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Signal Processing & Biomedical Technology Unit

CENTRE FOR RESEARCH & TECHNOLOGY - HELLAS
Informatics & Telematics Institute

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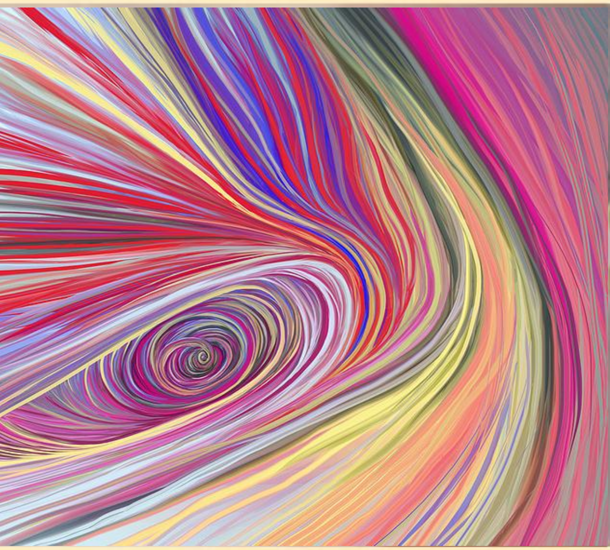

Emotions, Action Representation and EEG: A Signal Processing Perspective

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Outline

Advanced Signal Processing Techniques

EEG

- Emotions (Recognition/Elicitation)

EEG

- Action Representation (Music stimuli perception)

Focus place

Advanced Signal Processing Techniques

EEG

- Emotions (Recognition/Elicitation)

EEG

- Action Representation (Music stimuli perception)

Emotions

Emotions are connected to the human personality and play an important role in the brain architecture and human behavior

Emotional Development

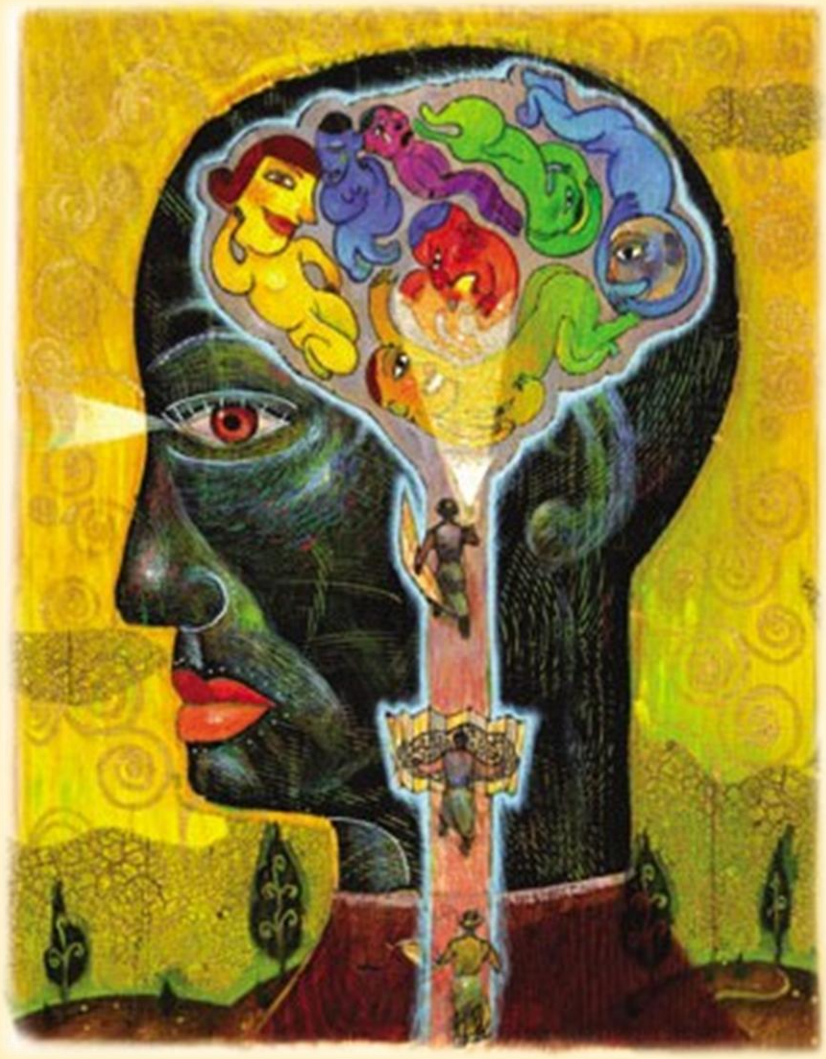
Complex interactions of the biological nature with the environment based on

- observation
- experience
- response
- (self-) regulation

Affective domain of Bloom's taxonomy

Emotion Understanding

- Multi-facet processes based on the behavioral and neurological domains
- They cannot be understood as the result from one emotional center of the brain
- The emotional differences are mainly due to associated brain networks



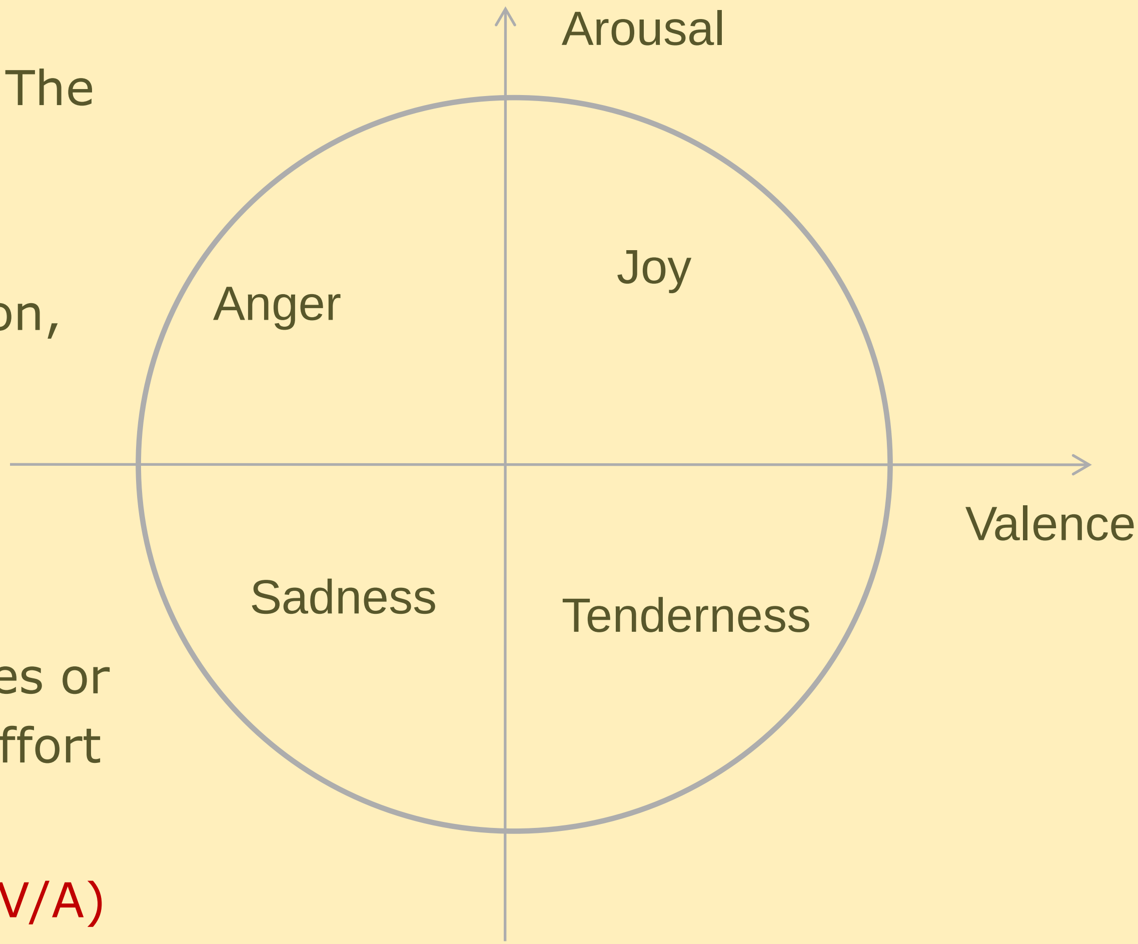
Ned Kalin: *Kalin's dream*

Emotion Modeling

Bio-informational theory of emotion (Lang's Model): The emotions are

- approached as action characteristics (motivation, physiology/behavior, cognitive factors)
- organized as sourced by vivid organic desires reflected in specific senses or defensive desires in an effort to avoid a situation

2D Valence-Arousal Model (V/A)

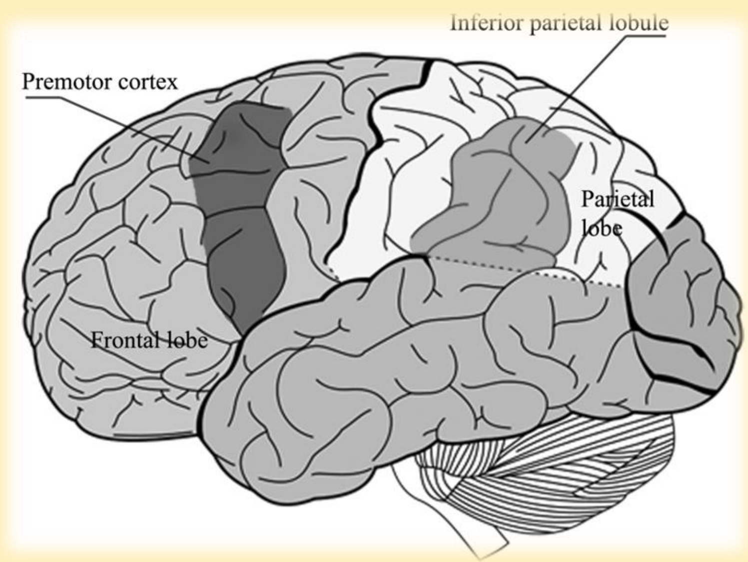


Emotion Elicitation

Senses stimulation (visual, audio)

Emotional empathy

The role of mirror neurons



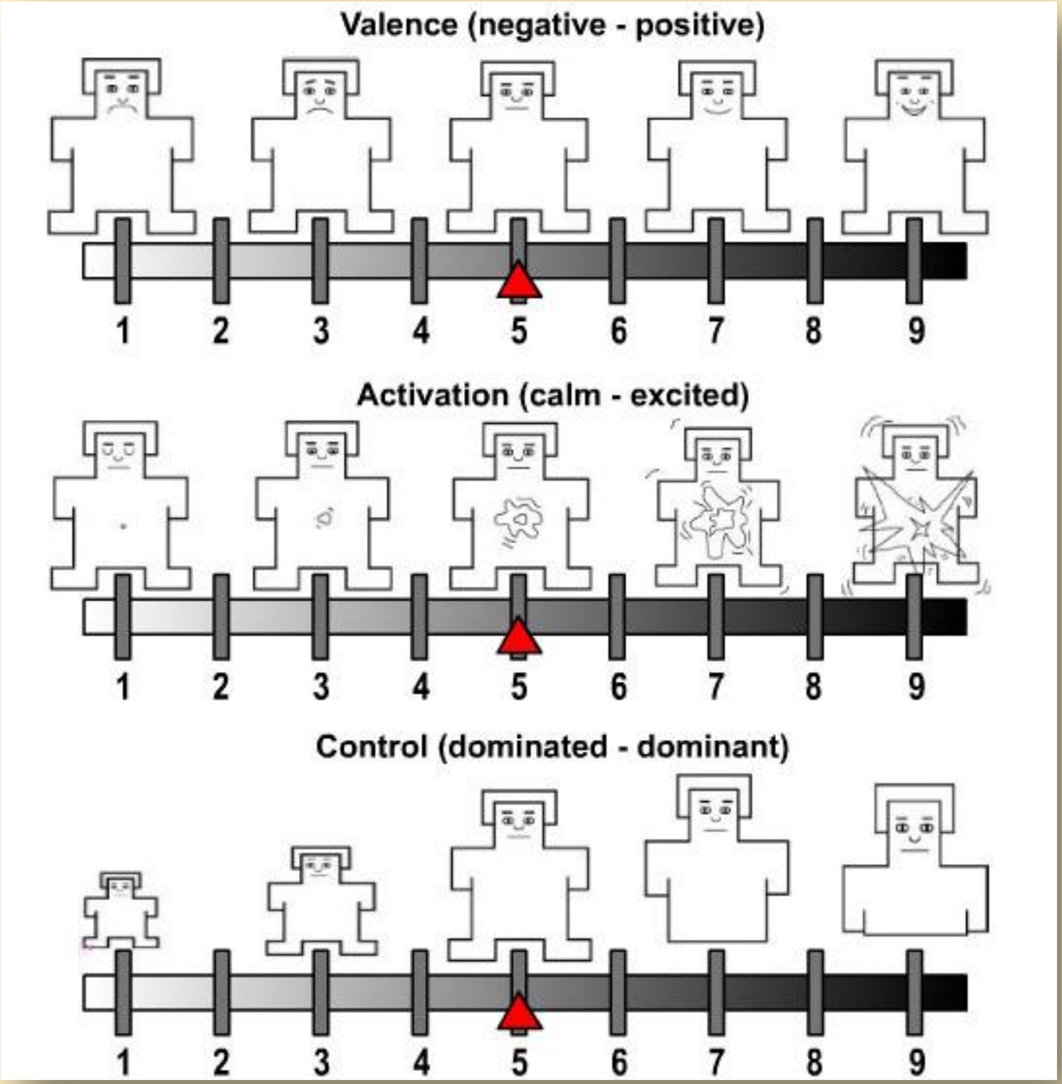
μ-rhythm (8-12 Hz)

Pictures of Facial Affect (POFA)- Ekman

International Affective Picture System (IAPS)-Lang *et al.*

V/A (Self-) Quantification

Self-Assessment Manikin (SAM) (Bradley & Lang, 1994)



