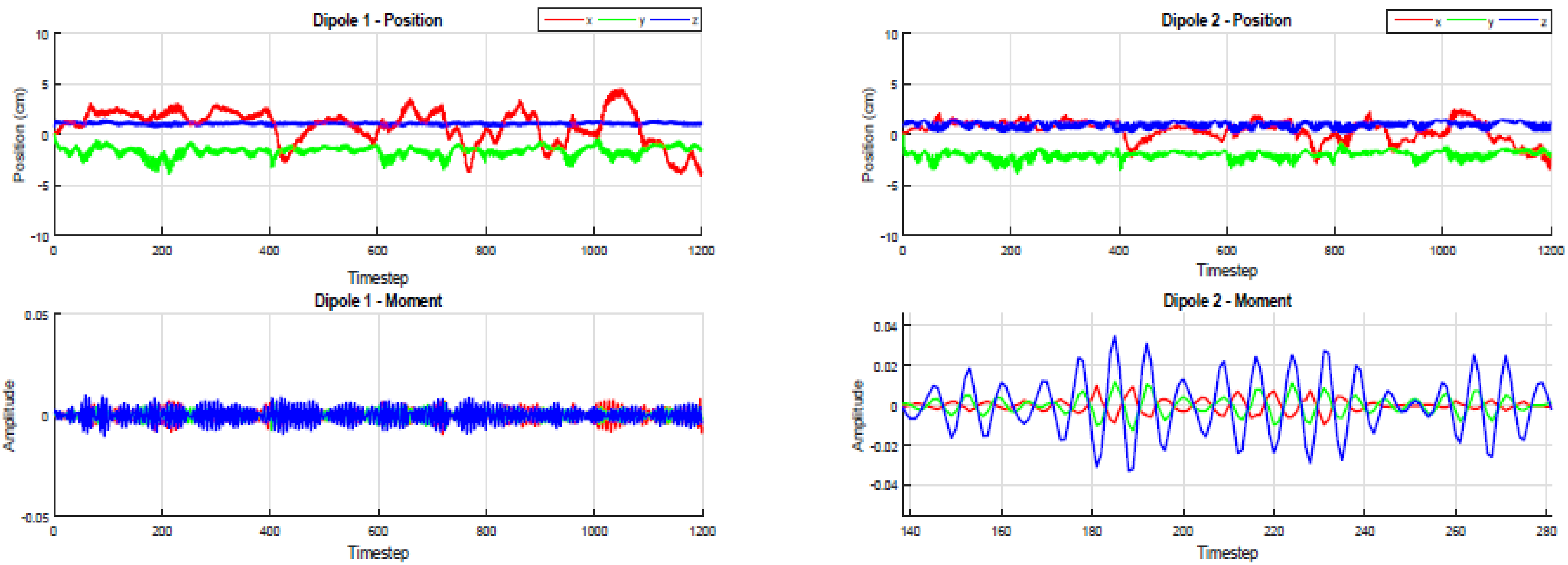

(a) Subject 1

Recovered position and oscillations - subject 2

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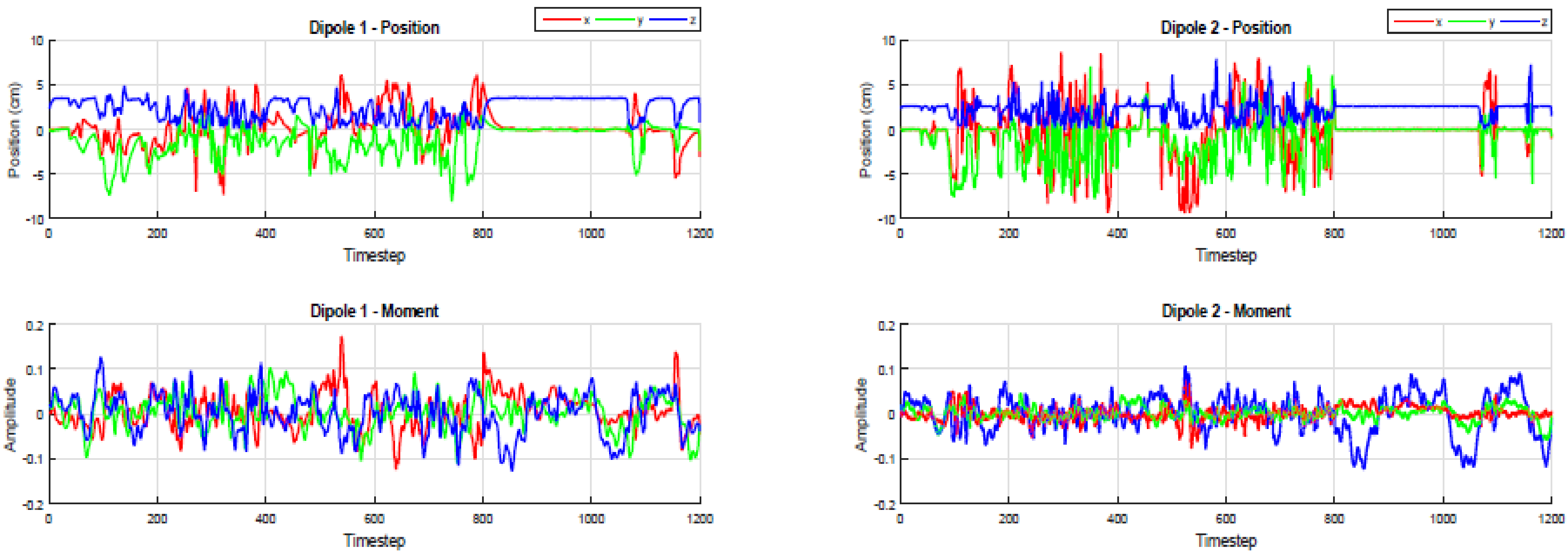

