Emotion Detection Using Physiological Signals

M.A.Sc. Thesis Proposal
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Outline

- Emotion Detection Overview
  - EEG for Emotion Detection

- Previous Works
  - Key methods and recognition results

- Proposed Work
  - Feature Extraction
  - Classification Algorithm

- Project Plan

- Conclusion
Emotion Detection

- Emotion detection is essential tool in developing affect sensitive applications
  - Human-Machine Interaction: detect, recognize and response to emotions
  - Alternate emotion communication pathway for Autism

- Classify emotions based on input signals
  - 2D/3D face images
  - Audio recordings
  - Body movements
  - Physiological signals

- 6 universal basic emotions:
  - fear, anger, sadness, happiness, surprise, and disgust
Physiological Signals for Emotion Recognition

- Complement to other detection modalities
  - Poor Image/audio quality or inaccessible
  - Robust against possible artefacts of human social masking

- Physiological signals have been used in the literature:
  - Blood volume pulse (BVP)
  - Electromyography (EMG)
  - Skin Conductance (SC), Skin Temperature (SKT)
  - Electrocardiogram (ECG), Respiration (RESP)

- Fear: Increase of instantaneous heart rate, skin conductivity and systolic blood pressure (Russel, 2005)
- Sadness: Decrease heart rate
- Anger: Increase of heart rate, systolic and diastolic blood pressure

EEG-based Emotion Detection

- **Electroencephalogram (EEG)**
  - is the measurement of electrical activity on the scalp, produced by neuron activity within the brain

- **Frontal EEG asymmetry** constitutes the most prominent expression of emotion in brain signals.

- **Correlation to Emotional States**
  - Previous EEG studies generally suggest:
    - right frontal lobe -> negatively valenced emotions,
    - left frontal -> positively valenced experiences
Problem Statement

- Define a *statistical learning method* that can provide *very stable and successful* emotional classification performance over six emotional states
  - *the extraction of the features in order to achieve optimum classification performance*

**Challenges**

- *Emotion is subjective matter that influenced by past experience, culture and context.*
- *Large number of unknown patterns to known ones, challenging in prediction model*
Russel proposed a circumplex Model in Emotion that links Neural activity to subjective emotions in a 2D model. Consistent with the empirical observations within the central nervous system, affective states are products of two independent neurophysiological systems:

- **Arousal**: degree of excitation
  - spans from calmness to excitement
- **Valence**: judgement of a situation
  - Spans from positive to negative

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Electrodes placements
- International 10-20 system

Mirror Neuron Response
- the activation of the neural representation of an emotion by simply observing that emotion

Emotion Elicitation
- Images from the IAPS (International Affective Picture System)
- Images are labeled with valence or arousal in a scale of 1-9

Sampling Rate: 256Hz – 1024 Hz

Channel Selection
- the asymmetrical neural pathway at the frontal lobes
EEG for Emotion Detection

- Multi-channels Recordings
EEG for Emotion Detection: System Model

- **Pre-processing:** removal of artifacts and noises
- **Feature Extraction:**
  - *EEG signals are high dimensional, with redundancy information*
  - *Project signal into feature space to reduce dimensionality or increase the separability of the classes*
  - *Reduce the complexity of the classifier*
Previous Works: Extraction of Features

- **Statistical features proposed by Picard**\(^1\)
  - Mean, standard deviation of the absolute values of the raw signal,
  - Mean of the absolute values of the first and second differences of the raw signal,
  - Mean of the absolute values of the second differences of the normalized signals

- **Wavelet-based features**
  - Wavelet energy and entropy after \(L\) level of discrete decomposition using Daubechies fourth-order orthonormal bases

- **Adaptive Filtering and Higher Order Crossing Analysis**\(^2\)
  - Oscillation nature of the time series
  - Filter and count, iterative process, the number of zero-crossings after applying each filters are used as features

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### Previous Works: Key Methods and Recognition Results

- For the case of 6 basic emotions

<table>
<thead>
<tr>
<th>Method</th>
<th>Recognition Rate (%)</th>
<th>Single Channel</th>
<th>Combined Channels</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Statistical features</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>37.5 (MD, F3/F4)</td>
<td></td>
<td>44.90 (MD, CB₂)</td>
</tr>
<tr>
<td><strong>Wavelet-based features</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>34.60 (3-NN, Fp2)</td>
<td></td>
<td>32.70 (QDA, CB₃)</td>
</tr>
<tr>
<td><strong>Higher Order Crossings</strong></td>
<td>62.3 (QDA, F3/F4)</td>
<td></td>
<td>83.3 (SVM, CB₄)</td>
</tr>
</tbody>
</table>

