Facial Expression Image Mapping for BCI using EI Type Classification

Seongah Chin, Chung-yeon Lee, Jaedong Lee

Division of Multimedia of Sungkyul University

Department of Computer Science of Korea University

XICOMLAB

VISUAL & VIRTUAL REALITY COMPUTING LABORATORY

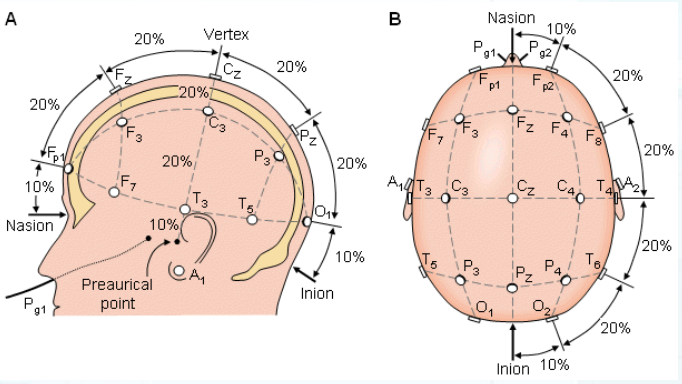
Outline

- **Introduction**
- **Related Works**
- **Methodology**
  - BCI Experimental Protocol
  - EEG Data Analysis
  - EEG Fuzzy Model
  - EI Fuzzy Model
  - Facial Animation
- **Experimental Results**
- **Conclusion**

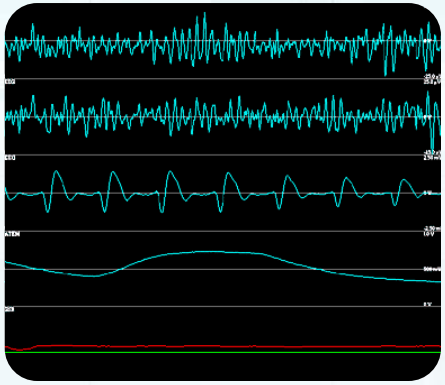
Introduction

- **Brain-Computer Interface (BCI)**
  - BCI uses electrophysiological brain signals as meaningful data to manipulate remote devices or applications.
  - The electrical activity captured by some electrodes is used to carry out feature extraction and pattern classification.

Synapse illustration



The international 10-20 system



Brain signals

Introduction

- **Brain-Computer Interface (BCI)**
  - BCI studies have mainly aimed at improving medical applications for the benefit of people who suffer from severe muscular disorders.
  - Related applications have been used to be alternative communication means for motor-impaired people.

Wheelchair moving through BCI input

A paralytic expresses his intention using BCI

Keyboard Input with BCI

Introduction

- **Brain-Computer Interface (BCI)**
  - Recently, studies on BCI have been extended to entertainment areas such as human-computer interaction and games for healthy users.
  - The studies allow end-users to innovatively utilize BCIs to manipulate resources in games and virtual environments.

Honda ‘ASIMO’

Nintendo Wii 2.0 concept design

Emotiv Epoc

Introduction

- **Facial Expression**
  - Even in the same expression, it is not exactly identical but slightly distinctive because of various personalities.
  - Recognition of facial expression using BCI has become important for the entertainment industry.
  - However, Previous studies focused on recognition of facial expressions rather than creation of facial expressions synthesis using BCI.

Fear expressions in different personal traits

Surprise expressions in different personal traits

Introduction

- **Motivation**
  - Advanced non-verbal communication in virtual environment
  - The distinctive facial expressions of individual avatar
  - The next generation of smart interface
  - Online application of affective computing using BCI

Introduction

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  - Online application of affective computing using BCI

Haptic

Touch

Gesture

BRAIN

Related Works

- **BCI + Facial Expression**
  - Classification of six different facial expressions using EEG & EMG
    - Chin et al., 2008
    - Proposed extension of the filter bank common spatial patterns (FBCSP) algorithm to the multiclass paradigm
  - Gender difference in oscillatory brain responses during the presentation of facial expressions
    - Guntekin & Basar, 2007
    - Occipital β (15-25Hz) was significantly larger in women than men

Related Works

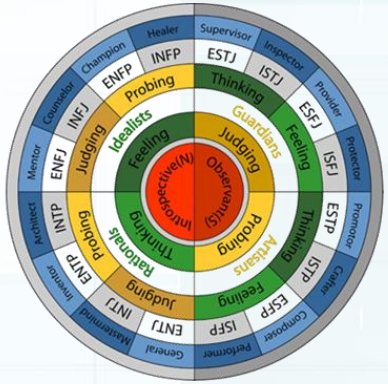
- **BCI + Facial Expression**
  - Investigating the production of emotional facial expressions using a combined EEG & EMG
    - Korb et al., 2009
    - Studied between spontaneous emotional facial expressions and voluntarily posed expressions in brain activations using a combined EEG and EMG.
    - The findings indicate that the most consistent theory of difference is that the motor cortex (M1) do not have to be revitalized for emotional facial expression.

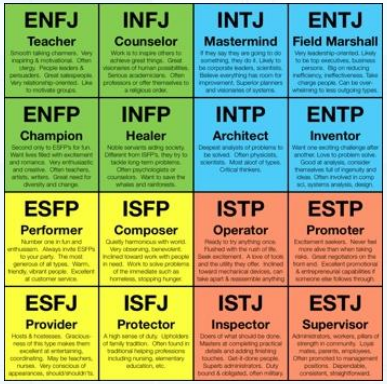
Related Works

- **BCI + Personality Psychology**
  - Relationship between personality types and cortical activity
    - Gram et al., 2005
    - Using the Myers-Briggs Type Indicator (MBTI)
    - The α bandwidth were generally coherent with Eysenck's biology theory of extraversion-introversion.
    - The implications show that the α values become relatively greater than the β ones in E type and that the β values are greater than the α ones in I type.