(b) Subject 2

Real EEG data (VEP) - Primary visual cortex

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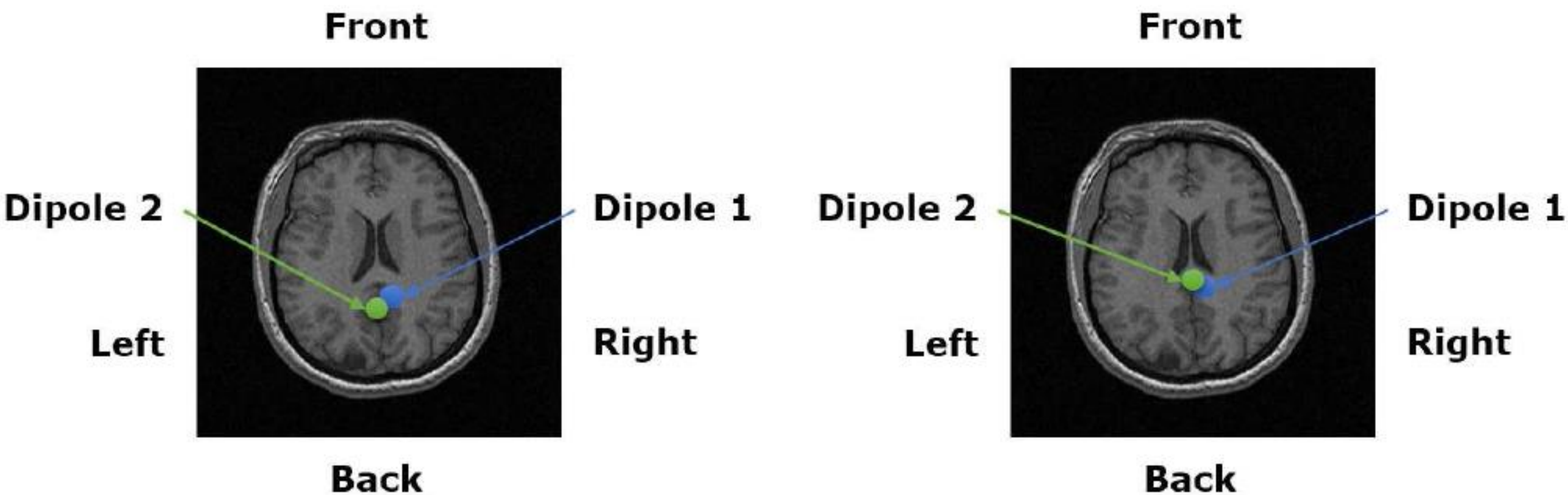