- HOC: alpha (8–12 Hz) and beta (13–30 Hz) bands only
- SVM: *Support Vector Machine*, k-NN: *k-Nearest Neighbor*,
- QDA: *Quadratic Discriminant Analysis*, MD: *Mahalanobis Distance*

Motivations

- In previous works, feature selection methods are not adaptive
  - *Fixed type of wavelets used for projection into feature space*

- Further research is needed
  - *To improve recognition rates and discover unknown aspects of emotion mechanisms performed in the human brain*

- Selection of features should be more adaptive to the time series
Proposed Works: Preprocessing

- Rejecting Artifacts Based on Channel Statistics
  - Independent Component Analysis (ICA)
  - Fast Fourier Transform (FFT)
  - Discard sub-bands of the EEG signals (could potentially lose valuable EEG information)
Proposed Work: Empirical Mode Decomposition (EMD)

- **EMD Process**
  - Data driven process, decomposition based on time series oscillation mode
  - Data series can be decomposed into $M$ intrinsic mode functions (IMFs) and a residue.
  - Representation of the EEG signal on the EMD space

- **Extract Features using EMD**
  - Intrinsic Mode Functions (IMFs) as features
  - Statistically determine the number of IMFs to keep
  - Determine the statistical features of the IMFs
Proposed Work: Classification

- Combined channel case or single channel use for classification

**Classification methods to use**

- Quadratic Discriminant, Analysis (QDA), k-nearest neighbor, Mahalanobis distance, and support vector machines (SVMs)

**Support Vector Machine**

- Separate the training data in feature space by a hyper-plane defined by the type of kernel function used.
## Work Plan and Implementation Schedule

<table>
<thead>
<tr>
<th>Milestones</th>
<th>Timeline</th>
</tr>
</thead>
<tbody>
<tr>
<td>Artefacts Removal on EEG recordings</td>
<td>May – June 2011</td>
</tr>
<tr>
<td>Investigate Feature Extraction Methods</td>
<td>July – September 2011</td>
</tr>
<tr>
<td>Implementing Classification Approaches (SVM, kNN etc.)</td>
<td>October – December 2011</td>
</tr>
<tr>
<td>Feature Level and decision level fusion</td>
<td>January – February 2012</td>
</tr>
<tr>
<td>Experiment Results Analysis</td>
<td>January – March 2012</td>
</tr>
<tr>
<td>Thesis Writing</td>
<td>April – May 2012</td>
</tr>
</tbody>
</table>
For the proposed project, I believe it’s possible to uniquely map EEG recordings to the affect states of a subject for the following reasons,

- **Asymmetry of activity in the prefrontal cortex when emotion is present**
- **Emotion is a linear combination of two independent neural systems: valence and arousal**
- **Increased neural activity in different pathways can be used as an indicator of specific emotions**

Statistical methods will be investigated
Thanks!  Questions?
The statistical features used to form the proposed FV s are defined as:

1. the mean of the raw signal ($\mu_x$),
2. the standard deviation of the raw signal ($\sigma_x$),
3. the mean of the absolute values of the first differences of the raw signal ($\delta_x$),
4. the mean of the absolute values of the first differences of the standardized signal ($\delta_x$),
5. the mean of the absolute values of the second differences of the raw signal ($\gamma_x$), and
6. the mean of the absolute values of the second differences of the standardized signal ($\gamma_x$).
Sub-bands of the EEG signals

<table>
<thead>
<tr>
<th>Band</th>
<th>Frequency</th>
<th>Location of Origin</th>
<th>Reason for Activity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Delta (noise)</td>
<td>0-4 Hz</td>
<td>Thalamus</td>
<td>Slow-wave sleep</td>
</tr>
<tr>
<td>Theta</td>
<td>4-7 Hz</td>
<td>Hippocampus and cortex</td>
<td>Idle</td>
</tr>
<tr>
<td>Alpha</td>
<td>8-12 Hz</td>
<td>Posterior regions, occipital lobe, cortex</td>
<td>Closed eyes and idle state in cortex</td>
</tr>
<tr>
<td>Beta</td>
<td>12-30 Hz</td>
<td>Cortex (e.g. Motor and sensory)</td>
<td>Active/busy, concentrate/alert</td>
</tr>
<tr>
<td>Gamma</td>
<td>30-100 Hz</td>
<td>Cortex</td>
<td>Sensory processing and cognitive task</td>
</tr>
</tbody>
</table>

- Beta waves are connected to an alert state of mind, whereas alpha waves are more dominant in a relaxed person. Research has also shown a link between alpha activity and brain inactivation, which also leads to the same conclusion.

- This beta/alpha ratio could therefore be an interesting indication of the state of arousal the subject is in.

- Delta band contains mostly noise such as pulses, neck movement, and eye blinking