Analysis Techniques

New brain imaging techniques

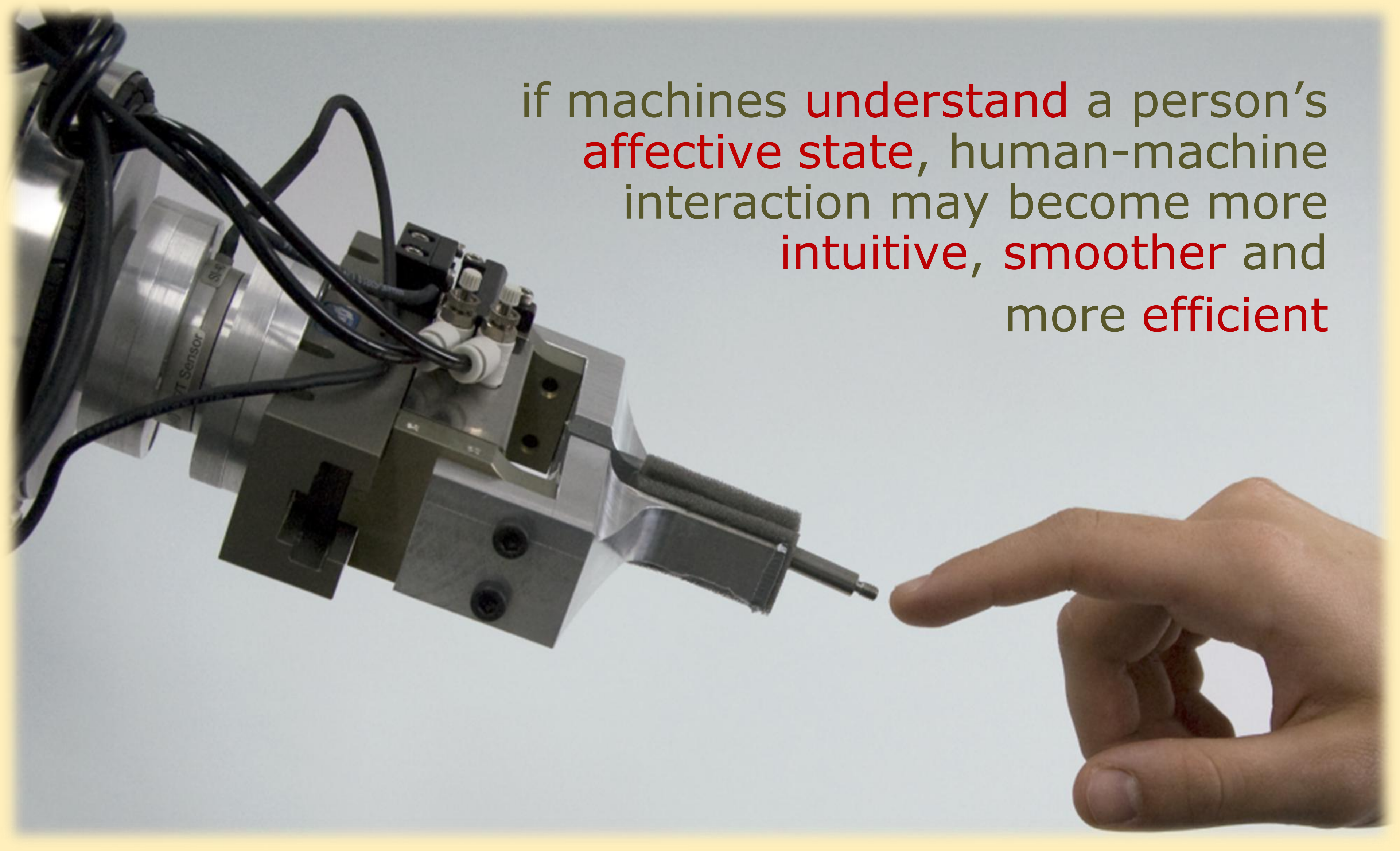
- positron emission tomography (PET)
- functional magnetic resonance imaging (fMRI)

New brain signal analysis techniques

- EEG
- MEG

during emotional stimulation

Human-Machine Interaction



if machines **understand** a person's **affective state**, human-machine interaction may become more **intuitive**, **smoother** and more **efficient**

Human-Machine Interaction

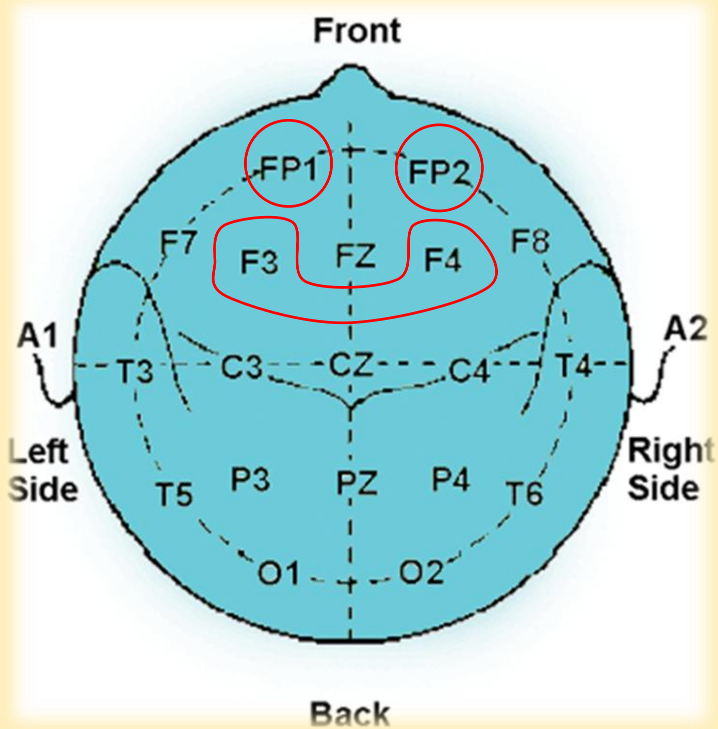
- Affective Computing
- Emotion Recognition
- EEG-based Emotion Recognition

EEG-based Emotion Recognition

- Emotion elicitation
- Data recording and preprocessing
- Classification

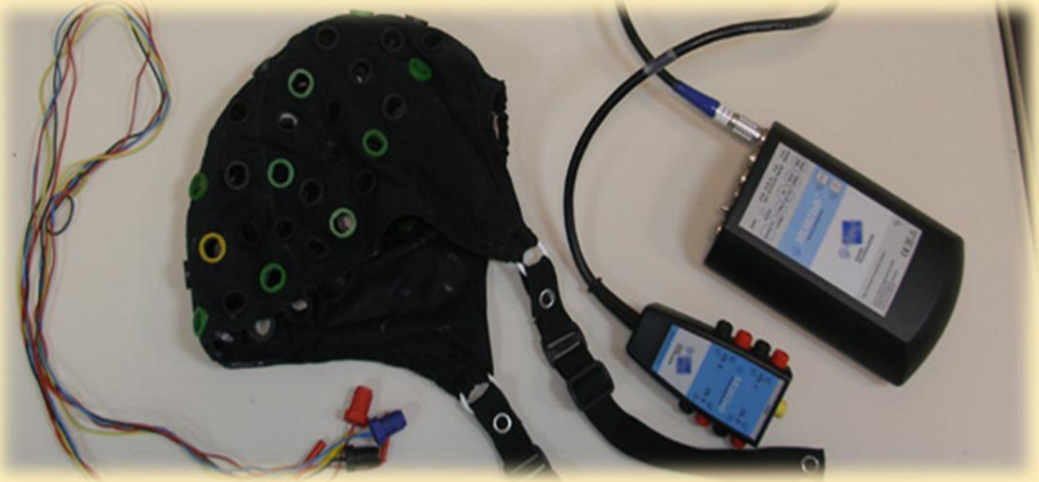
EEG Acquisition

- Prefrontal Cortex Asymmetry
- Three Channels: Fp1, Fp2, F3/F4
- 256 samples/second
- 16 bit Analog to digital conversion
- Band-pass filtering 8-30Hz (alpha & beta bands)



EEG Acquisition (hardware)

g.tec (Medical & electrical engineering, Guger Technologies, www.gtec.at): 4 EEG bipolar channels, passive electrodes, Filters: 0.5–30 Hz, Sensitivity: 100 μV, Data transfer: wireless, Bluetooth 'Class I' technology



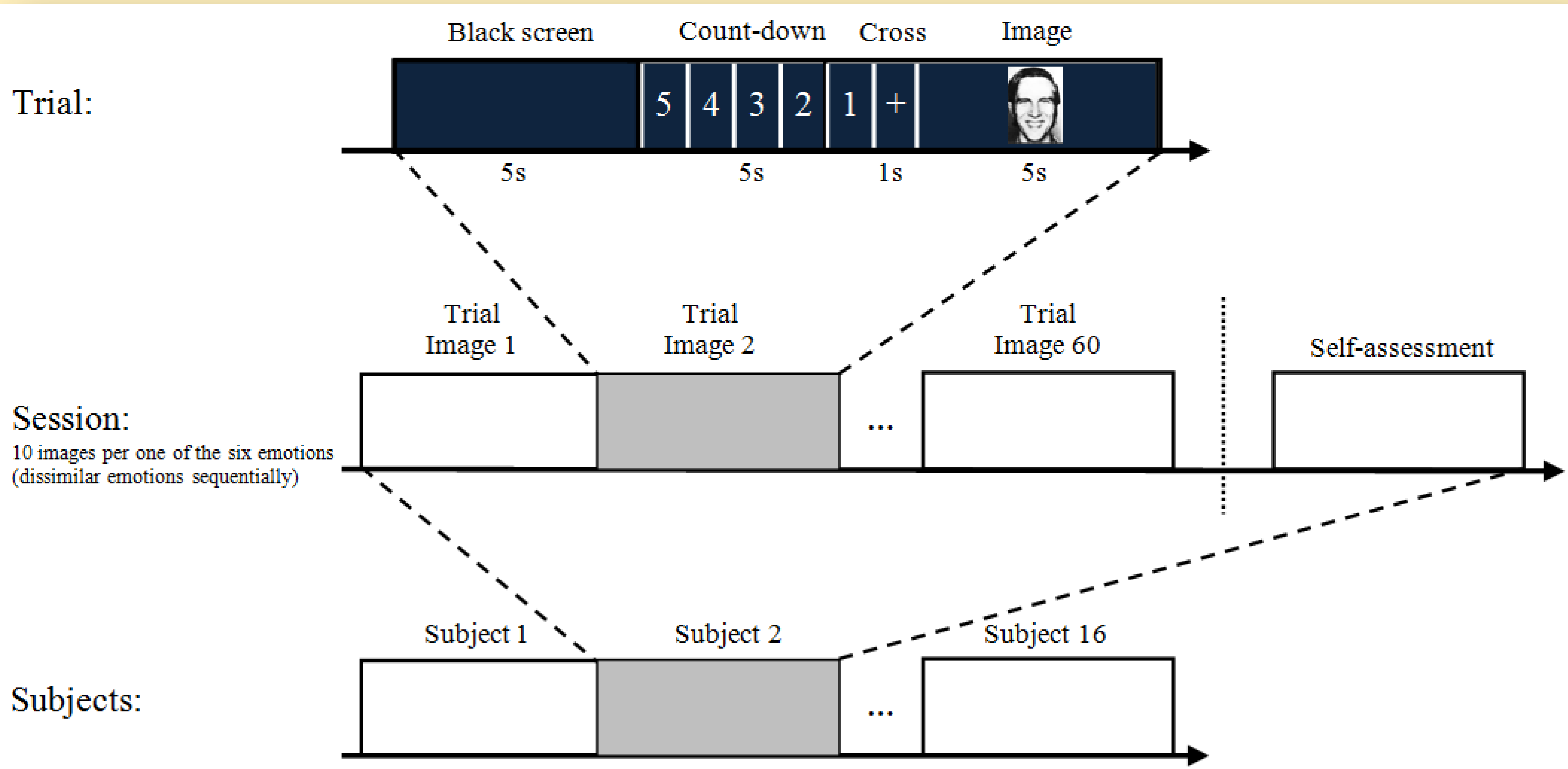
Emotiv EPOC (www.emotiv.com): 14 channel (plus CMS/DRL references, P3/P4 locations). Channel names based on the International 10-20 locations are: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4.

EEG Acquisition (hardware)

g.tec

Emotiv EPOC

Experiment protocol



Methodological Approaches

- Emotion Elicitation Method
  - POFA
    - HOC
    - HAF
  - IAPS
    - MDI/AsI
    - wAsI/EMD

Methodological Approaches

- Emotion Elicitation Method
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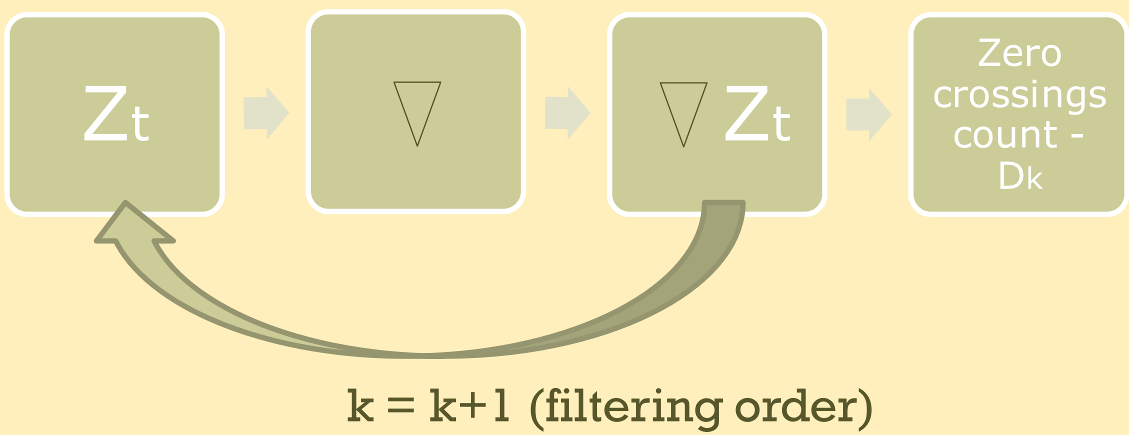
Methodological Approaches-HOC

Higher Order Crossings (HOC): for a zero-mean time series $\{Z_t\}$ $t=1, \ldots, N$



where $\nabla Z_t = Z_t - Z_{t-1}$ and $D_k \geq D_{k-1}$

Methodological Approaches-HOC: FV/Classifiers

- Feature Vector: D_k , k=1, ..., K
- Baseline comparison:
  - Statistical Values-based and
  - Wavelet-based
- Classifiers
  - *Quadratic Discriminant Analysis (QDA)*
  - *k-Nearest Neighbor* (k-NN)
  - *Mahalanobis Distance (MD)*
  - *Support Vector Machine (SVM)*

All combinations for 2, 3, 4, and 5 emotions – All emotions classification (6 basic emotions)

Methodological Approaches-HOC: Results

CB1={channel 1 (Fp1), channel 2 (Fp2)}
CB2={channel 1 (Fp1), channel 3 (F3/F4)}
CB3={channel 2 (Fp2), channel 3 (F3/F4)}
CB4={channel 1 (Fp1), channel 2 (Fp2), channel 3(F3/F4)}

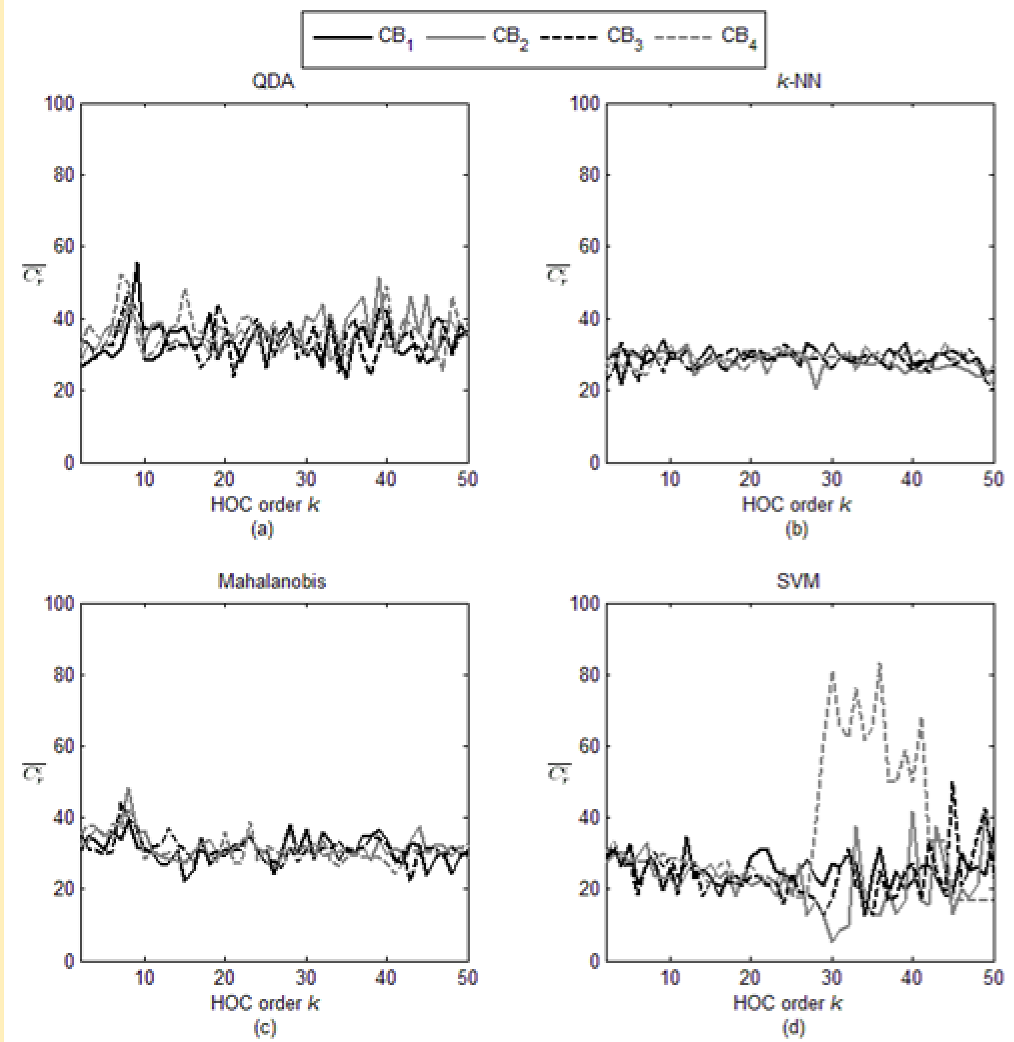


Fig. 5. $\overline{C_r^c}$ values for the combined-channel case for all classification methods vs. the k order of the HOC analysis.