(a) Subject 1 (b) Subject 2

The arrows point the estimated source locations

Curse of dimensionally

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- **How to recover higher number of brain dipoles ?**
- **A single PF for each dipole ?**

Learning to decode human emotions with Echo State Networks (ESN)

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Data collection

- Visual Stimuli (Affective images)
- EEG recorded from 26 volunteers
- Features extraction

ESN

- Generated ESN with different reservoirs size:
- 10, 30, 50, 100, 150, 300, 500

Clustering

- k-means
- Fuzzy C-means

Classification

- Linear discriminant analysis (LDA)
- k-nearest neighbor (kNN)
- Naive sBaye (NB)
- Support Vector Machines (SVM)
- Decision Tree (DT)
- Ensemble (Vote)

Valence and Arousal

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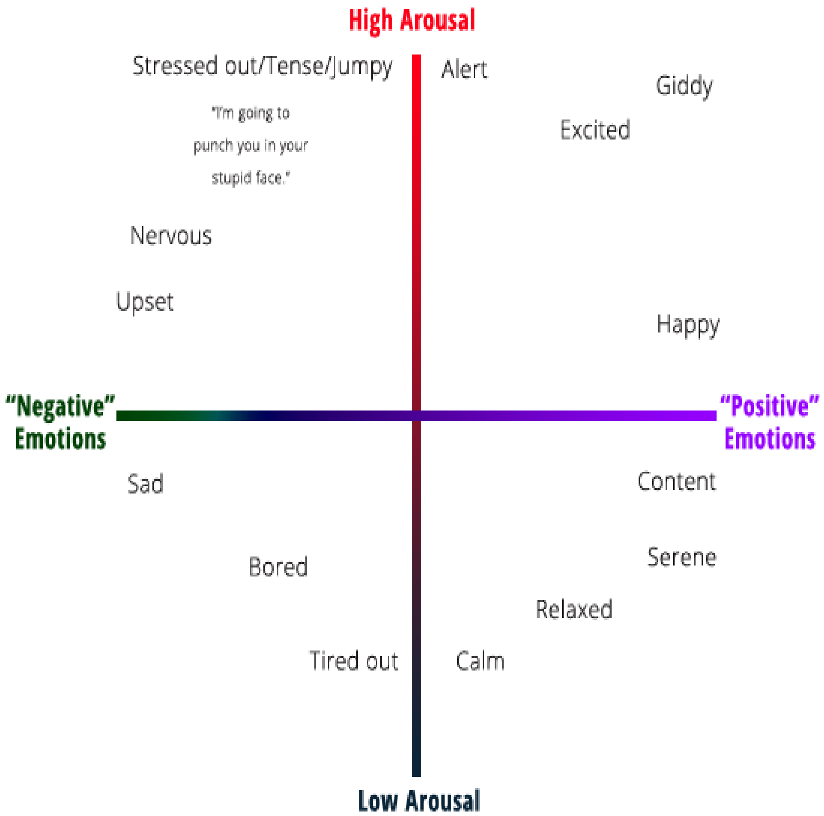
- Arousal – intensity of the emotions
- Valence - the sign of the emotions