Related Works

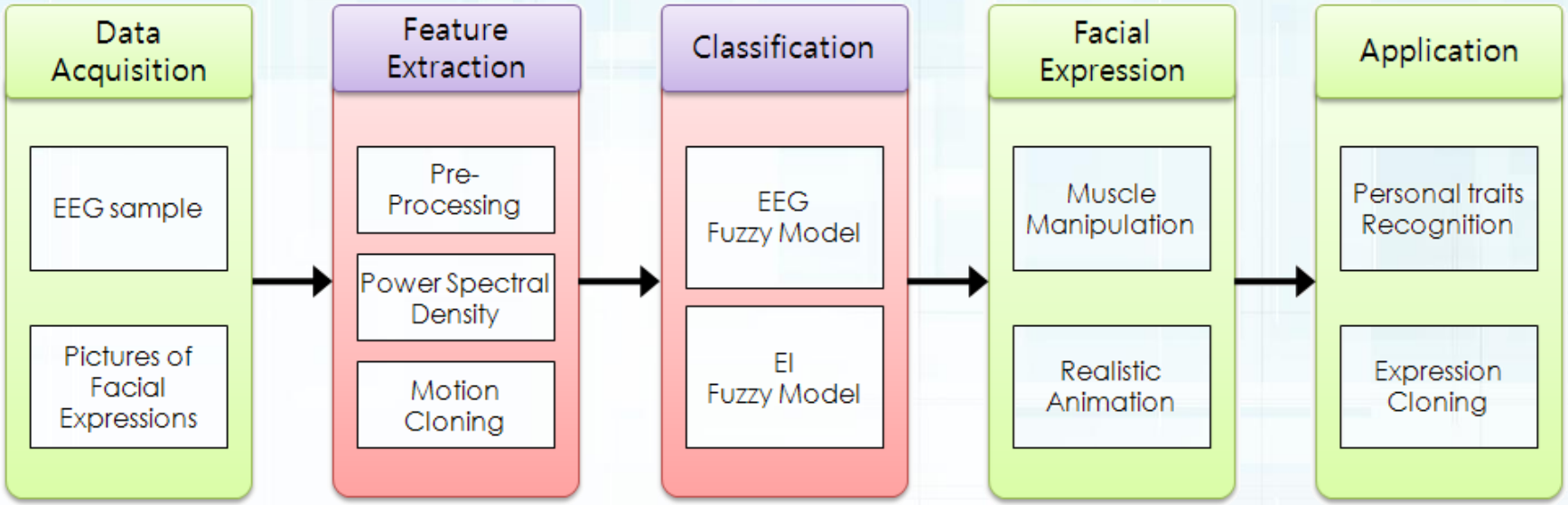
- **MBTI (Myers-Briggs Type Indicator)**
  - A psychometric questionnaire designed to measure psychological preferences in how people perceive the world and make decisions
  - Fundamental to the MBTI is the theory of psychological types of consciousness as originally developed by Carl Jung
  - The four pairs of preferences or dichotomies are:
    - Extraversion vs. Introversion
    - Sensing vs. iNtuition
    - Thinking vs. Feeling
    - Judgment vs. Perception





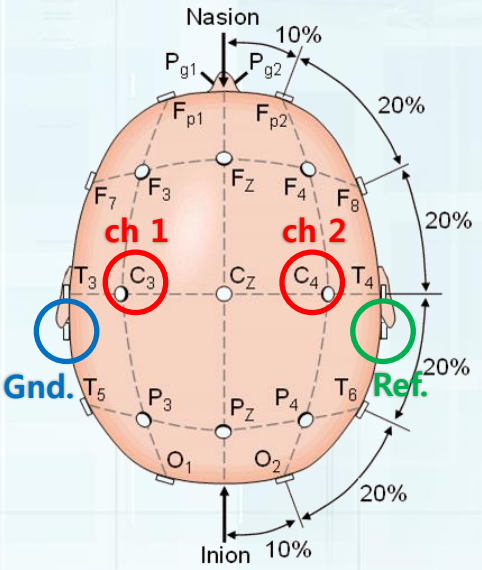
Methodology

- **Flowchart**



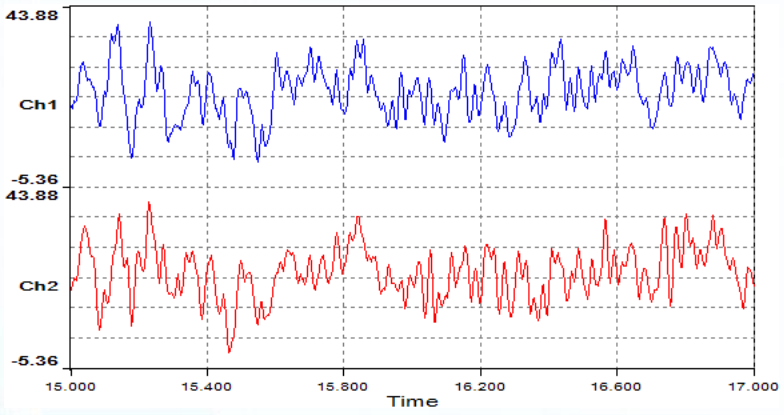
Methodology

- **BCI Experimental Protocol**
  - EEG were sampled at 256Hz for 120sec using QEEG-4 (Neuromedi Inc.) while 8 Subjects were calmly watching a blank screen
  - Ag/AgCl electrodes were placed on C3 & C4 (according to the 10-20 system)
  - Ground and reference electrodes were placed on each mastoid process
  - Noise-proof room with 22-26℃ temperature
  - Subjects also answered the examination of MBTI GS form after EEG acquisition for tracing their personal traits