Methodological Approaches-HOC: Results

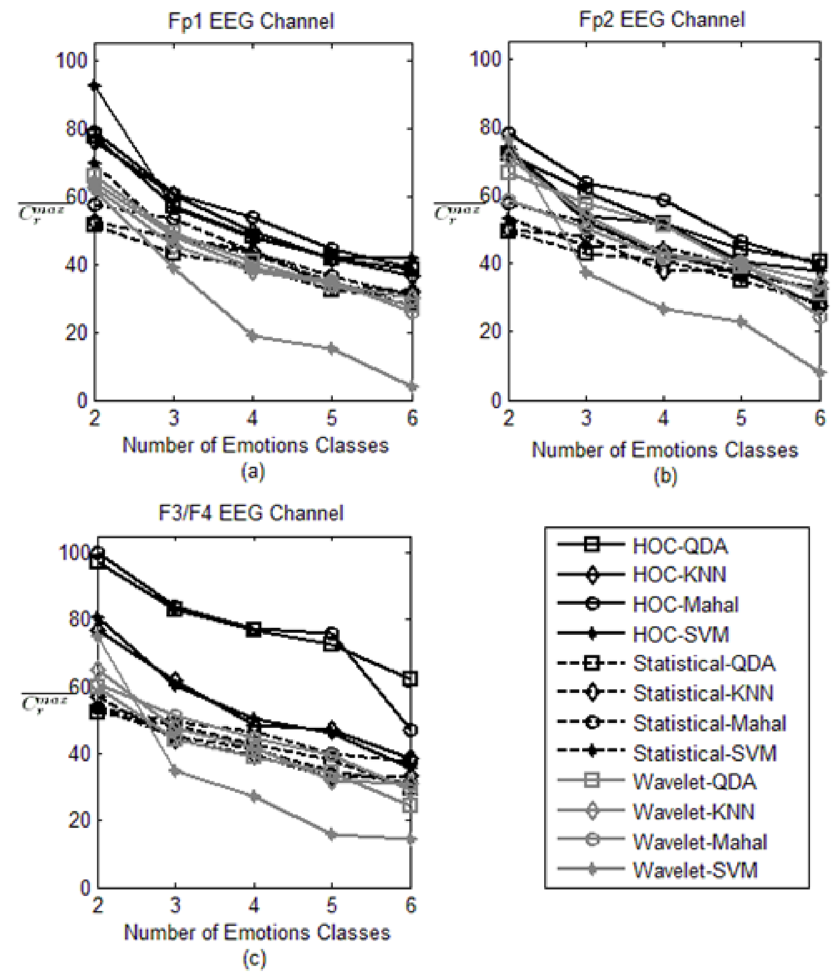


Fig. 4. $\overline{C_r^{max}}$ values for the proposed method (HOC-EC) against the S-EC and W-EC, for the single-channel case for all classification methods and all possible combinations of emotion classes.

Methodological Approaches-HOC: Results

TABLE II
$\overline{C_r}$ VALUES (%) OF EACH EMOTION OF THE PROPOSED HOC-EC COMPARED WITH S-EC AND W-EC USING THE QDA CLASSIFIER FOR THE SINGLE-CHANNEL CASE (CHANNEL 3)

Emotions	*Happiness*	*Surprise*	*Anger*	*Fear*	*Disgust*	*Sadness*
Happiness	**54.17** **(35/46.43)**	8.33 (25/21.42)	0 (5/10.74)	12.50 (0/3.57)	12.50 (15/8.92)	12.50 (20/8.92)
Surprise	0 (22.73/17.86)	**75** **(36.36/35.71)**	0 (4.55/17.86)	0 (15.91/10.71)	0 (9.09/12.50)	25 (11.36/5.36)
Anger	7.14 (16.67/25)	0 (12.50/15.62)	**50** **(27.08/25)**	25 (8.33/9.38)	17.86 (12.50/9.38)	0 (22.92/15.62)
Fear	3.57 (16.67/25)	0 (25/16.67)	21.43 (4.16/0)	**53.57** **(29.17/41.67)**	7.14 (0/8.33)	14.29 (25/8.33)
Disgust	0 (20.83/0)	0 (16.67/0)	0 (4.33/0)	12.50 (8.17/0)	**62.50** **(29.17/50)**	25 (20.83/50)
Sadness	10.72 (7.14/0)	0 (7.14/0)	3.57 (0/0)	7.14 (35.71/75)	0 (21.43/0)	**78.57** **(28.58/25)**

All $\overline{C_r}$ values are derived from a 100-iteration cross validation process [40]. The format (%/%) corresponds to the $\overline{C_r}$ values derived from S-EC and W-EC, respectively, i.e., (S-EC/W-EC).

Methodological Approaches-HOC: Results

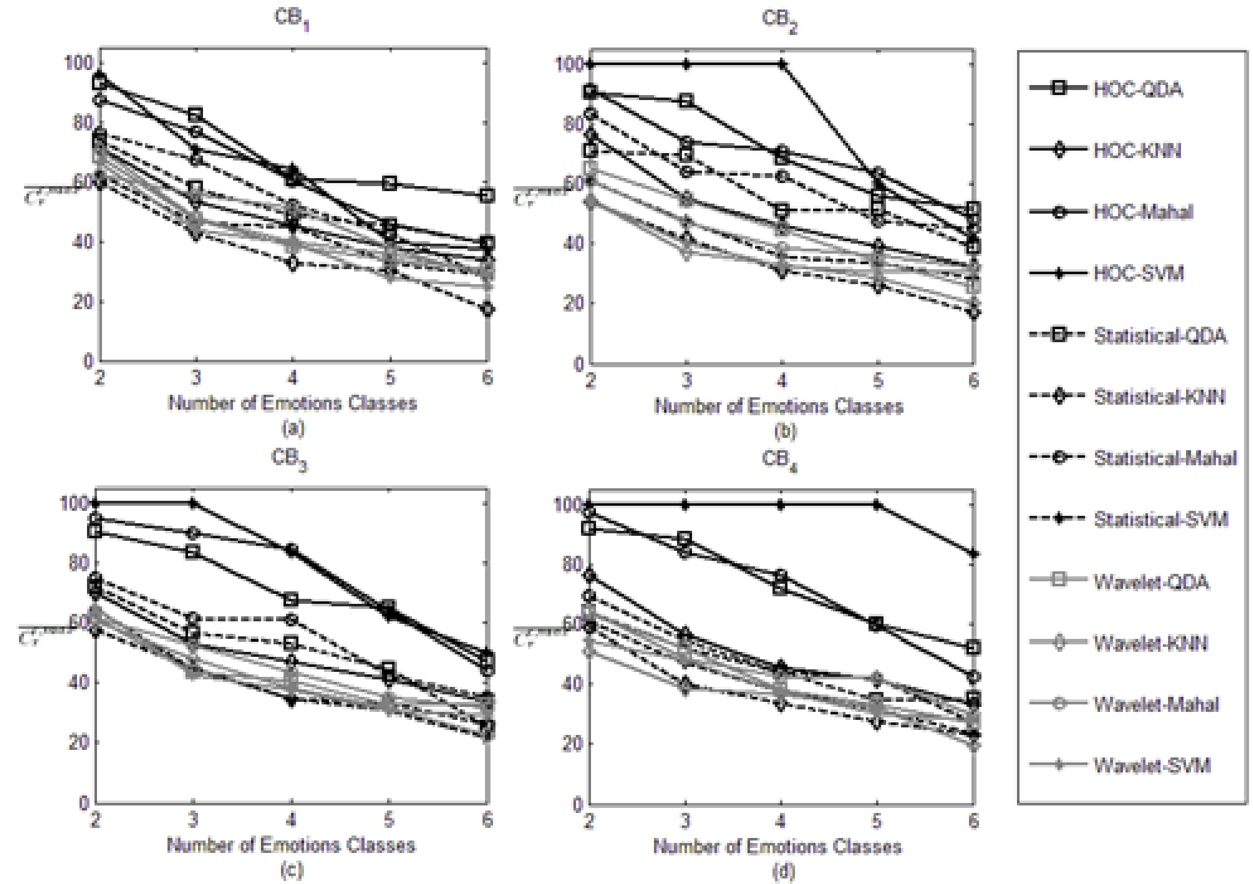


Fig. 6. $\overline{C_r^{c,max}}$ values for the proposed method (HOC-EC) against the S-EC and W-EC, for the combined-channel case for all classification methods and all possible combinations of emotion classes.

Methodological Approaches-HOC: Results

TABLE IV

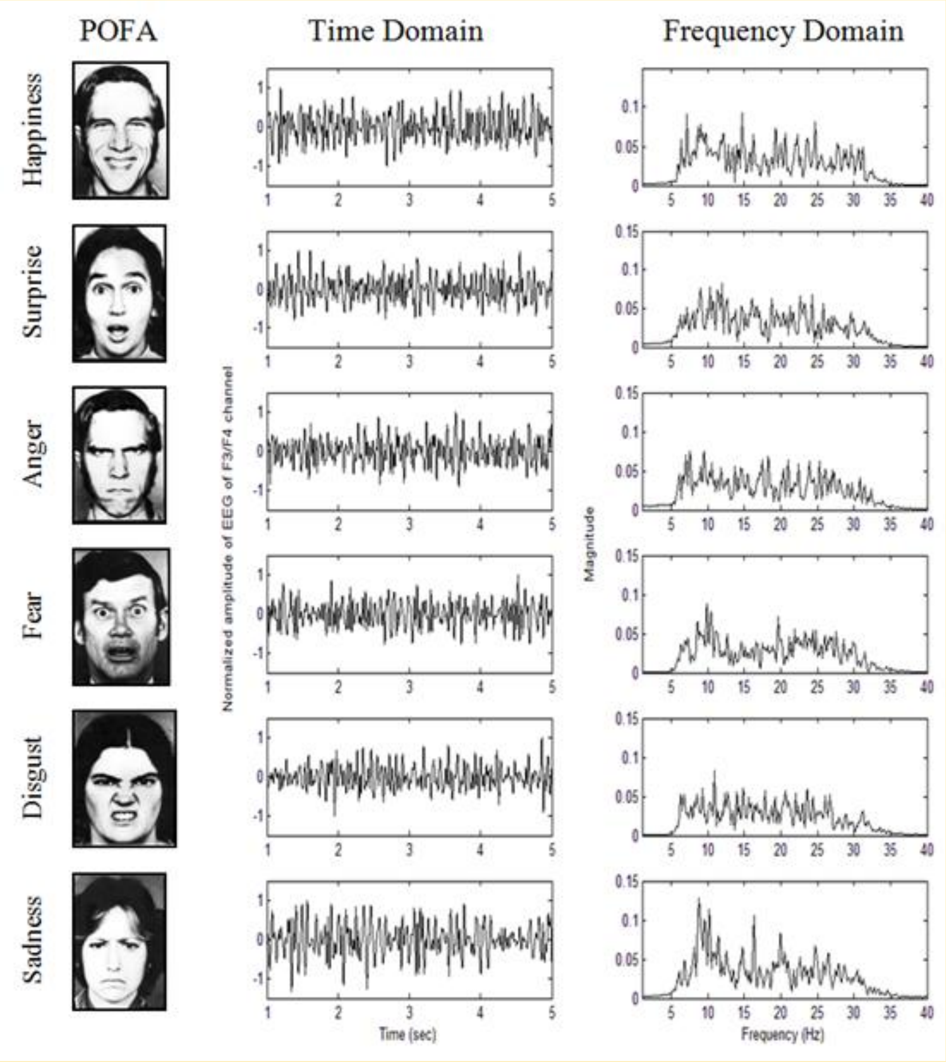
BEST $\overline{C_r^{max}}$ AND $\overline{C_r^{c,max}}$ VALUES (%) FOR THE CASE OF SIX EMOTION CLASSES OF THE PROPOSED HOC-EC COMPARED WITH S-EC AND W-EC. THE CORRESPONDING CLASSIFIERS AND CHANNELS (OR CHANNEL COMBINATIONS) ARE GIVEN IN PARENTHESES

Method	Analyzed Case	
	Single-Channel Case $\overline{C_r^{max}}$	Combined-Channels Case $\overline{C_r^{c,max}}$
HOC-EC	62.30 (QDA, F3/F4)	83.33 (SVM, CB_4)
S-EC	37.50 (MD, F3/F4)	44.90 (MD, CB_2)
W-EC	34.60 (*3*-NN, Fp2)	32.70 (QDA, CB_3)

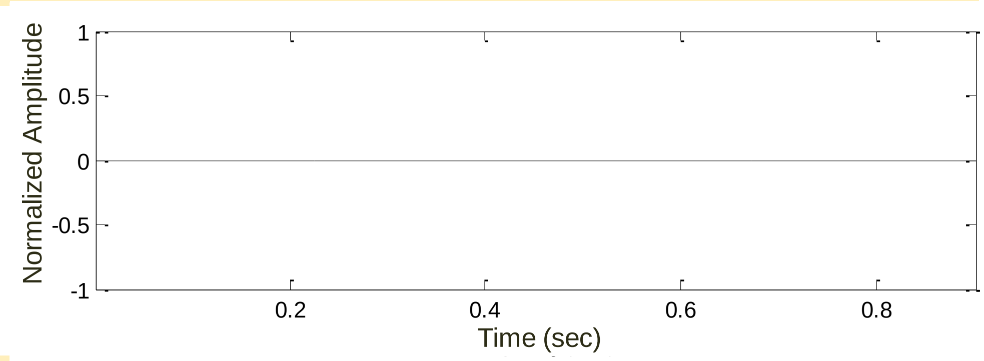
Methodological Approaches

- Emotion Elicitation Method
  - POFA
    - HOC
    - HAF
  - IAPS
    - MDI/AsI
    - wAsI/EMD