+ valence ⇔ positive emotion

- valence ⇔ negative emotion



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Data Preprocessing

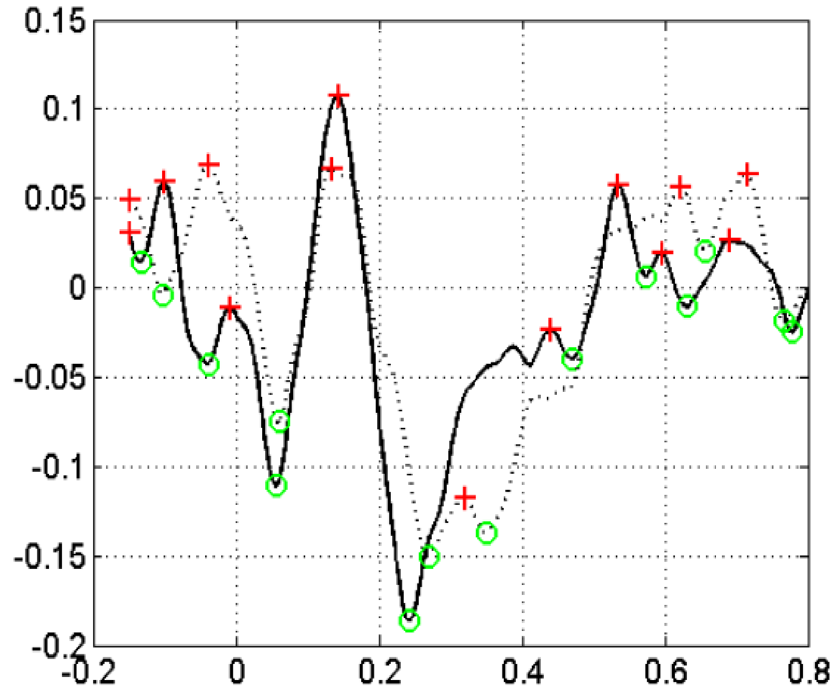
- Preprocessed (filtered, eye-movement corrected, epoched).
- Extracted 12 temporal features
  - the first 3 minimums (Amin1, 2,3)
  - the first 3 maximums (Amax 1,2,3),
  - their associated latencies

  (Lmin 1,2,3 & Lmax 1,2,3)
- Total of 252 features

(21 channels x12 features)

- Data normalization

  Xnorm = (X - Xmean) / std(X)



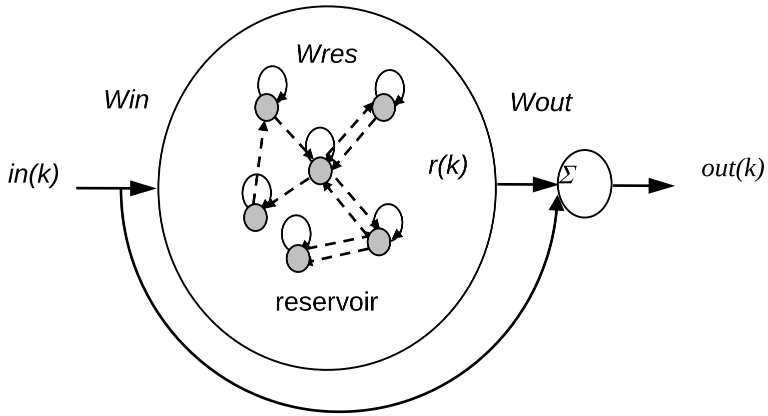
Extracted features from averaged ERPs: positive (line) and negative (dot) valence state

Echo State Networks (ESN)

- Class of recurrent neural networks (RNN)
- **<u>Classical ESN approach:</u>**

- The reservoir weights are generated randomly, only the output weights Wout are trained.

- Usually applied for time-series regression problems.



- **<u>Our ESN approach</u>**

- The reservoir weights are initially tuned through “intrinsic plasticity” (entropy maximization) and the output layer is substituted by clustering or classification technique.

- Applied for feature selection.