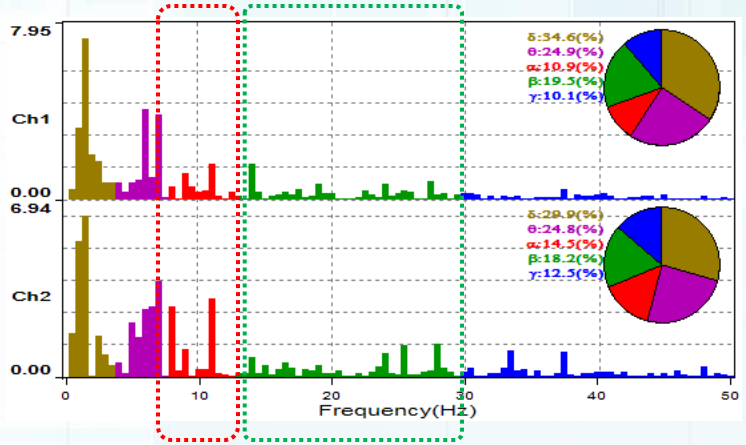


Methodology

- **EEG Data Analysis**
  - Eliminated the first and last 30sec to select valid data
  - Extracted the absolute values of α (8-12.9Hz) and β (13-29.9Hz) from power spectral density (PSD) of each EEG signal



Raw EEG signals



PSDs (red: α, green: β)

Methodology

- **Power Spectral Density**
  - Decompose raw EEG signals into components of frequency using DFT (discrete Fourier transform)

$$H(f_n) = \sum_{k=0}^{N-1} h_k e^{-j2\pi kn/N} \qquad h_k = \frac{1}{N}\sum_{n=0}^{N-1} H_n e^{-2\pi kn/N}$$

  - Sum of the frequency values data decomposed by DFT

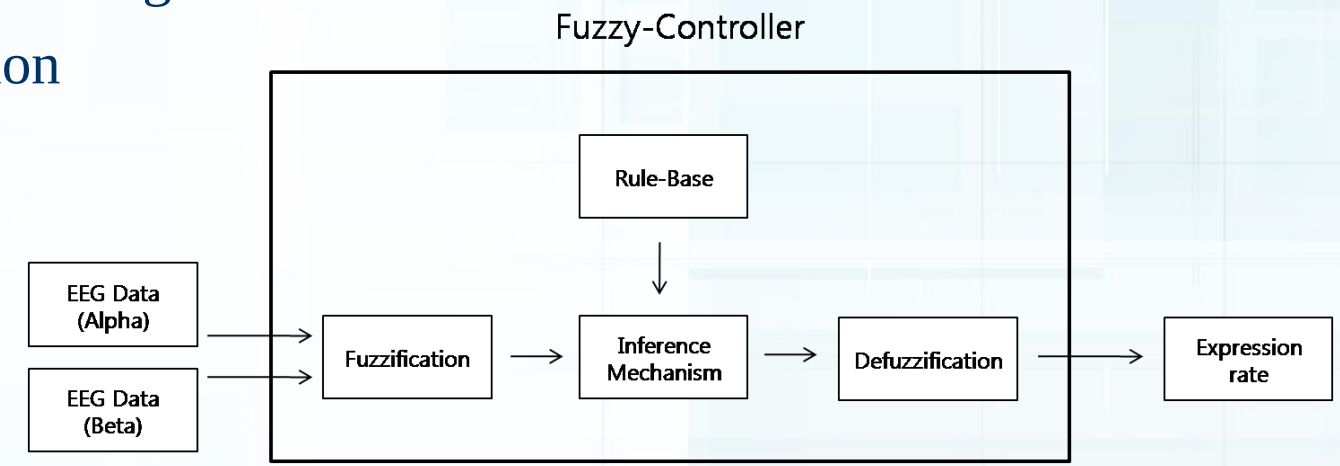
$$Total\ Power = \sum_{k=0}^{N-1} |h_k|^2 = \frac{1}{N}\sum_{n=0}^{N-1} |H_n|^2$$

  - Power spectral density that is satisfied above theorem

$$\begin{cases} P(f_0) = P(0) = \frac{1}{N^2}|H_0|^2 \\ P(f_n) = \frac{1}{N^2}\left[|H_n|^2 + |H_{N-n}|^2\right], \quad n = 1, 2, \cdots, (\frac{N}{2} - 1) \\ P(f_{n/2}) = P(f_c) = \frac{1}{N^2}|H_{N/2}|^2 \end{cases}$$

Methodology

- **Structure of Fuzzy System**
  - Fuzzification
  - Fuzzy rule base
  - Fuzzy inference engine
  - Defuzzification



Concept diagram of the fuzzy system for classification personal traits using EEG data

Methodology

- **EEG Fuzzy Model**
  - Analyzed subjects' α and β values of PSDs in consideration of their personal traits
  - The results shows that α values of E types are greater than I types and β values of E types are smaller than I types as same as Gram's study
  - We choose E-I types for the component of personal traits to classify using BCI

	α	β
E	51.50485	2.342032
I	25.34696	3.728912

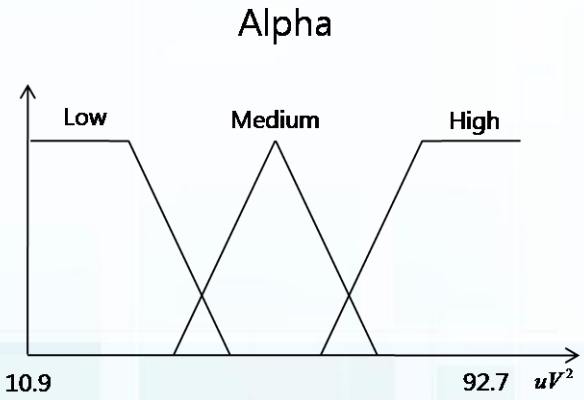
Average α and β values of PSDs on E and I

max		min	
α	β	α	β
92.7	10.2	10.9	0.7

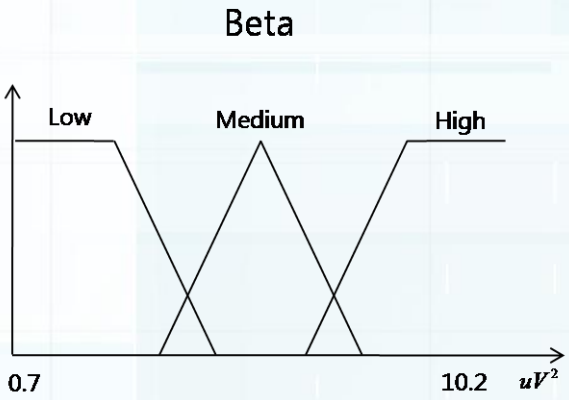
Maximum and minimum of α and β values

Methodology

- **EEG Fuzzy Model**
  - EEG fuzzy model was built on the basis of the α and β values of the power spectrum using the Fuzzy logic toolbox in Matlab
  - Two fuzzy sets were required to design the EEG fuzzy model
  - Each set is composed of 3 memberships: Low, Medium and High