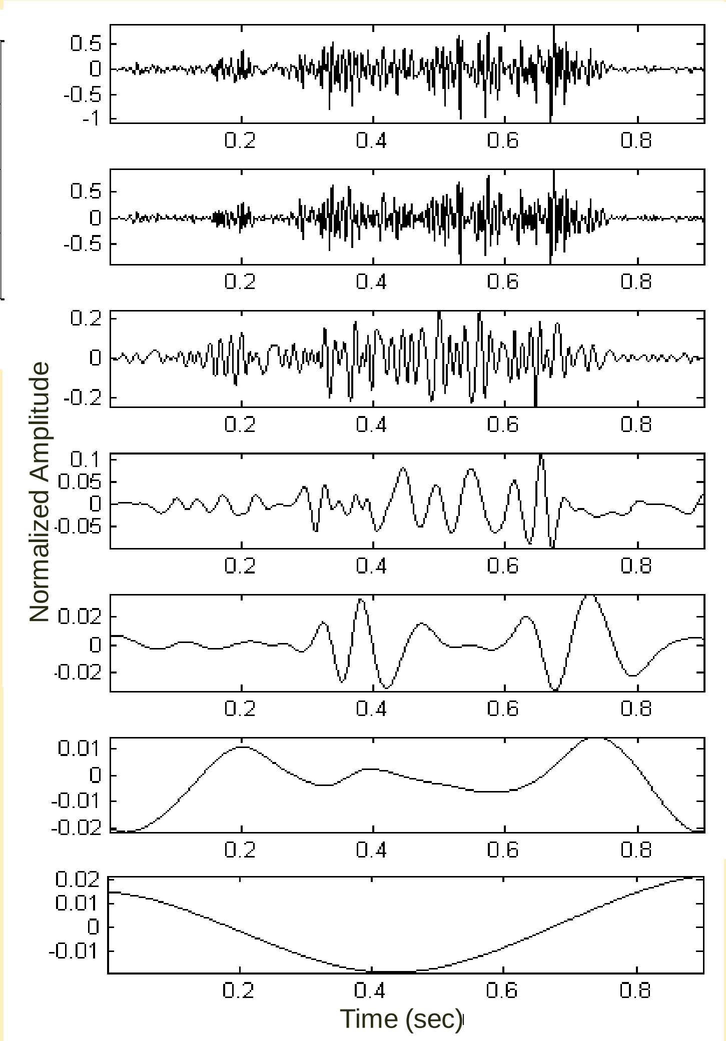
Methodological Approaches-HAF: Spectral Motivation



Methodological Approaches-HAF: EMD



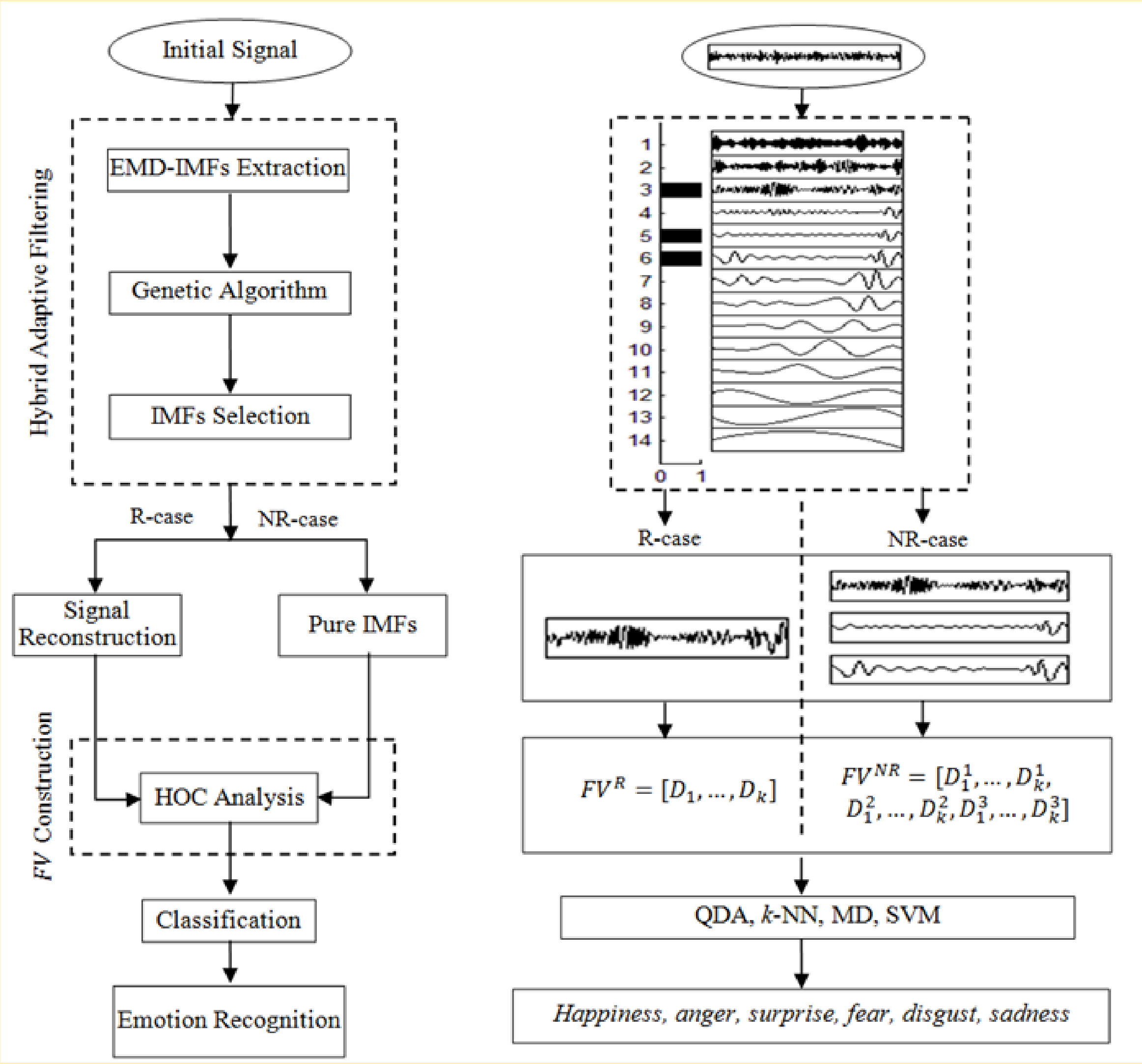
$$x[n] = \sum_{i=1}^{K} c_i[n] + r_K[n]$$



Methodological Approaches-HAF: Analysis Scheme

GA: Energy-based Fitness Function (directly related to the power spectrum of the EEG signal)
Fractal Dimension (FD)-based Fitness Function (the dynamical complexity of cortical networks, measured by means of the FD, reflects the degree of synergism between neurons:

- high neural synergism and low complexity, could reflect a resting state of cortical networks.
- low neural synergism and high complexity, could correspond to active information processing in the cortex



Methodological Approaches-HOC: FV/Classifiers

Feature Vector: FV^{R}, FV^{NR}

Baseline comparison:

- Statistical Values-based and
- Wavelet-based

Classifiers

- *Quadratic Discriminant Analysis (QDA)*
- *k-Nearest Neighbor* (k-NN)
- *Mahalanobis Distance (MD)*
- *Support Vector Machine (SVM)*

All combinations for 2, 3, 4, and 5 emotions – All emotions classification (6 basic emotions)

Methodological Approaches-HAF: Results

TABLE 2

C_I^R VALUES (%) OF EACH EMOTION OF THE PROPOSED HAF-HOC (FDFF) COMPARED WITH HOC-EC, S-EC, AND W-EC USING THE QDA CLASSIFIER FOR CHANNEL 2

Emotions	*Happiness*	*Surprise*	*Anger*	*Fear*	*Disgust*	*Sadness*
Happiness	**71.34** **(54.17/35/46.4)**	0 (8.33/25/21.42)	0 (0/5/10.74)	0 (12.50/0/3.57)	20 (12.50/15/8.92)	8.66 (12.50/20/8.92)
Surprise	0 (0/22.73/17.86)	**71.34** **(75/36.36/35.71)**	14.33 (0/4.55/17.86)	14.33 (0/15.91/10.71)	0 (0/9.09/12.50)	0 (25/11.36/5.36)
Anger	0 (7.14/16.67/25)	0 (0/12.50/15.62)	**77.33** **(50/27.08/25)**	0 (25/8.33/9.38)	11.56 (17.86/12.50/9.38)	11.11 (0/22.92/15.62)
Fear	0 (3.57/16.67/25)	11.43 (0/25/16.67)	0 (21.43/4.16/0)	**82.67** **(53.57/29.17/41.67)**	2.79 (7.14/0/8.33)	3.11 (14.29/25/8.33)
Disgust	0 (0/20.83/0)	0 (0/16.67/0)	10.20 (0/4.33/0)	6.02 (12.50/8.17/0)	**78.67** **(62.50/29.17/50)**	5.11 (25/20.83/50)
Sadness	13.17 (10.72/7.14/0)	0 (0/7.14/0)	8.33 (3.57/0/0)	0 (7.14/35.71/75)	16.67 (0/21.43/0)	**61.83** **(78.57/28.58/25)**

All $\overline{C_I^R}$ values are derived from a 56-iteration cross validation process. The format (%/%/%) corresponds to the $\overline{C_I^R}$ values derived from HOC-EC, S-EC and W-EC, respectively, i.e., (HOC-EC/S-EC/W-EC).

Methodological Approaches-HAF: Results

TABLE 5

BEST $\overline{C_I^{max}}$ AND $\overline{C_C^{max}}$ VALUES (%) FOR THE SIX BASIC EMOTIONS OF THE PROPOSED HAF-HOC COMPARED WITH HOC-EC, S-EC AND W-EC. THE CORRESPONDING CLASSIFIERS, CHANNELS (OR CHANNEL COMBINATIONS) AND R- OR NR-CASE ARE GIVEN IN PARENTHESES

Method	Analyzed Case	
	Individual-Channel Case $\overline{C_I^{max}}$(%)	Combined-Channels Case $\overline{C_C^{max}}$(%)
HAF-HOC (FDFF)	77.66 (SVM, Fp2, NR)	85.17 (SVM, CB_4,, R)
HAF-HOC (EFF)	67.89 (QDA, Fp2,R)	77.28 (QDA, CB_1, R)
HOC-EC	62.30 (QDA, F3/F4)	83.33 (SVM, CB_4)
S-EC	37.50 (MD, F3/F4)	44.90 (MD, CB_2)
W-EC	34.60 (*3*-NN, Fp2)	32.70 (QDA, CB_3)

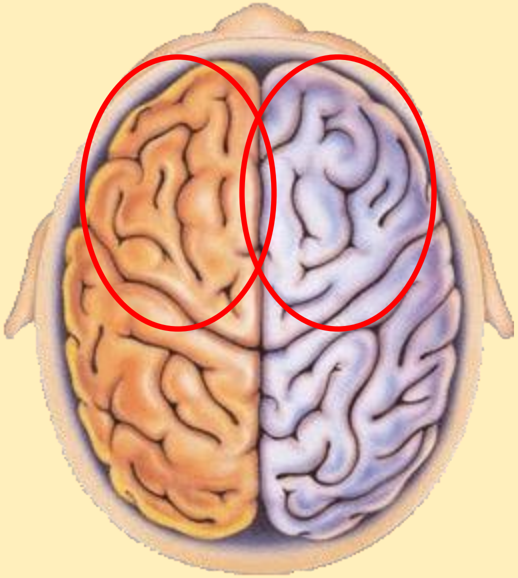
Methodological Approaches

- Emotion Elicitation Method
  - POFA
    - HOC
    - HAF
  - IAPS
    - MDI/AsI
    - wAsI/EMD

Methodological Approaches-MDI/AsI: Frontal Brain Asymmetry

Left frontal area

Right frontal area

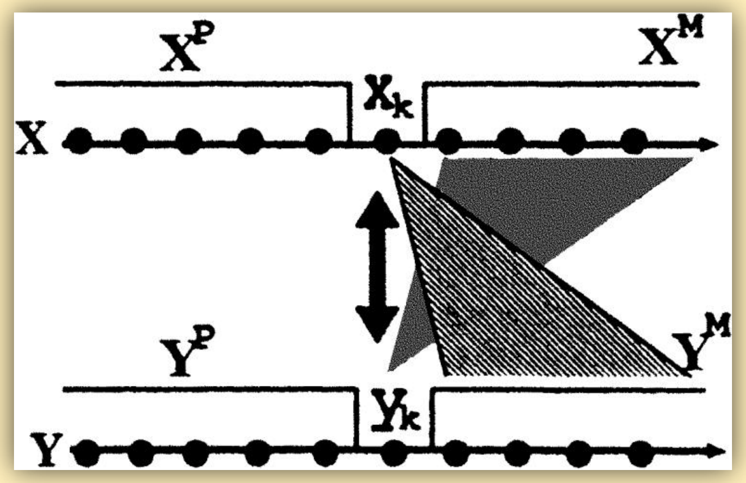


Experience of positive emotions

Experience of negative emotions

Methodological Approaches-MDI/AsI: MDI

- Given three time series *X*, *Y*, and *Z*, observed simultaneously from a system (e.g., brain)



- MDI Computes the total amount of information *S*, that is first generated in *X* and propagated to *Y* taking into account the existence of *Z*

$$S: I(x_k \to Y^M | X^P Y^P Z^P y_k z_k) =$$

$$\sum_{m=1}^{M} \frac{1}{2} log \frac{|R(X^P Y^P Z^P x_k y_k z_k)| \cdot |R(X^P Y^P Z^P y_k z_k y_{k+m})|}{|R(X^P Y^P Z^P y_k z_k)| \cdot |R(X^P Y^P Z^P x_k y_k z_k y_{k+m})|}$$

Methodological Approaches-MDI/AsI: AsI

- Compute the total amount of information flow between left and right frontal cortex when a subject is relaxed (S_r)