Data clustering results

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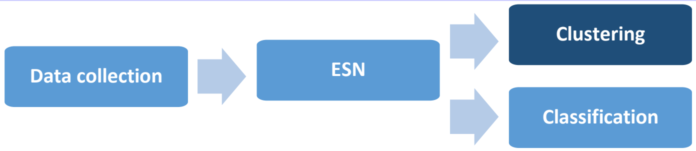
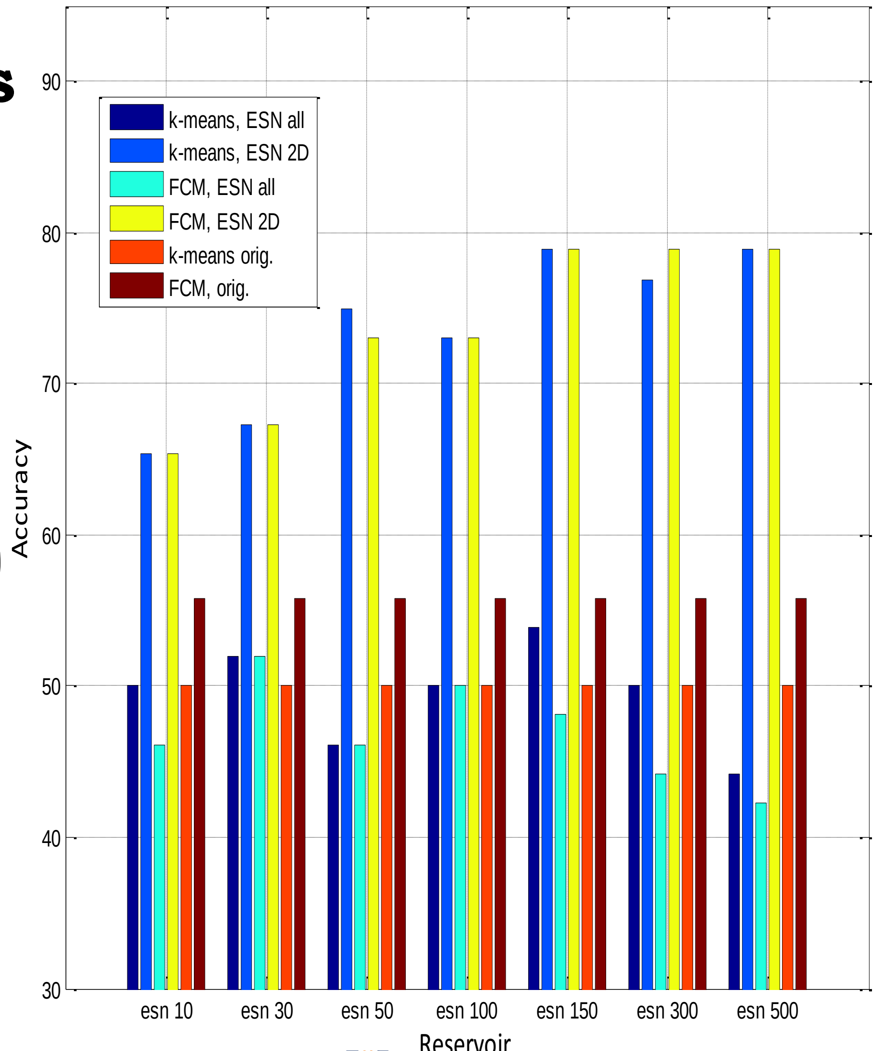


- **k-means and fuzzy C-means (FCM) clustering**
- **Reservoir size: (10, 30, 50, 100, 150, 300 or 500)**
- **Original 252 features (orig.)**
- **2D ESN neurons**
- **All ESN neurons**



Best: 2D feature space (>78%)