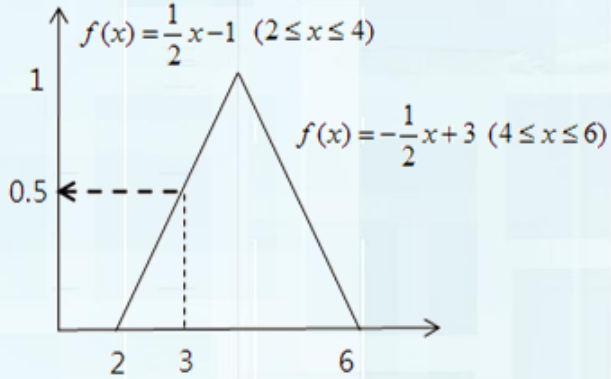
Fuzzy set of alpha



Fuzzy set of beta

Methodology

- **EEG Fuzzy Model**
  - Fuzzification is the process that transforms α and β values into a specific fuzzy membership
  - The α and β values are input each fuzzy member function and transformed
  - Finally, the personal-trait is made up by applying the two transformed memberships to the fuzzy rule
  - The personal traits can be derived as VI, I, M, E, VE



A fuzzy member function

	β-LOW	β-MEDIUM	β-HIGH
α-LOW	M	I	VI
α-MEDIUM	E	M	I
α-HIGH	VE	E	M

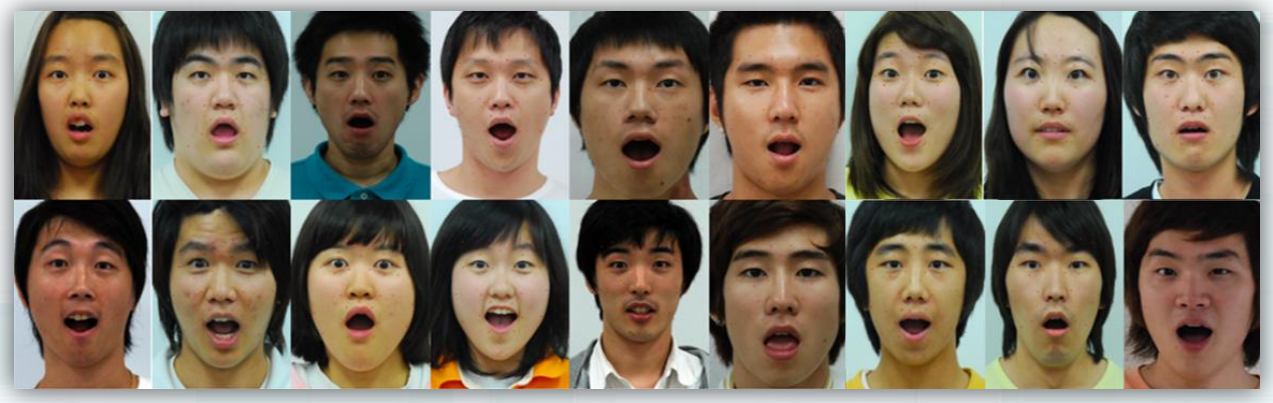
The fuzzy rule

Methodology

- **EI Fuzzy Model**
  - The personal trait that was classified by EEG fuzzy model is required to be mapped with facial expressions
  - Six fuzzy sets of expressions including five memberships were needed to be defined with respect to facial motion capture data to connect facial expressions and EI types

Methodology

- **EI Fuzzy Model**
  - Six facial expressions and a neutral face were acquired by taking pictures from 30 subjects (20 extrovert and 10 introvert) who were acting facial expressions of 6 emotional states
    - Pictures were taken by Nikon D80 with 10.2 megapixels resolution
    - The camera was fixed in 200cm front of the subject using tripod
  - Subjects respond the examination of MBTI GS form



Surprise expressions

Methodology

- **EI Fuzzy Model**
  - Feature points were attached on faces with regard to the position of the facial muscles
  - Calculate distances between the feature points on the neutral face and each facial expression
  - Get the personal-trait factors α_i using below equation,

$$\alpha_i = d_i / d_m, \quad i = 1,2...30$$

    - d_i is the distance between neutral face and d_m is the minimum of the distances

Methodology

- **EI Fuzzy Model**

Trial	Distance	α	Trial	Distance	α
1	169.375	3.3821	16	148.428	2.96383
2	218.82	4.36941	17	180.544	3.60511
3	148.27	2.96067	18	206.906	4.13151
4	167.824	3.35113	19	87.6641	1.75048
5	147.76	2.95048	20	74.5587	1.48879
6	93.1612	1.86025	21	152.112	3.03738
7	155.048	3.09602	22	50.0799	1
8	129.969	2.59524	23	134.941	2.69451
9	123.463	2.46531	24	188.685	3.76767
10	93.5949	1.86891	25	64.0469	1.27889
11	130.893	2.61368	26	129.445	2.58477
12	105.901	2.11464	27	105.565	2.10793
13	119.604	2.38825	28	61.563	1.22929
14	89.6326	1.78979	29	68.9783	1.37736
15	105.896	2.11454	30	105.352	2.10367

