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Subject Independent Affective States Classification Using EEG Signals

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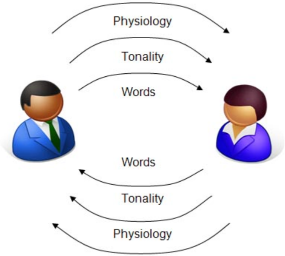
Outline

Research Motivations

- Human Interfaces
  - Information is transferred through multiple channels [1]:
    - Linguistic language (7%)
    - Facial Expressions (55%)
    - Paralanguage (posture, touch, gesture..) (38%)



- Current Human-Computer Interfaces
  - Contextual information expressed through non-verbal expression is lost. E.g., emotional states
  - Not adaptive or user-centered

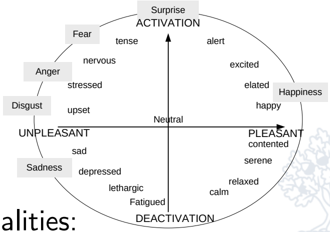
Cognitive-affect Interfaces

- Responds to user's emotion, cognition and motivation
  - Emotion influences learning, decision making, regulates self-behavior and influence the interactions between each other[1]
- Emotion is a unique personal expression influenced by
  - culture background
  - personal experience
  - social context etc.
- Potential Applications
  - Human Machine Interface (HMI)
  - Health and rehabilitation applications
  - Multimedia content indexing and retrieving

[1] Mehrabian, A. (1968). Communication without words. Psychology Today, 2 (9), 52-55

General Challenges

- Affect is the raw neurophysiological expression of emotion
  - 2-D representation of Affect:
  - valence: unpleasant to pleasant
  - arousal: relaxed to aroused

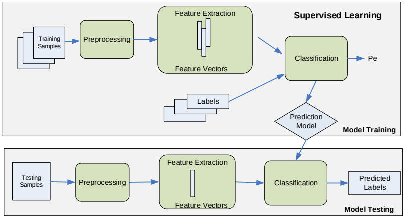


- Prior Affective Signal Processing Modalities:
  - Facial expression, Voice, Gesture...
  - Physiological signals: heart rate, Galvanic Skin Response (GSR), ..
- EEG-Based Analysis Systems
  - Works with inaccessible and non-cooperative cases (autism disorders)
  - Less influenced by non-emotional factors

Research Objectives

- To design and implement an EEG-based affective interface for ubiquitous applications.
  - To examine the characteristics of brain oscillations during a cognitive process, e.g., emotional expression.
  - To exam the efficacy of current in-market commercial-grade EEG headsets for the affective states classification application
- EEG signal directly reflects the neural activity of the brain:
  - Brain networks in the limbic system are associated with affect expression
  - Brain imaging (fMRI) study shown strong correlation between emotion expressions and asymmetrical brain activity

EEG-based Affective Signal Processing System

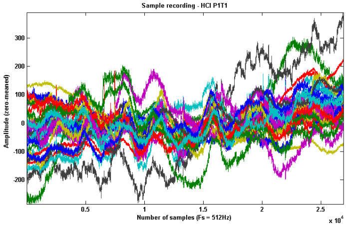


- A supervised learning system with key Components as:
  - Signal preprocessing, feature extraction and selection, classification
  - Off-line model development followed by a cross-validation process simulating online testing

Preprocessing of the Input EEG Signals

- To reduce noises, artefact and other external interferences
  - muscle movement, e.g., heart-beat, neck movement, or eye-movement

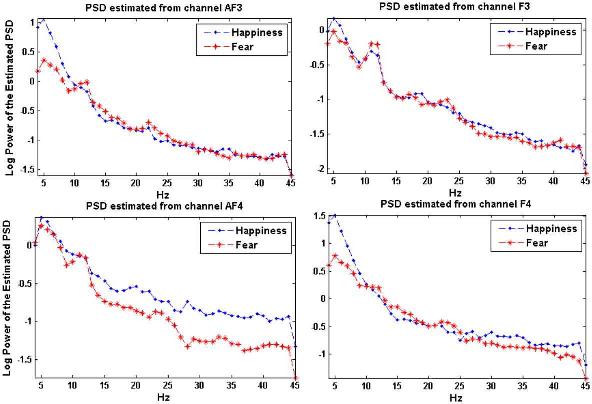
- Key components
  - Electrode referencing (e.g., to the common average)
  - Baseline offsets and linear trends removal (linear regression)
  - Bandpass filtering (4-45Hz)



Feature Extraction Algorithms for EEG Analysis

- EEG oscillation characteristics that can be used in this study:
  - Spectral domain: event-related potentials
  - Time-domain: oscillation patterns
  - Complexity analysis: fractal dimensions, higher order crossings
- Event Related Potential (ERP) based algorithm used in this study
  - Frequency components within 4-30Hz were extracted first
  - Energy within each 1-2 Hz narrow-bands (through STFT) were computed and used as features
- ANalysis Of VAriance (ANOVA) for Feature Selection
  - Preserve original meaning of the features, e.g., the sensor location and spectral value of the features
  - A small F value (or large P values) of a feature indicates that it is ineffective in discriminating the two classes (or groups)
  - Thus, this feature should be discarded

Feature Extraction Algorithms Cont.