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Data classification results

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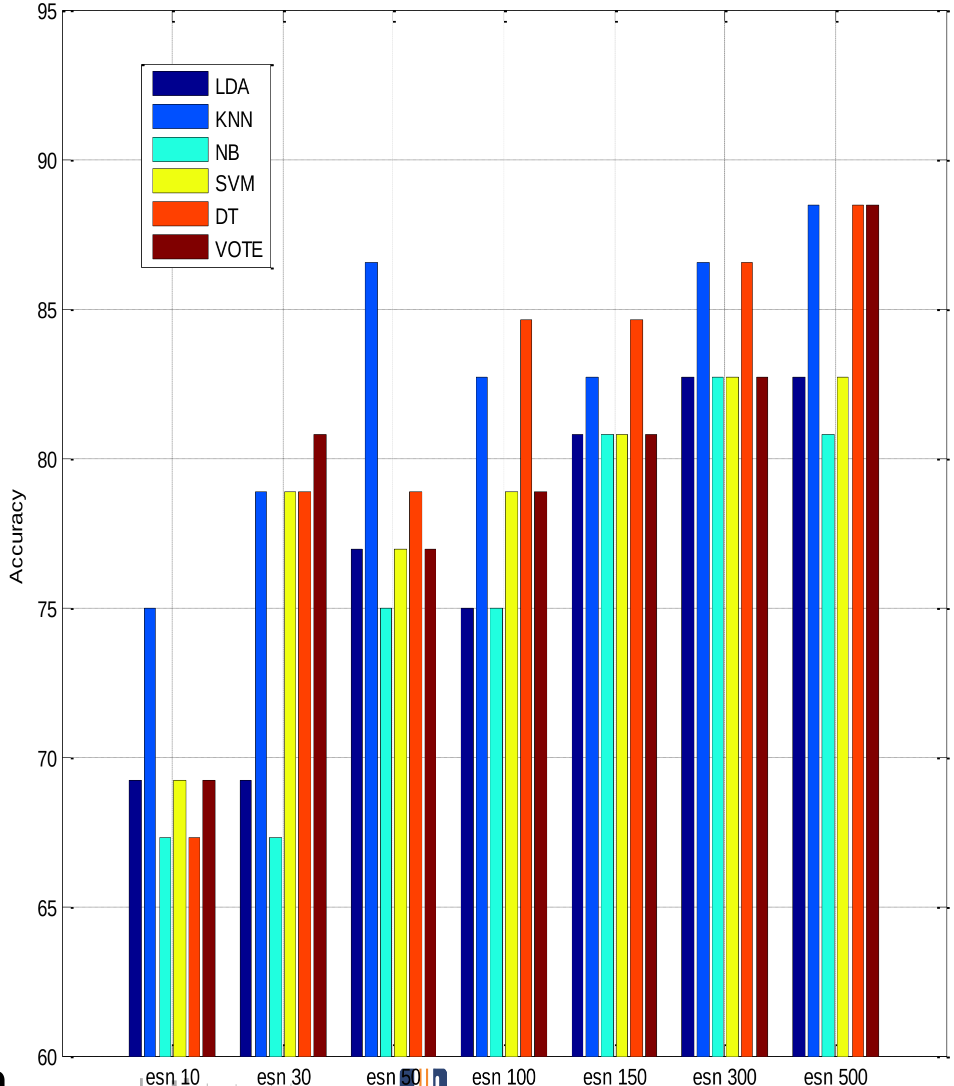
- Original 252 features [60% - 71% accuracy].
- Vote (>88%)



Comparison with state of the art

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Co-funded by the Erasmus+ Programme of the European Union

	Participant	Emotional classes	Classifier	Result
	4 subject dependent	3	NB	58.00%
	10 subject dependent	2	SVM	93.50%
	1 subject dependent	3	QDA	66.66%
	15 subject dependent	2	SVM	82.00%
	11 subject dependent	3	KNN	82.00%
	20 subject dependent	5	SVM	70.50%
	5 subject dependent	3	KNN	90.77%
	11 subject independent	2	SVM	85.41%
Our results	**26 subject independent**	2	k-means and fuzzy C-means	**78.85%**
Our results	**26 subject independent**	2	KNN, DT, Vote	**88.46%**