Personal-trait factors of surprise expressions

Methodology

- **EI Fuzzy Model**
  - Calculate the individual motion data set using the motion cloning system that has developed by this laboratory in previous research

    (Chin, "Emotional intensity-based facial expression cloning for low polygonal applications", IEEE TSMCC, vol.39, no.3, 2009, pp.315-330)

$$m'_i(t) = m_i(t-1) + \Delta_i \times \alpha \times s_j$$

    - Δ_i is the difference between marker position of previous frame in source
    - α is the personal-trait factor
    - s_j is part ratios of 3D facial model between the source and target
    - i is marker index, j is facial part index and t is frame index
    - *m_i is motion data of source and m'_i is motion data of target*
  - According to the magnitude of the individual motion data, we arranged the facial motion data on the horizontal axis in EI fuzzy sets to derive the expression rates

Methodology

- **EI Fuzzy Model**
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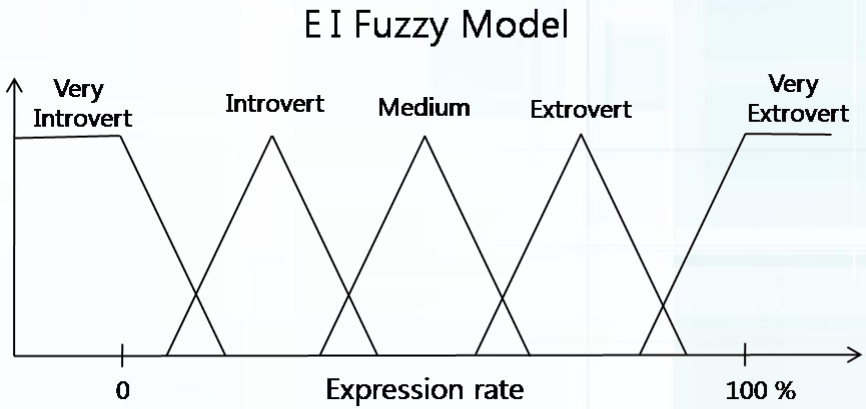
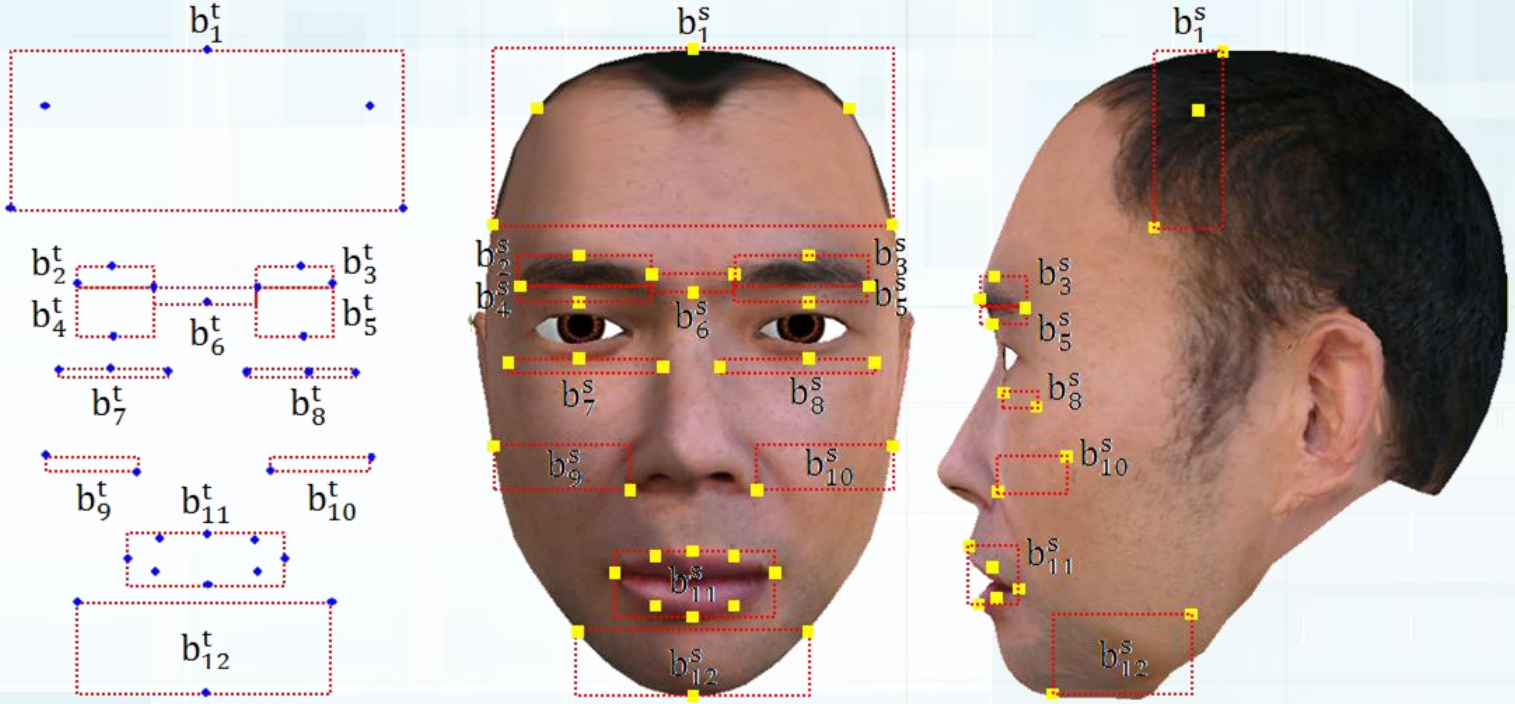


  - According to the magnitude of the individual motion data, we arranged the facial motion data on the horizontal axis in EI fuzzy sets to derive the expression rates