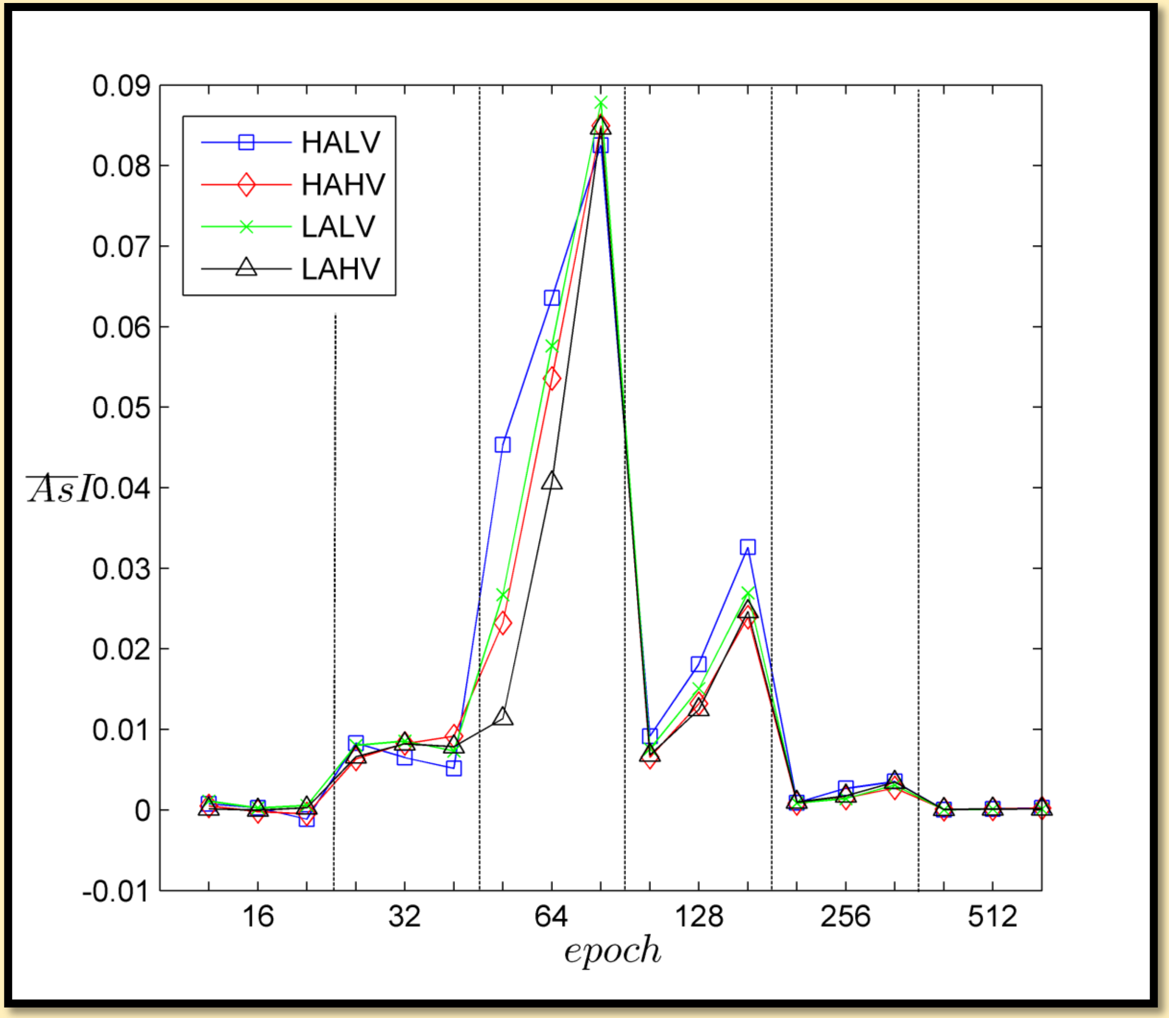
- Compute the total amount of information flow between left and right frontal cortex when a subject is emotionally aroused (S_p)

- According to the asymmetry concept:

$$S_r > S_p$$

- Define an Asymmetry Index (*AsI*): $AsI = (S_r - S_p) \times \frac{\sqrt{2}}{2}$

Methodological Approaches-MDI/AsI: Results



Methodological Approaches-MDI/AsI: FV/Classifiers

- Feature Vector: HOC
- Baseline comparison:
  - Cross-correlation coefficient between potentials of the EEG electrodes *i* and *j* for the frequency band *ω*
- Classifiers
  - *Quadratic Discriminant Analysis (QDA)*
  - *k-Nearest Neighbor* (k-NN) (3-NN for results)
  - *Mahalanobis Distance (MD)*
  - *Support Vector Machine (SVM)*

Methodological Approaches-MDI/AsI: Results

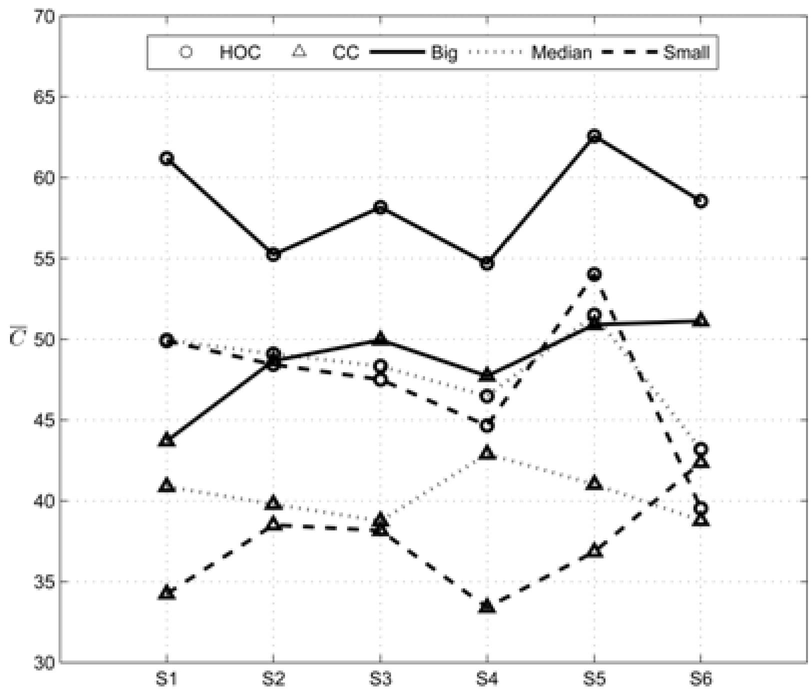


Fig. 4. Classification rates, $\bar{C}$, for HOC and CC methods for Big and Small AsI groups, and median $\bar{C}$ derived from all 50 randomly created groups with equal signal number with Big AsI groups.

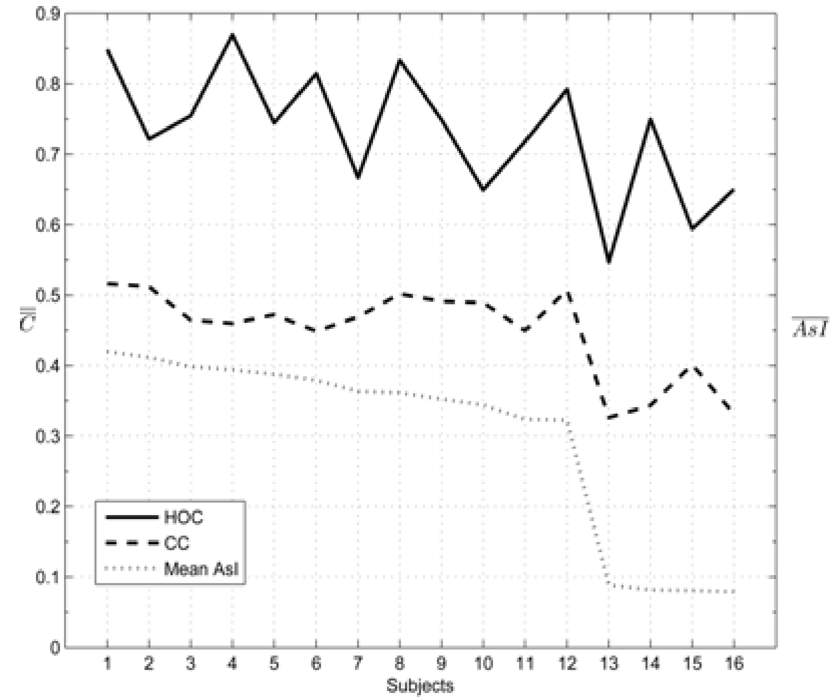


Fig. 5. Mean classification rates, $\bar{\bar{C}}$, for HOC and CC methods, all subjects. In black dotted line the mean AsI is also depicted in descending order.

i) S1: class1: *LA*, class2: *HA* and class3: the respective Relax signals, ii) S2: class1: *LV*, class2: *HV* and class3: the respective Relax signals, iii) S3: class1: *LALV*, class2: *HALV* and class3: the respective Relax signals, iv) S4: class1: *LAHV*, class2: *HAHV* and class3: the respective Relax signals, v) S5: class1: *LALV*, class2: *LAHV* and class3: the respective Relax signals, vi) S6: class1: *HALV*, class2: *HAHV* and class3: the respective Relax signals.

and

Methodological Approaches-MDI/AsI: Results

DI=(L-R)/(L+R)

where L and R are the power of specific bands of the left and right hemispheres, respectively

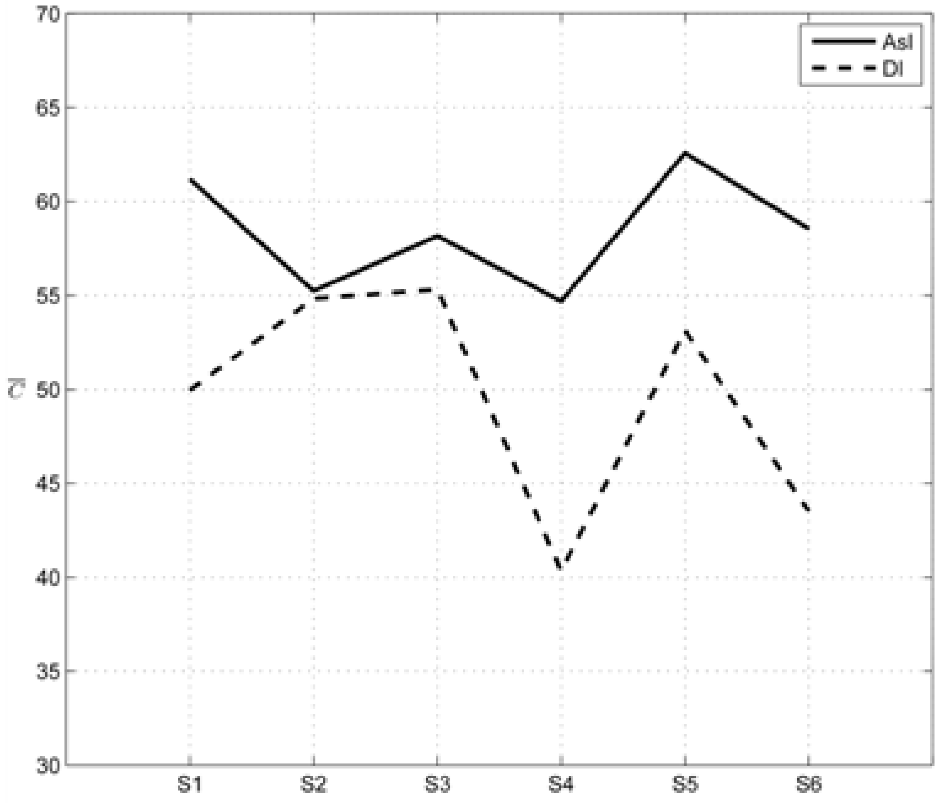
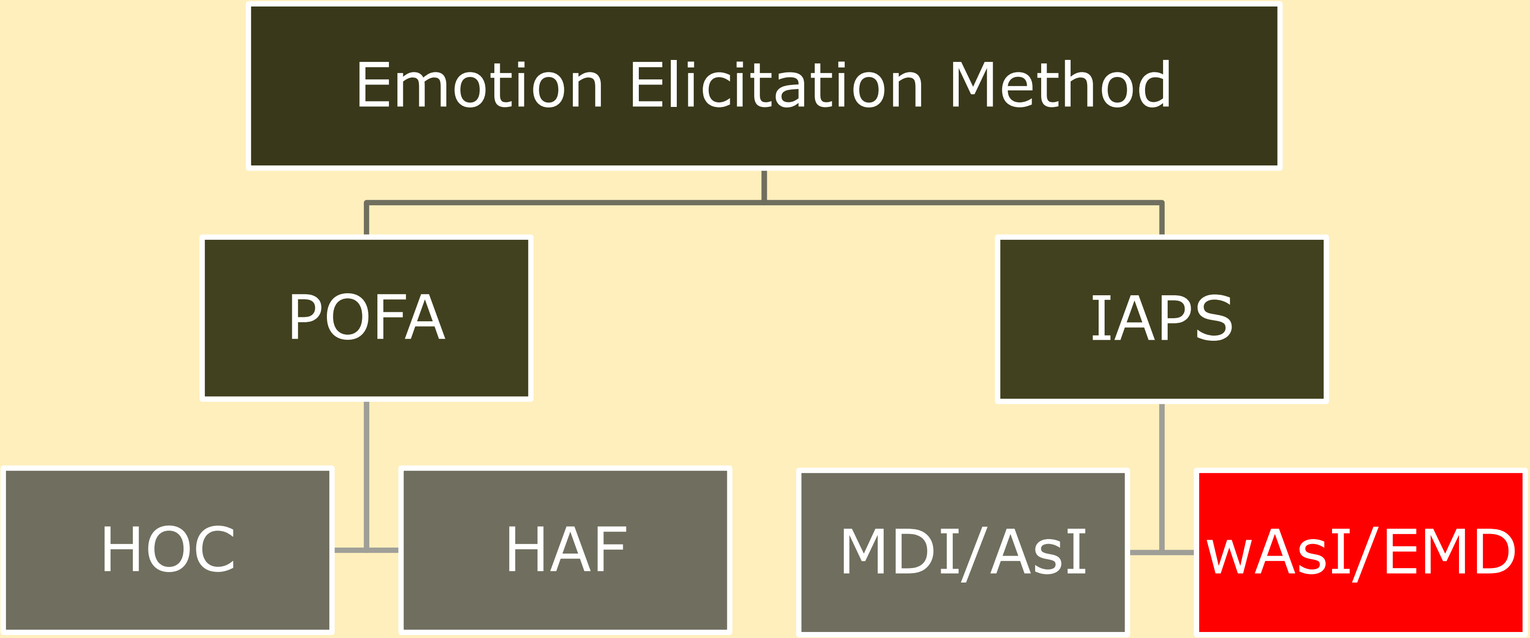


Fig. 6. Classification rates, $\bar{C}$, for HOC method for Big groups of AsI and DI indexes.