PSD features comparison for Happiness and Fear states (P3Trial5)

- Very distinguishable ERP variations among some channels under different emotional states

Experimental Setup: MAHNOB-HCI-Tagging Database

- 30 Subjects, 527 Trials selected for this experiment
- As stimuli, 14 video clips were selected based on a preliminary study (vote of confidence)
- Stimuli were in the range of 34.9s -117s (within the 1min-10mins criterion [1])
- Self-report of felt emotions using Key words and dimensional representation

[1] Jonathan Rottenberg, Rebecca D. Ray, and James J. Gross. Emotion elicitation using films, pages 9-28. Series in affective science. Oxford University Press, 2007.

Experimental Setup: Data Annotation

Mapping of the 9-keywords based emotional states to high-low arousal and valence states

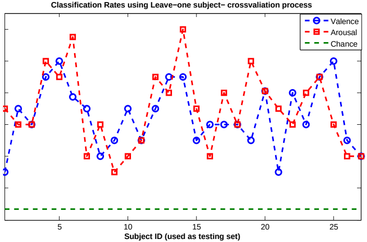
States	Arousal	Valence
Low	Sadness, Neutral, Disgust	Fear, Anger, Disgust, Sadness, Anxiety
Medium	Happiness, Amusement	Surprise, Neutral
High	Surprise, Fear, Anger, Anxiety	Happiness, Amusement

Experimental Setup

- Subject-independent affective classification study on MAHNOB-HCI-Tagging database
- Narrow-band features with ANOVA feature selection mechanism
- Leave-one subject-out cross validation procedure for evaluating the proposed system
  - support vector machines (with RBF kernel)
  - 10 iterations, averaged results reported
- Two experiments were carried out in this study
  - Full 32 channel vs. channel reduction in reference to commercial headsets

Experimental Results: Without Channel Reduction

- Averaged Correct Classification Rates (CCR) for Arousal and Valence States using SVM classifier with RBF kernels

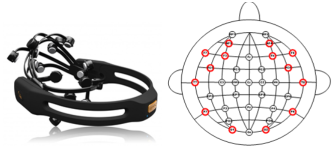


- Better performance than the published performance in [1] using the same database, subject-independent
  - Close to the subject-dependent ones reported in recent literature

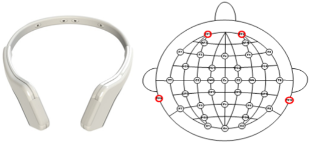
[1] Soleymani, M.; Lichtenauer, J.; Pun, T.; Pantic, M.; , "A Multimodal Database for Affect Recognition and Implicit Tagging," Affective Computing, IEEE Transactions on , vol.3, no.1, pp.42-55,

Experimental Results: With Channel Reduction

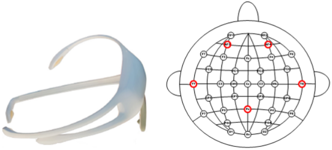
Sensor Location for in-market Consumer grade EEG headsets:



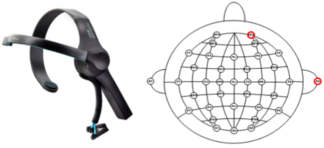
a) Emotive Epoch (14 channels)



c) InteraXon Muse (4 channels)



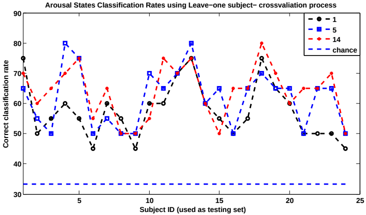
b) Emotive Insight (5 channels)

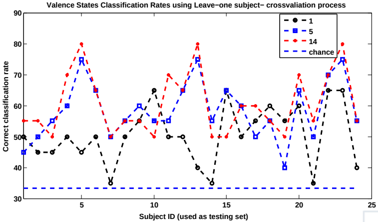


d) Neurosky Mindwave Mobile (1 channel + ref)

Experimental Results: With Channel Reduction Cont.

Averaged CCR with Reduced Channels





- As an attempt to determine how suitable these headsets are for this intended application
- Our next step is to systematically search the optimal (N desired) sensor locations for a specific application

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Experimental Results Summary

Averaged CCR for all Sensor Setup:

Averaged CCR(%)	Biosemi Active II(32)	Emotiv Epoch (14)	Emotiv Insight (5)	Neurosky (1)
Arousal	64.74%	63.96%	61.86%	57.5%
Valence	62.75%	60.63%	58.54%	50.63%
Feature Selection	ANOVA	None	None	None

- Classification accuracy decreases dramatically when a signal electrode headset was used

Conclusions

- A framework for EEG signal processing on affect detection was designed, tested and evaluated
  - Narrow-band spectral power were used as features
  - One-way ANOVA was used as feature selection method
  - Good generalization property were achieved, near single-subject recognition performance
  - System performance with reduced channels were also evaluated
- Future Works
  - Adaptive learning methods should be explored
  - Semi-supervised learning methods should be our next step

Thank You
(Q & A)