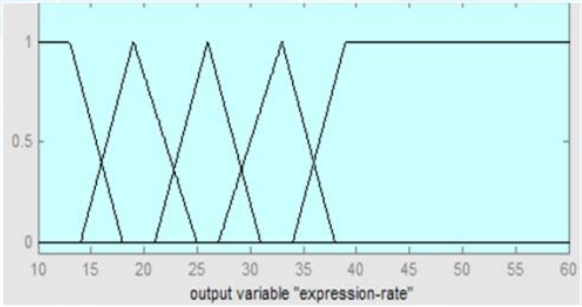
Methodology

- **EI Fuzzy Model**
  - 12 Parts of Face

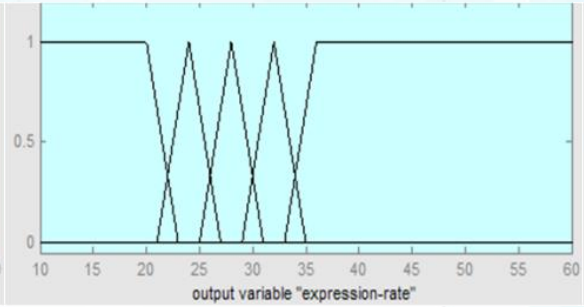


Methodology

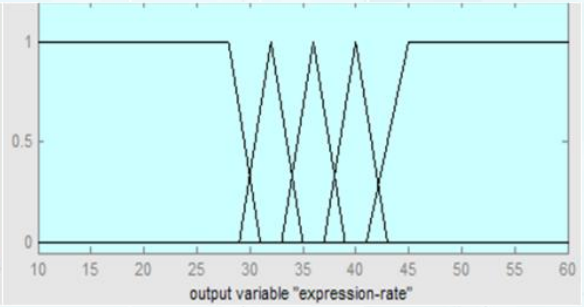
- **EI Fuzzy Model**
  - EI fuzzy models of six facial expressions



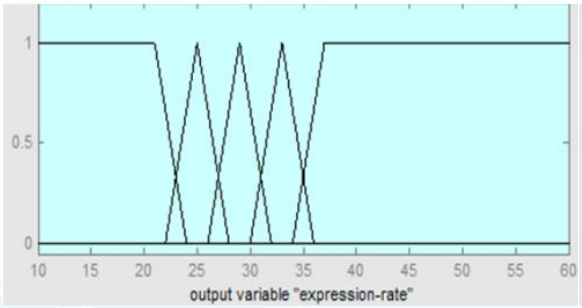
(a) surprise



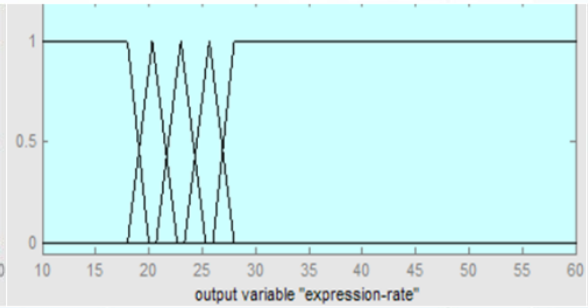
(b) happiness



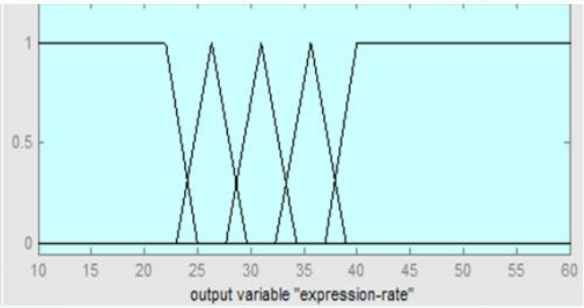
(c) sadness



(d) fear



(e) anger



(f) disgust

Methodology

- **EI Fuzzy Model**
  - Max-Min method (Mamdani, 1974)

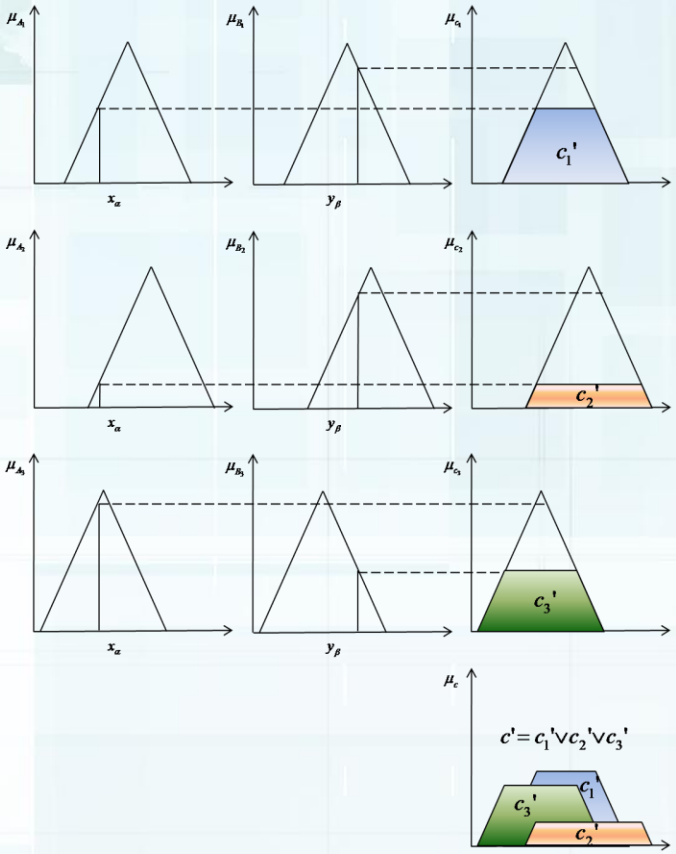
$$\lambda_i = \mu_{A_i}(x_\alpha) \wedge \mu_{B_i}(y_\beta)$$

$$\mu_{C_i}'(z) = \lambda_i \wedge \mu_{C_i}$$

$$\mu_{C}'(z) = \mu_{C_1}'(z) \vee \mu_{C_2}'(z) \vee \cdots \vee \mu_{C_n}'(z)$$