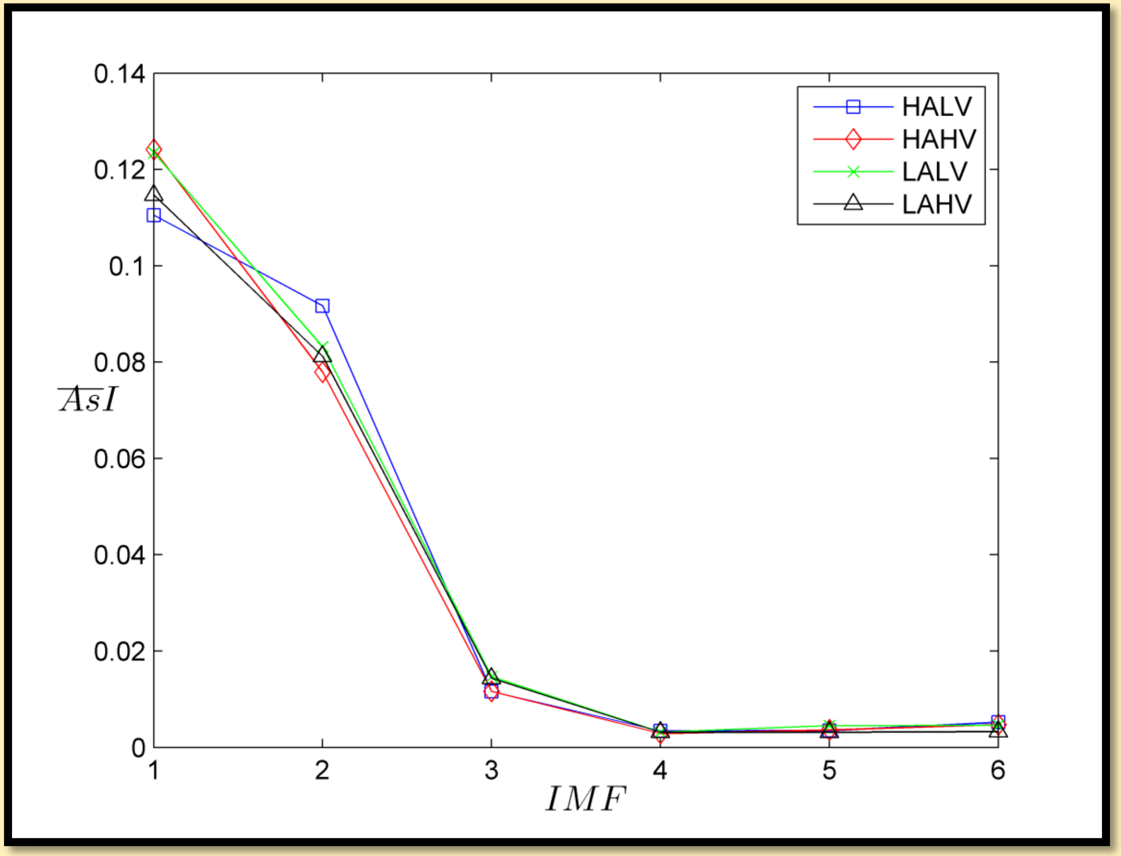
Methodological Approaches



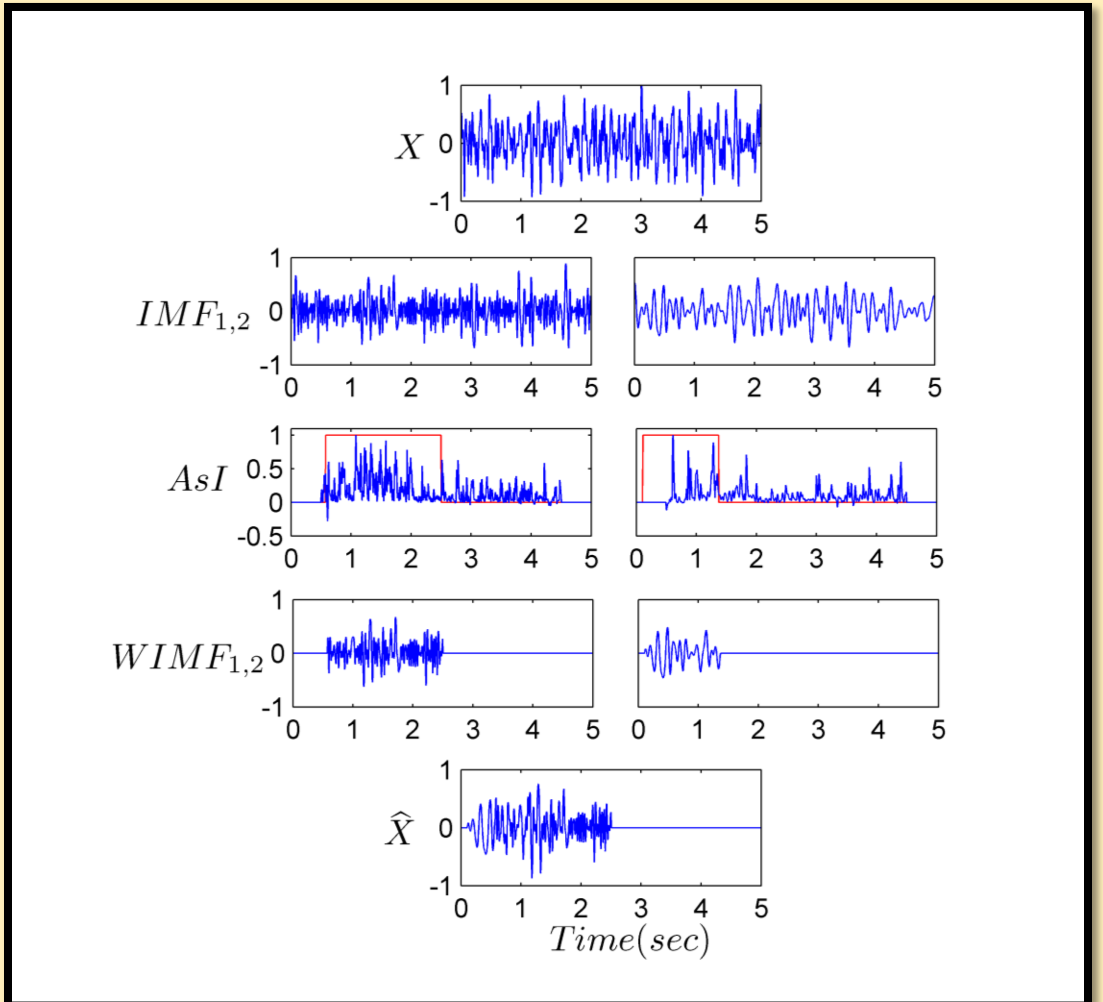
Methodological Approaches-AsI/EMD (in progress)

- Decompose *X*, *Y* and *Z* signals into IMFs.
- Apply a windowed *AsI* calculation to each one of the *M* IMFs
- Extract specific segments according to *AsI* value across the IMF
- Reconstruct an ‘emotionally’ filtered signals from the segmented IMFs

Methodological Approaches-AsI/EMD (in progress)



Methodological Approaches-AsI/EMD (in progress)



Partial Conclusions

- Effective feature extraction approaches
- Evaluation of emotion elicitation
- Use of the information shared between specific EEG locations in the brain
- Asymmetry concept and MDI
- Presentation of an Asymmetry Index
- EEG emotion-oriented segmentation
- Contribution to more pragmatic EEG-based Emotion Recognition systems

Focus place

Advanced Signal Processing Techniques

EEG

- Emotions (Recognition/Elicitation)

EEG

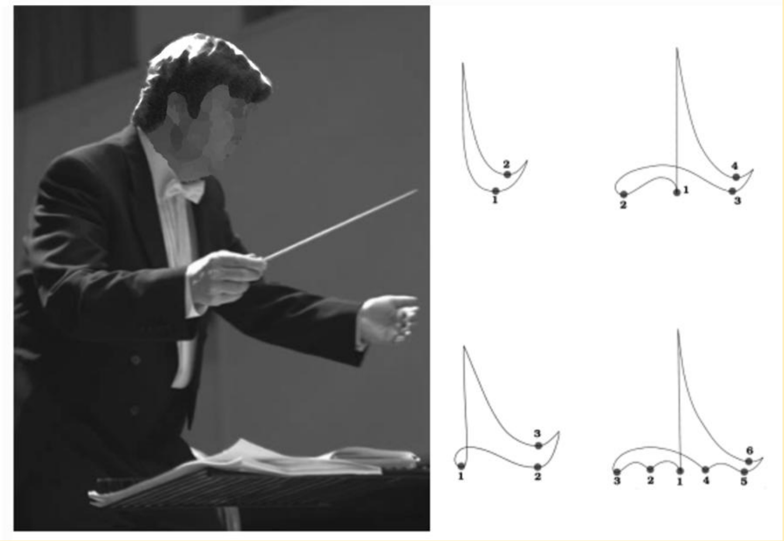
- Action Representation (Music stimuli perception)

Music-Motor Interactions

- Music and motion are two strongly related notions:
  - Paradigm 1: auditory-motor interactions during the perception of heard musical performance (i.e., orchestral performance influenced by musical direction).
  - Paradigm 2: auditory-motor interactions during the perception of heard motion-reflecting musical excerpts (i.e., ‘Promenade Theme’) as music elicits conscious experiences like emotions, imagery actions.
- The trained musical brain bears mechanisms that are responsible for heard action recognition processes, such as the auditory mirror neuron system.

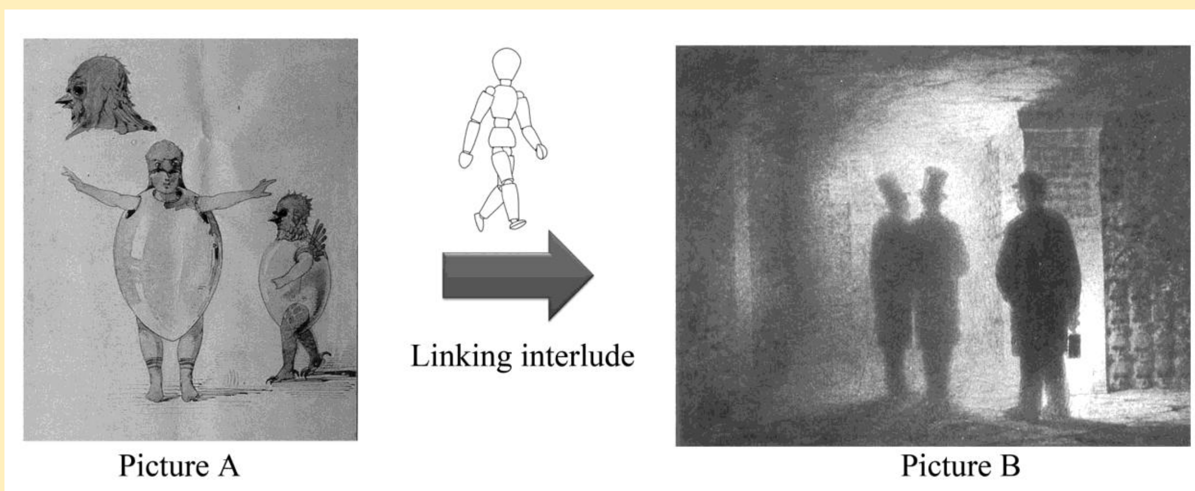
Music Conducting (Paradigm 1)

- Conducting is the art of conveying elements of musical expression to a musical ensemble by means of gestures and hand trajectories.
- The acoustic result of an orchestral performance is influenced by musical direction.
- Inverse procedure: action representations induced during the passive listening of their associated musical features of expression.



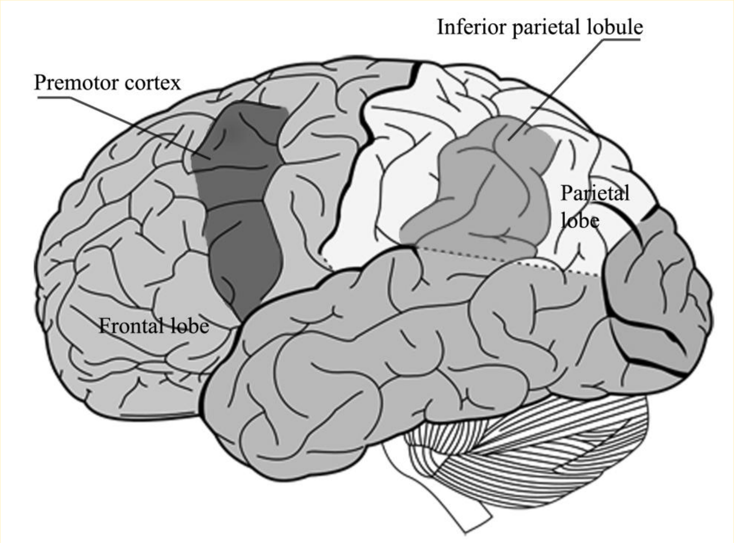
‘Promenade’ Theme (Paradigm 2)

- In 1874, Modest Mussorgsky composed his famous piano suite ‘Pictures at an exhibition’: an imaginary tour through an art collection.
- The composer adopted a programmatic music form, by musically describing each painting, connecting these descriptions with a walking step-like music theme (‘Promenade’) that imitates walking around in a real exhibition.
- Mussorgsky’s work constitutes a fine paradigm where representations of human-like movements are conveyed by structural music features.



Auditory Mirror Neuron System

- A mechanism that encodes the meaning of actions linked to imitation, the understanding of intentions and empathy.
- Location: premotor cortex and inferior parietal lobule.
- Auditory MNS: Action representation processes induced by their associated heard actions.
- Implication of the Auditory MNS in language evolution: association of limb gestures to vocalizations.
- Activity of the MNS is reflected over the sensorimotor cortex through Mu-rhythm desynchronization (8-12 Hz).



Audio-motor processes in music perception

- Motor-related brain areas play a major role in music perception and performance (Koelsch & Siebel, 2005; Zattore, Chen, & Penhune, 2007).
- Supplementary motor area (SMA) and the pre-SMA along with the pre-motor cortex are linked to the perception of musical rhythm and beat (Bengtsson et al., 2009; Chen et al., 2008; Grahn & Brett, 2007; Thaut, 2003).
- Auditory features that are primarily processed in the auditory cortex are combined with motion information conveyed by the musical signal in the posterior inferior frontal gyrus and adjacent premotor cortex in order to integrate the musical experience (Szakacs & Overy, 2006).
- Activation of a fronto-parietal network comprising the premotor areas during music performance and music imagery tasks (Meister et al., 2004).
- Shared networks for auditory and motor processing, including the premotor cortex and Broca's area (Bangert et al., 2006; Lahav, Saltzman, & Schlaug, 2007).

Study 1

Sensorimotor response in terms of Mu-rhythm fluctuations of musicians and non-musicians due to:

- Passive listening of orchestral performance and possible implication of the MNS.
- Perception of conducting gestures accompanied by the related orchestral performance.
- Perception of conducting gestures alone (control state).

Study 2

Sensorimotor response of musicians and non-musicians due to:

- Passive listening of motion reflecting musical stimulation (Mussorgsky’s “Pictures at an Exhibition”).
- Influence of the musical excerpt on the perception of the related simulated human action.

Materials

- Subjects:
  - Study 1: 10 orchestral musicians (OM: 8 males and 2 females; age 28.3±5.8 years) and 10 non-musicians (NM: 7 males and 3 females; age 27.8±6.6 years).
  - Study 2: 10 advanced music students (AMS: 5 males and 5 females; age 34.6 ± 10.1 years) 10 non- musicians (NM: 7 males and 3 females; age 27 ± 5.9 years).
- EEG recordings were conducted using g.MOBIlab portable biosignal acquisition system (Sampling frequency of 256 Hz).
- The stimuli were designed in Adobe Audition 2.0 and Adobe Premiere 7.0.
- The experiment was conducted through Max/MSP 4.5 where an external object was created in C++ using the g.MOBIlab API in order to achieve precise triggering.
- Real-time visualization of the acquired EEG data was available in Max/MSP.

Study 1 – Experiment structure

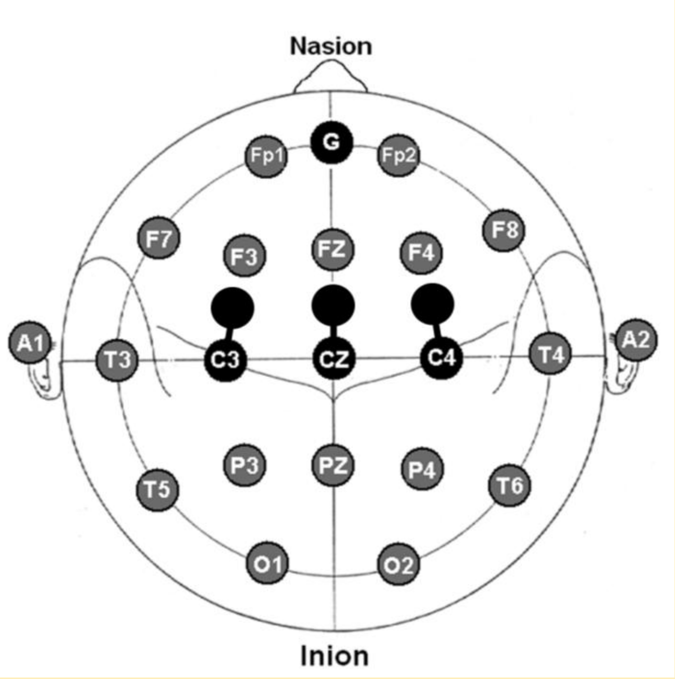
- Stimuli:
  - Auditory stimulus: the first 21 bars of Beethoven’s 5th symphony (21 s).
  - Visual stimulus: a video presenting a conductor directing the same musical excerpt (21 s).
- Experimental modes:
  - AS mode: 5 trials of auditory stimulation only.
  - AVS mode: 5 trials of synchronized auditory and visual stimulation.
  - MUTE mode: 5 trials of visual stimulation.
- Each trial preceded a relaxation time interval (2 s). Modes were presented pseudo-randomly.