  - Defuzzification
  - Center of gravity method

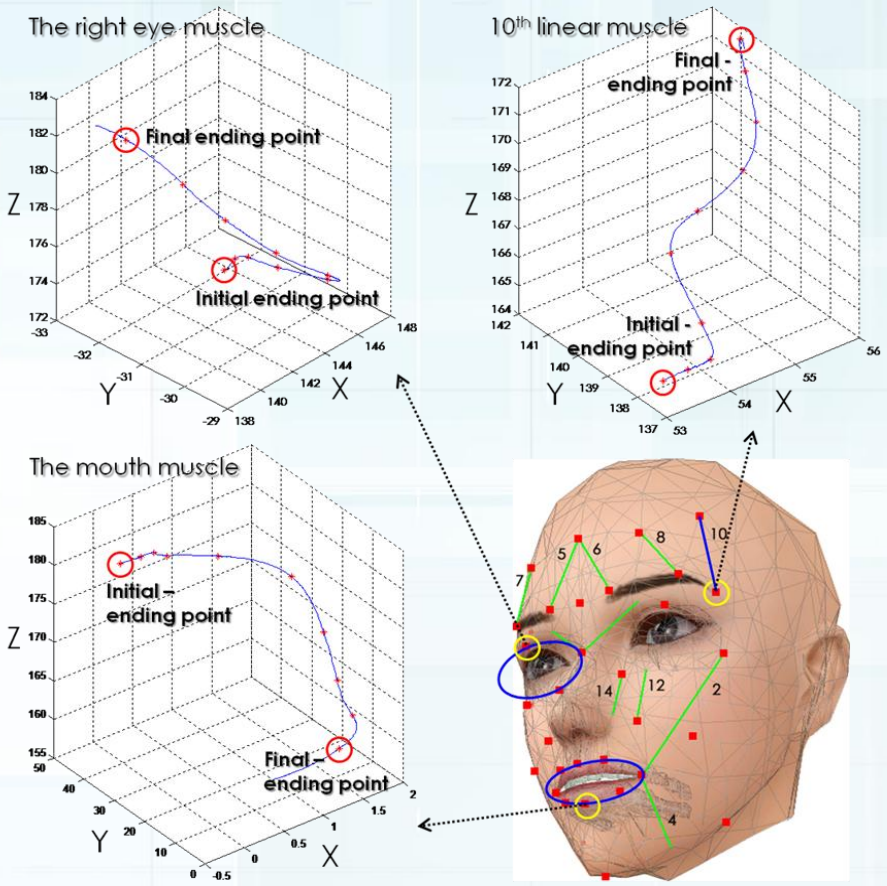
$$C' = \frac{\sum_i b_i \int \mu_{C_i}'(z)}{\sum_i \int \mu_{C_i}'(z)}$$



Example of fuzzy inference
by Max-Min method

Methodology

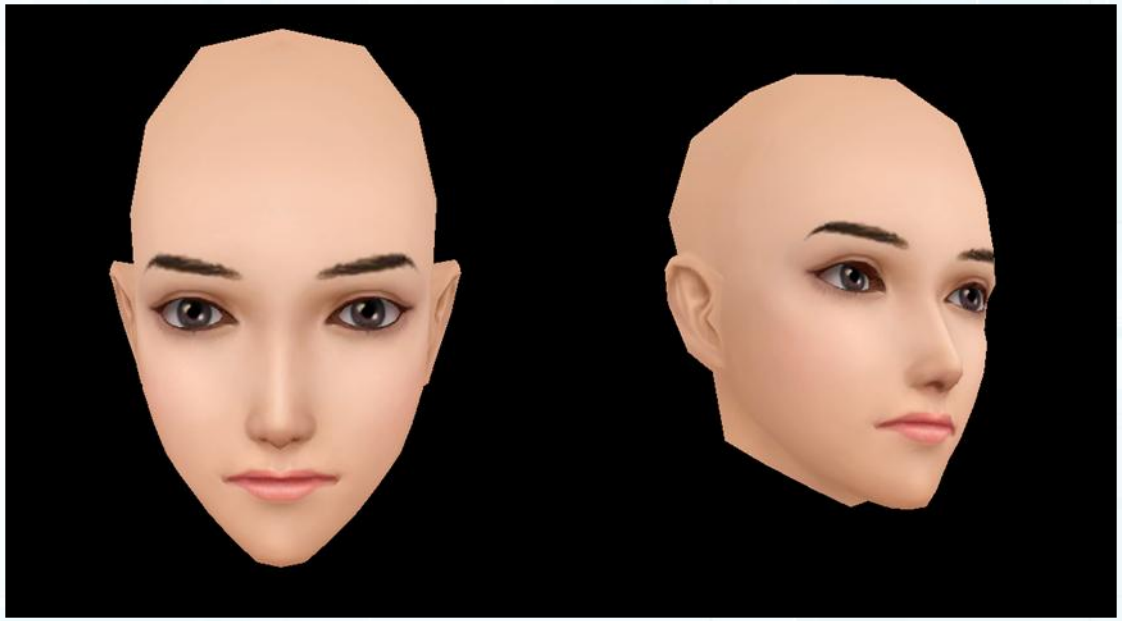
- **Facial Animation**
  - 3D facial expression synthesis based on 21 virtual muscles
  - Six facial expression synthesis using muscle manipulation
  - Realistic animation based on facial motion capture data