Study 2 – Experiment structure

- Stimuli:
  - Auditory stimulus: the first 2 bars of the first ‘Promenade’ (7.8 s).
  - Visual stimulus: a video presenting a human figure walking in the same tempo as that of musical excerpt (7.8 s).
- Experimental modes:
  - AS mode: 10 trials of auditory stimulation only
  - AVS mode: 10 trials of synchronized auditory and visual stimulation
- Each trial preceded a relaxation time interval (2 s). Modes were presented pseudo-randomly.

EEG Recordings

- EEG recordings: Three bipolar channels (positions C3, Cz, C4) over the sensorimotor cortex.
- Subjects sat still 1 m away from the screen
- Auditory stimuli provided by headphones; during AVS and MUTE trials the visual stimulus was presented on a PC monitor; during AS trials subjects stared at a blank screen
- Soundproof recording studio with low lighting conditions.
- Simplicity of stimuli prevented alpha wave desynchronization due to enhanced attention of the musicians’ groups .
- Real-time inspection of the EEG recordings to avoid artifacts.



Signal Processing

- The acquired EEG signals for fixed subject, experimental mode and electrode site were filtered (8-13 Hz) and normalized to their maximum value.

- Main processing:
  - Fractal analysis (Fractal dimension estimation)
  - Statistical analysis (ANOVA, Mann-Whitney)
  - Mobility analysis (Study 1) – Rhythmic waveform analysis (Study 2)

Fractal Analysis

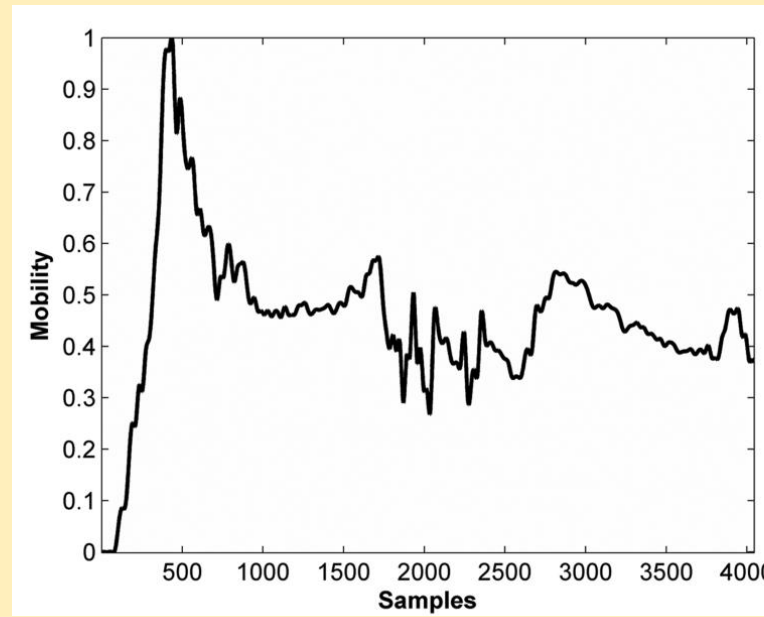
- Fractal dimension (FD) quantifies the complexity and self-similarity of a signal
- Euclidian dimension of a line (= 1) ≤ FD ≤ Euclidian dimension of a plane (=2)
- The FD of electrophysiological signals (EEG) allows the detection of different physio-pathological conditions.
- Common methods of FD estimation directly in the time domain:
  - Higuchi
  - Katz
  - Petrosian

Implementation

- The Time Dependent FD (TDFD) was computed for each EEG signal using a 2 s time window with 99% overlap.
  - Study 1: only the Higuchi method was implemented
  - Study 2: all three methods were implemented
- The TDFD signals were averaged across all trials for fixed subject, experimental mode and electrode site.
- Study 1: Two-way ANOVA [Group (OM, NM); Mode (AS, AVS, MUTE)] was applied on the mean values of the TDFD signals during stimulation.
- Study 2: Three-way ANOVA [Group (AMS, NM); Mode (AS, AVS); Method (Higuchi, Katz, Petrosian *c*)] was applied on the mean values of the TDFD signals during stimulation.
- Additional statistical tests were computed for each significant factor.

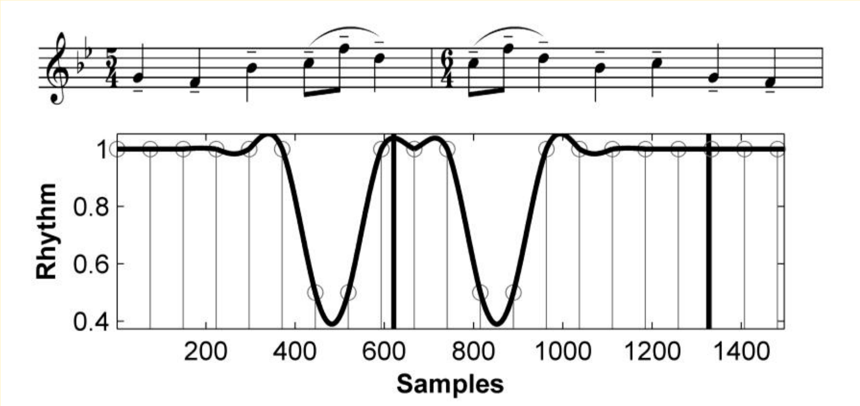
Mobility Analysis (study 1)

- Estimation of Pearson's correlation coefficient R between the average TDFD signal of each group and a signal representing the mobility of the video for each experimental mode and group.
- Mobility signal:
  - Video conversion into black and white
  - Segmentation into frames (260 frames)
  - For each frame (sum of intensity values of the frame) – (the sum of intensity values of a reference frame).
  - Linear interpolation in order to acquire a signal of the same size as the average TDFD signal.



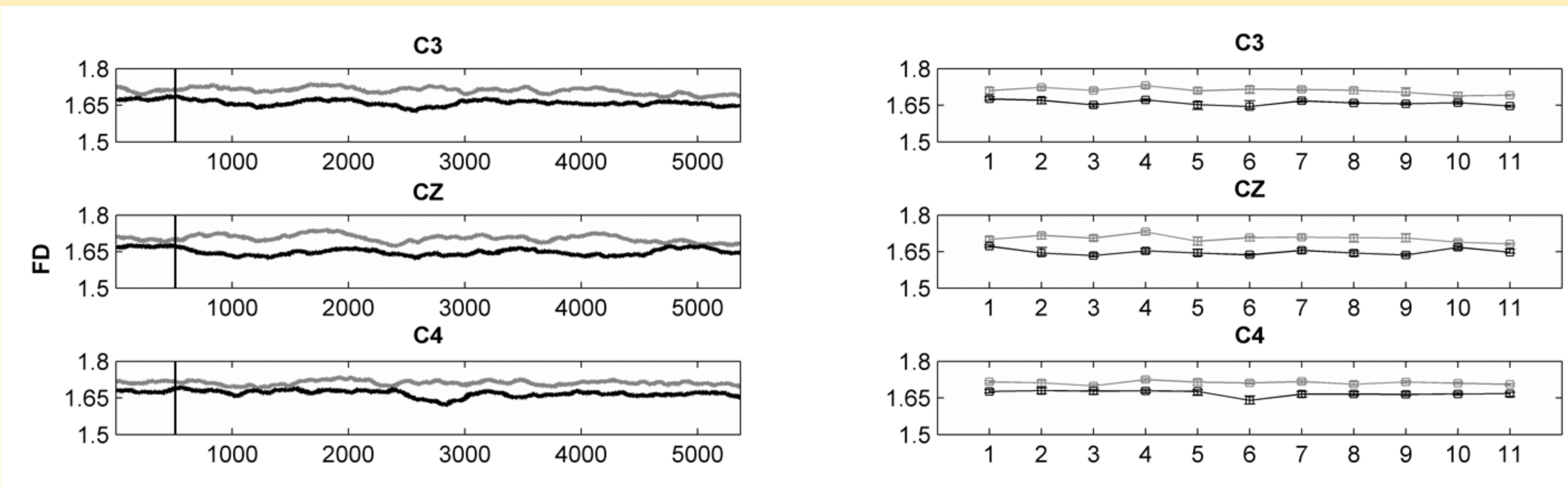
Rhytmic waveform analysis

- Pearson's time-dependent correlation coefficient (TDCC) R was estimated between the average TDFD signal of each group during stimulation period and a waveform representing the rhythmic fluctuations of the musical excerpt using a 512-sample window with 99%
- Rhythmic waveform:
  - The music notation of the theme (quarters and eights) was corresponded to the values of 1 and 0.5, respectively.
  - Linear interpolation was performed to acquire a signal of the same size as the TDFD.
- Significance level: p = 0.001.



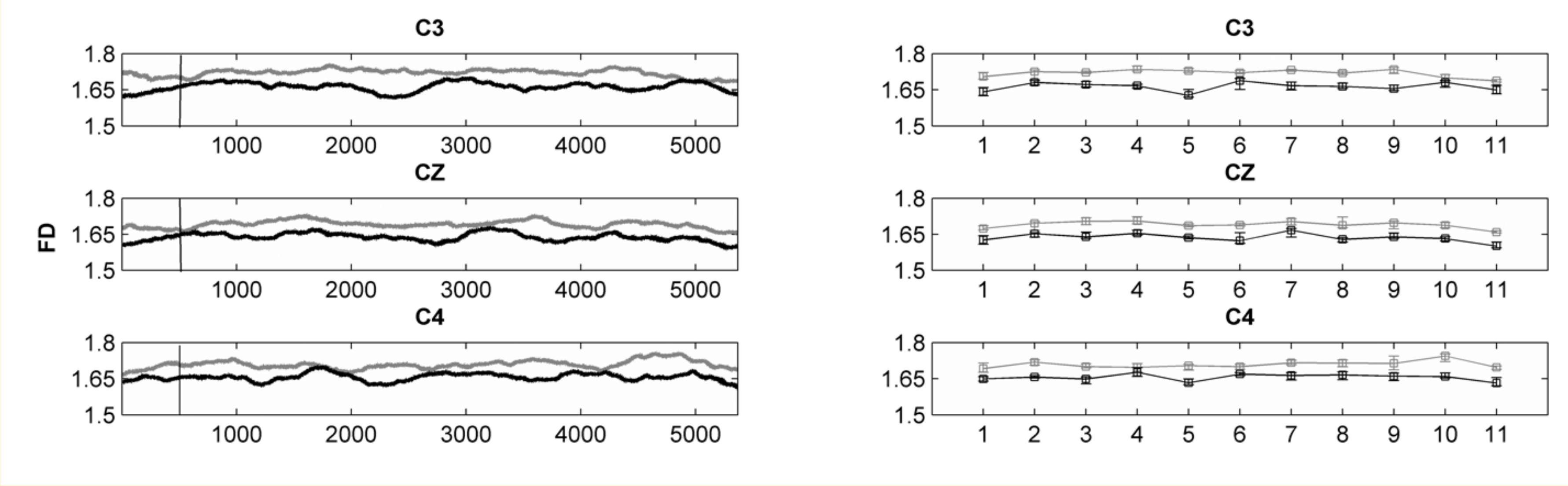
Results (Study 1)

- AS mode: Statistically significant differences for all electrode sites (OM vs. NM) -> Higher TDFD for the OM



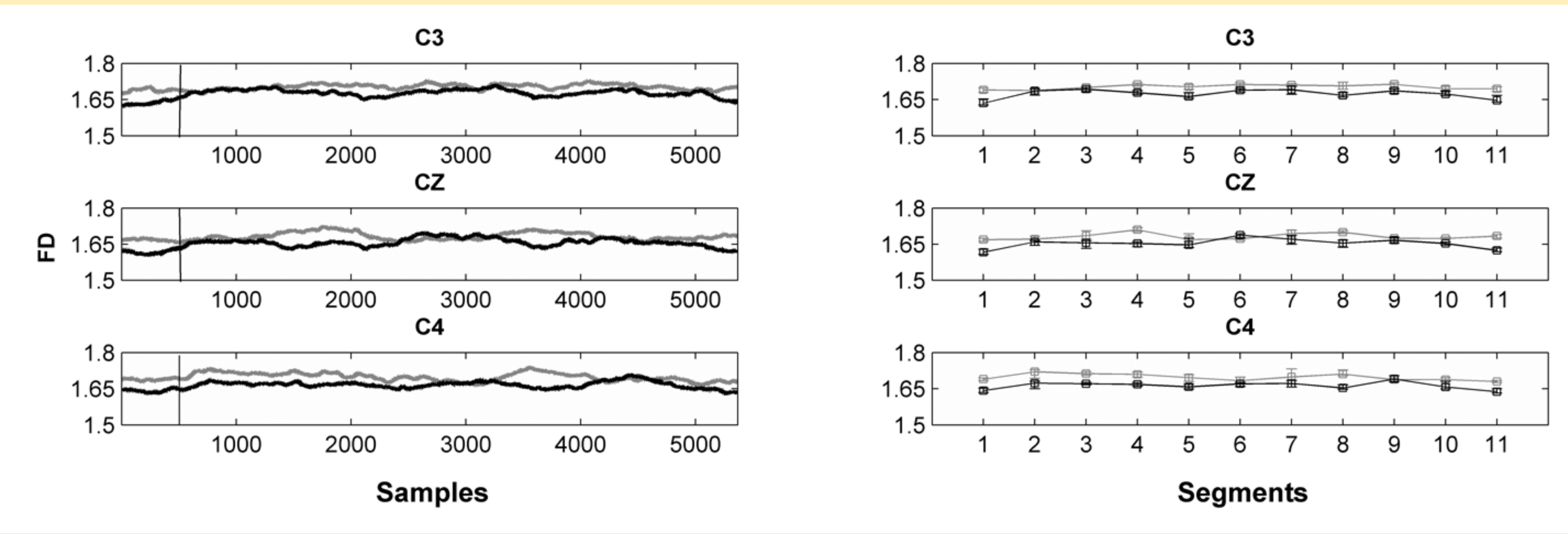
Results (Study 1)

- AVS mode: Statistically significant differences for Cz, C4 electrode sites (OM vs. NM) -> Higher TDFD for the OM



Results (Study 1)

- MUTE mode: No significant differences (OM vs. NM) -> TDFD signals of OM and NM converge



Results (Study 1): Mobility analysis

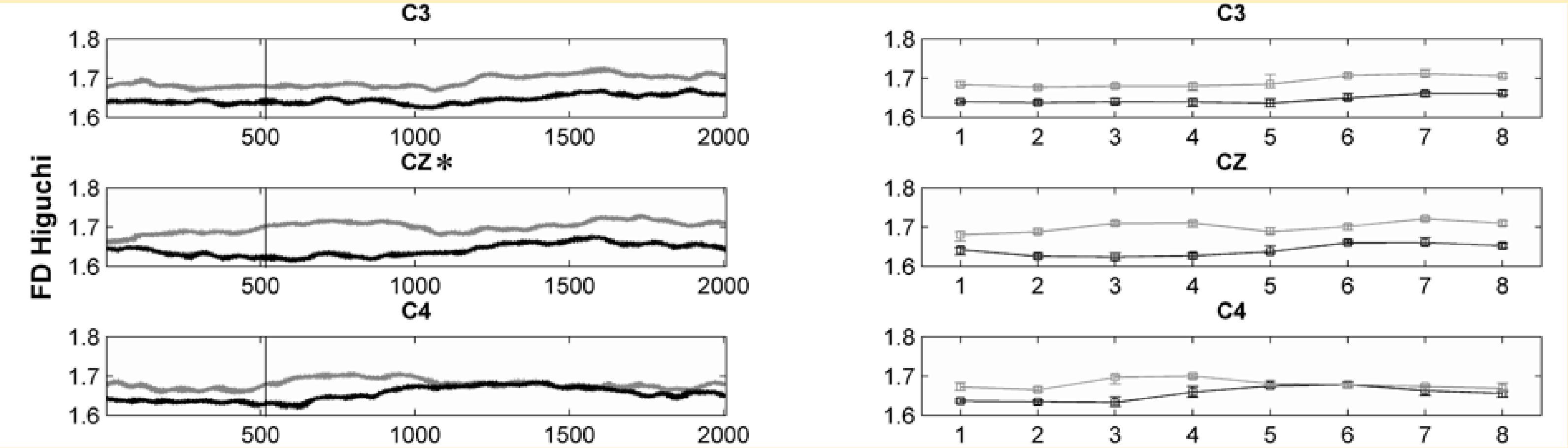
Mobility analysis:

- AVS mode: Higher correlation coefficient for the OM (C3: $R=0.3634$, $p<0.05$; Cz: $R=0.3813$, $p<0.05$; C4: $R=0.5284$, $p<0.05$) versus NM (C3: $R=-0.0393$, $p<0.05$; Cz: $R=0.0869$, $p<0.05$; C4: $R=0.3118$, $p<0.05$).

- MUTE mode: Higher correlation coefficient for the OM (C3: $R= 0.2759$, $p<0.05$; Cz: $R=0.1172$, $p<0.05$; C4: $R=-0.0532$, $p<0.05$) versus NM (C3: $R= -0.0697$, $p<0.05$; Cz: $R=0.1849$, $p<0.05$; C4: $R=0.0948$, $p<0.05$).

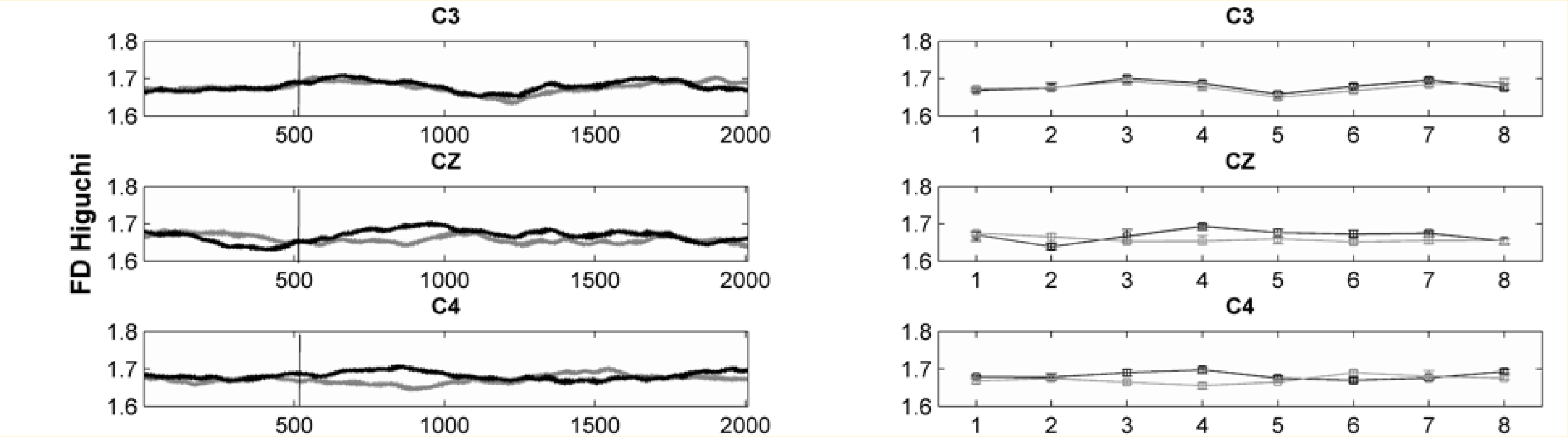
Results (Study 2)

- Higuchi's method yielded more consistent results as it was expected.
- AS mode: Statistically significant differences for the Cz electrode site (AMS vs. NM) -> Higher TDFD for the AMS



Results (Study 2)

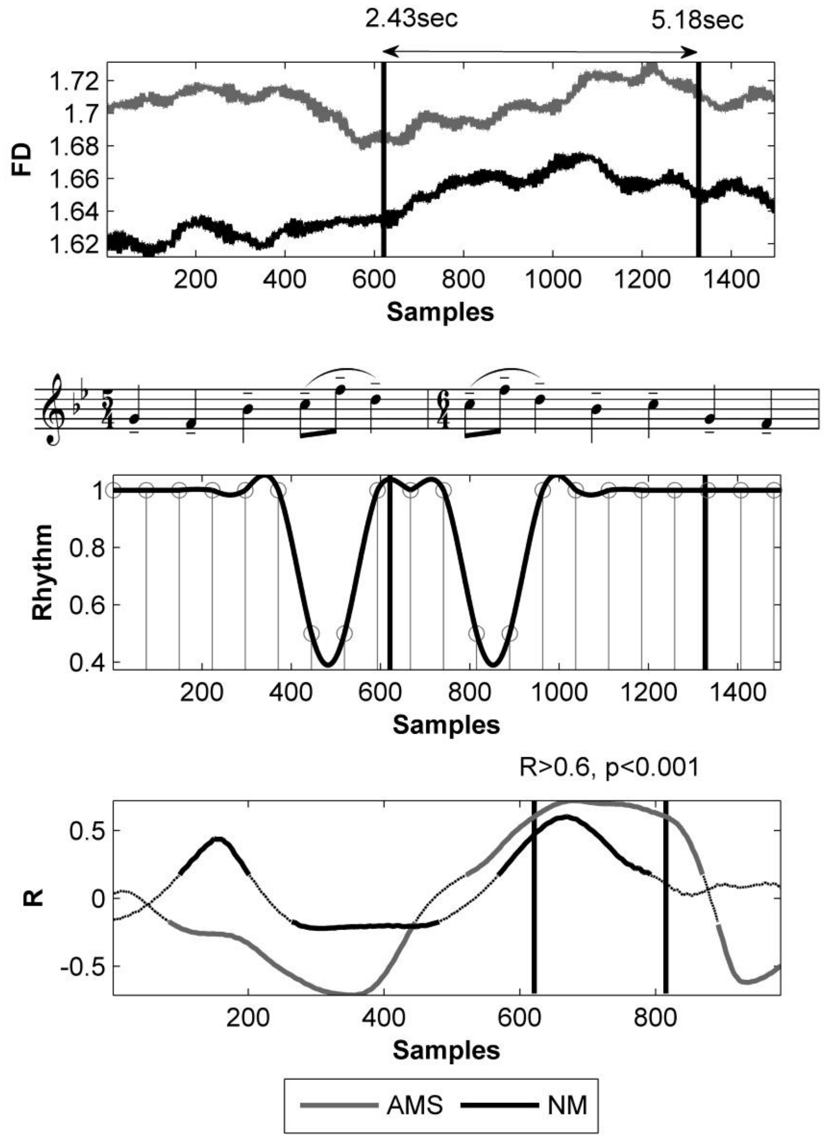
- AVS mode: No significant differences for all electrode sites (AMS vs. NM) -> TDFD signals of the AMS and NM converge due to the presence of human-like motion



Results of Study 2

Results (Study 2): Correlation analysis

Correlation analysis: Higher correlation coefficients (> 0.6) for the AMS in AS mode (2.43 – 5.18 sec after the stimulus onset)



Partial Conclusions

- During auditory stimulation the sensorimotor activity may be attributed to MNS activation, i.e., MNS is functioning as a linking mechanism between the auditory stimulus and its meaning.

- When the visual stimulus is accompanied by auditory stimulation musicians' perception is boosted.

- The differentiation in the sensorimotor response of musicians and non-musicians is attributed to the different level of musical education.

General Conclusions

- EEG analysis could reveal both emotional and cognitive responses during different affective- and motion-related stimulations
- Appropriate features derived from advanced signal processing could better express the differentiation in the underlying information

To Probe Further

Modeling of the dynamic character of emotions (catastrophe theory)

Transfer to other unexplored fields, such as emotions during sleep

Combination of other approaches (music therapy, pain regulation, psychology, disabled)

Relevant published work (http://psyche.ee.auth.gr)

Panagiotis C. Petrantonakis and Leontios J. Hadjileontiadis, “A Novel Emotion Elicitation Index Using Frontal Brain Asymmetry for Enhanced EEG-Based Emotion Recognition,” *IEEE Transactions on Information Technology in Biomedicine*, 2010 (submitted).

Panagiotis C. Petrantonakis and Leontios J. Hadjileontiadis, “Emotion Recognition from Brain Signals Using Hybrid Adaptive Filtering and Higher-Order Crossings Analysis,” *IEEE Transactions on Affective Computing*, in press.

Panagiotis C. Petrantonakis and Leontios J. Hadjileontiadis, “EEG-Based Emotion recognition using Higher-Order crossings,” *IEEE Transactions on Information Technology in Biomedicine*, vol. 14, no. 2, pp. 186-197, 2010.

Panagiotis C. Petrantonakis and Leontios J. Hadjileontiadis, "An Emotion Elicitation Metric for the Valence/Arousal and Six Basic Emotions Affective Models: A comparative Study,” *Proc. of the 10th IEEE International Conference on Information Technology and Applications in Biomedicine*, Corfu, Greece, November, 2010.

Panagiotis C. Petrantonakis and Leontios J. Hadjileontiadis, "Adaptive Extraction of Emotion-Related EEG Segments Using Multidimensional Directed Information in Time-Frequency Domain,” *Proc. of the 32nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (invited paper), Buenos Aires, Argentina, September, 2010.

Panagiotis C. Petrantonakis and Leontios J. Hadjileontiadis, "Frontal EEG asymmetry and Affective States: A Multidimensional Directed Information Approach,” *Proc. of the XII Mediterranean Conference on Medical and Biological Engineering and Computing (MEDICON 2010)(*3rd Young Investigator Award), Chalkidiki, Greece, May 2010.

Panagiotis C. Petrantonakis, Vagia Kaltsa, and Leontios J. Hadjileontiadis, "Selective EEG analysis for emotion recognition using multidimensional directed information criteria,” *Proc. of the 1st International Congress on Neurobiology and Clinical Psychopharmacology & European Psychiatric Association Conference on Treatment Guidance*, Thessaloniki, Greece, November 2009.

Panagiotis C. Petrantonakis and Leontios J. Hadjileontiadis, "EEG-Based Emotion Recognition Using Hybrid Filtering and Higher Order Crossings,” *Proc. of 2009 International Conference on Affective Computing and Intelligent Interaction*, Amsterdam, The Netherlands, September 2009.

Panagiotis C. Petrantonakis and Leontios J. Hadjileontiadis, "On Modelling User’s EEG Response During a Human-Computer Interaction: A Mirror Neuron System-Based Approach,” *Proc. of 4th European Congress for Medical and Biomedical Engineering (Finalist (top 10) at the Young Investigators Competition)*, Antwerp, Belgium, November 2008.

S. Hadjidimitriou and L. Hadjileontiadis, “Evaluation of Feature Relevance in Fractal-Quantified EEG Responses to Motion-Reflecting Musical Stimuli,” *Music Perception*, 2010. (submitted)

S. Hadjidimitriou, A. Zacharakis, P. Doulgeris, K. Panoulas, L. Hadjileontiadis, and S. Panas, “Revealing action representation processes in audio perception using Fractal EEG Analysis: A Mirror Neuron System-Based Approach,” *IEEE Transactions on Biomedical Engineering*, 2010. (in press)

S. Hadjidimitriou, A. Zacharakis, P. Doulgeris, K. Panoulas, L. Hadjileontiadis, and S. Panas, “Sensorimotor Cortical Response during Motion Reflecting Audiovisual Stimulation: Evidence from Fractal EEG Analysis”, *Medical and Biological Engineering and Computing*, vol. 48, no. 6, pp. 561-572, 2010.

P. Doulgeris, S. Hadjidimitriou, K. Panoulas and L. Hadjileontiadis, “Bispectral EEG analysis for knowledge scaffolding in music perception: A mirror neurons based approach,” *Journal of Computational methods in Sciences and Engineering*, 2008.

S. Hadjidimitriou, A. Zacharakis, P. Doulgeris, K. Panoulas, L. Hadjileontiadis, and S. Panas, “On detecting different levels of sensorimotor activity in musicians and non-musicians during musical direction: evidence from fractal EEG analysis,” in Proceedings of the 11th International Conference on Music Perception and Cognition, Seattle, Washington, 2010.

S. Hadjidimitriou, A. Zacharakis, P. Doulgeris, K. Panoulas, L. Hadjileontiadis, and S. Panas, “Monitoring of Musical ‘Motion’ in EEG Using Bispectral Analysis: A Mirror Neurons-based Approach”, *in IFMBE Proceedings, 4th European Conference of the International Federation for Medical and Biological Engineering*, Antwerp, Belgium, vol. 22, pp. 1290-1293, 2009.

P. Doulgeris, S. Hadjidimitriou, K. Panoulas, L. Hadjileontiadis and S. Panas, “Music perception as reflected in Bispectral EEG analysis under a Mirror Neurons-based approach,” *Studies in Computational Intelligence*, vol. 142, pp. 137-146, 2008.

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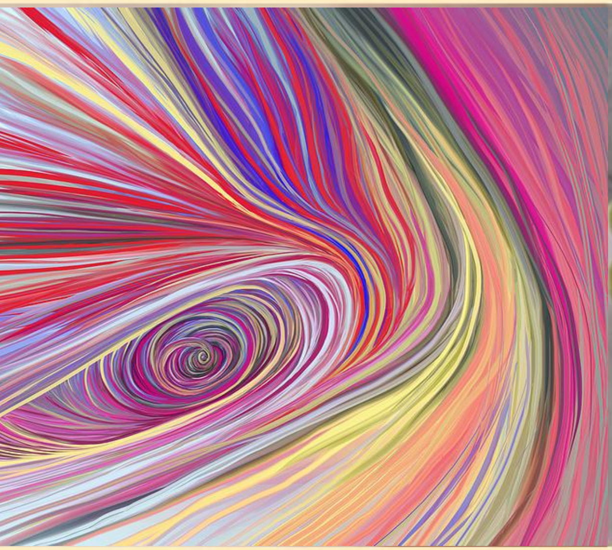
Telecommunications Division
Signal Processing & Biomedical Technology Unit

CENTRE FOR RESEARCH & TECHNOLOGY - HELLAS
Informatics & Telematics Institute

December 1, 2010, 16:00-17:00

Thank you!



Emotions, Action Representation and EEG: A Signal Processing Perspective

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