The location of muscles on 3D facial model and the motion plot of three markers

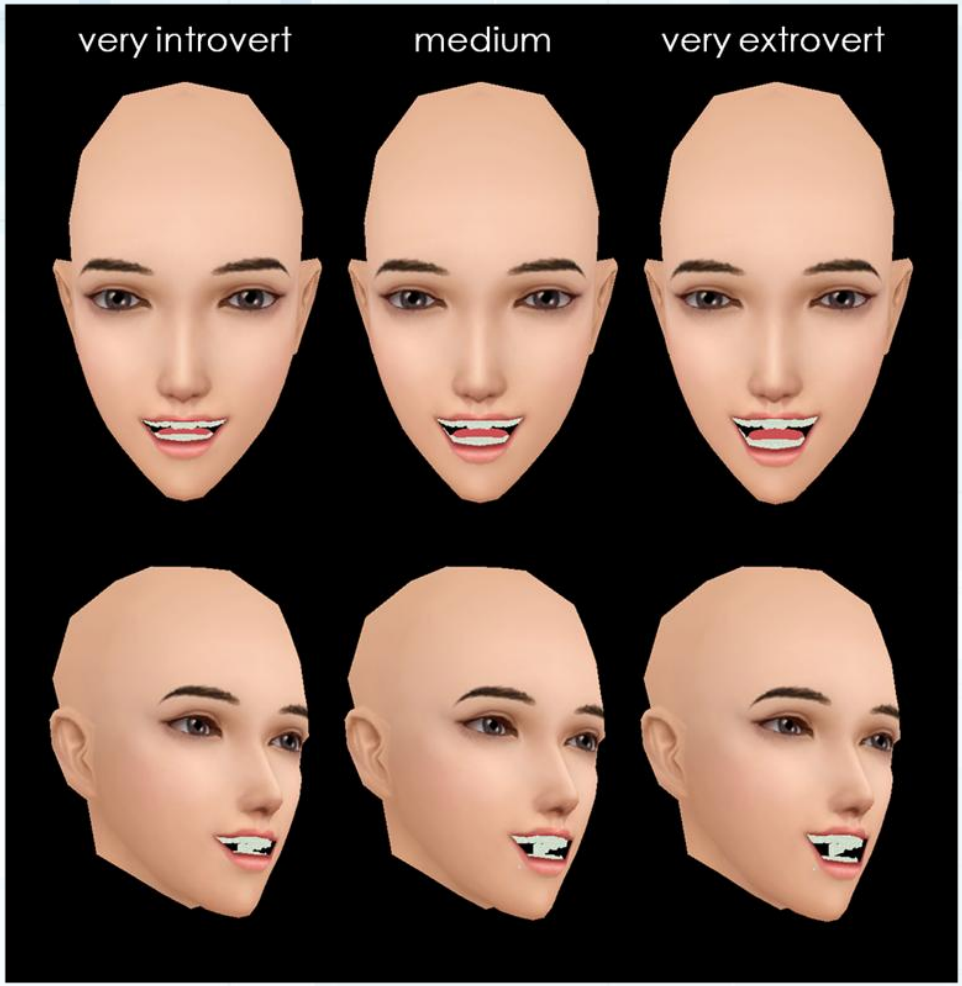
Experimental Results

- **Facial Expressions**
  - Neutral face of the 3D facial model



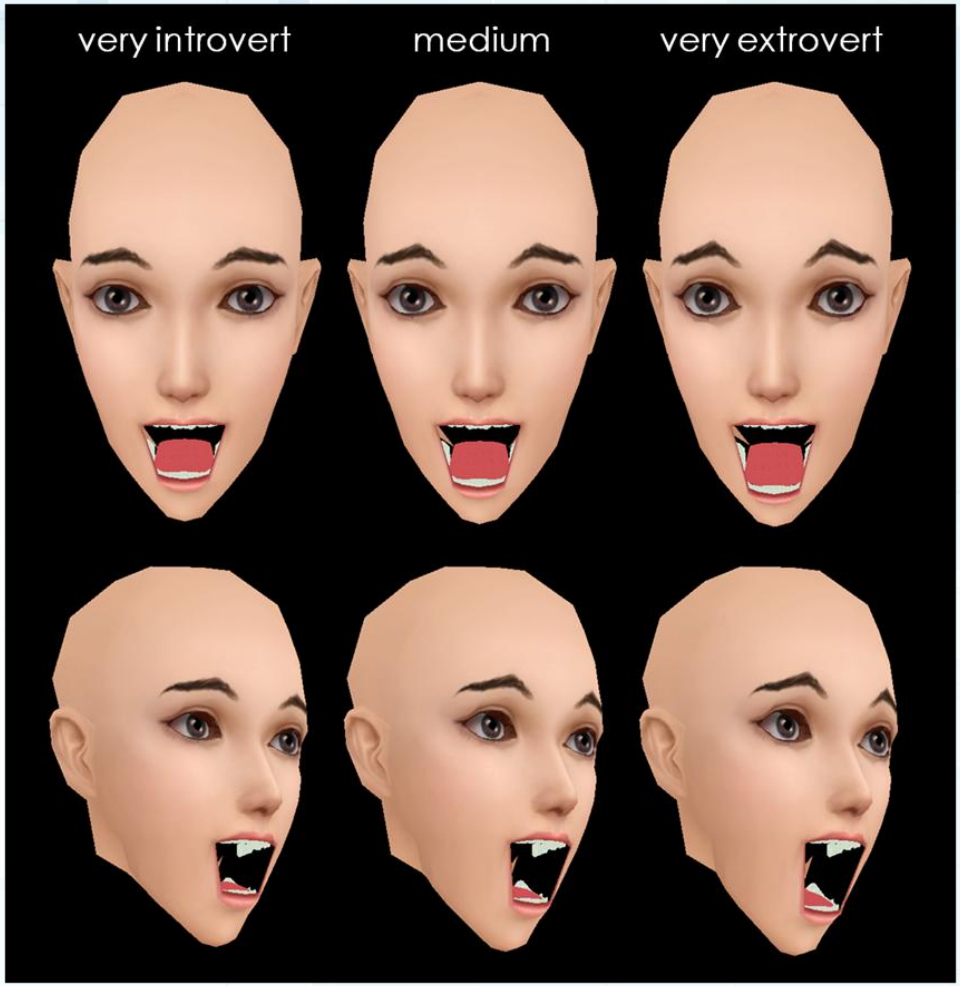
Experimental Results

- **Facial Expressions**
  - Happiness



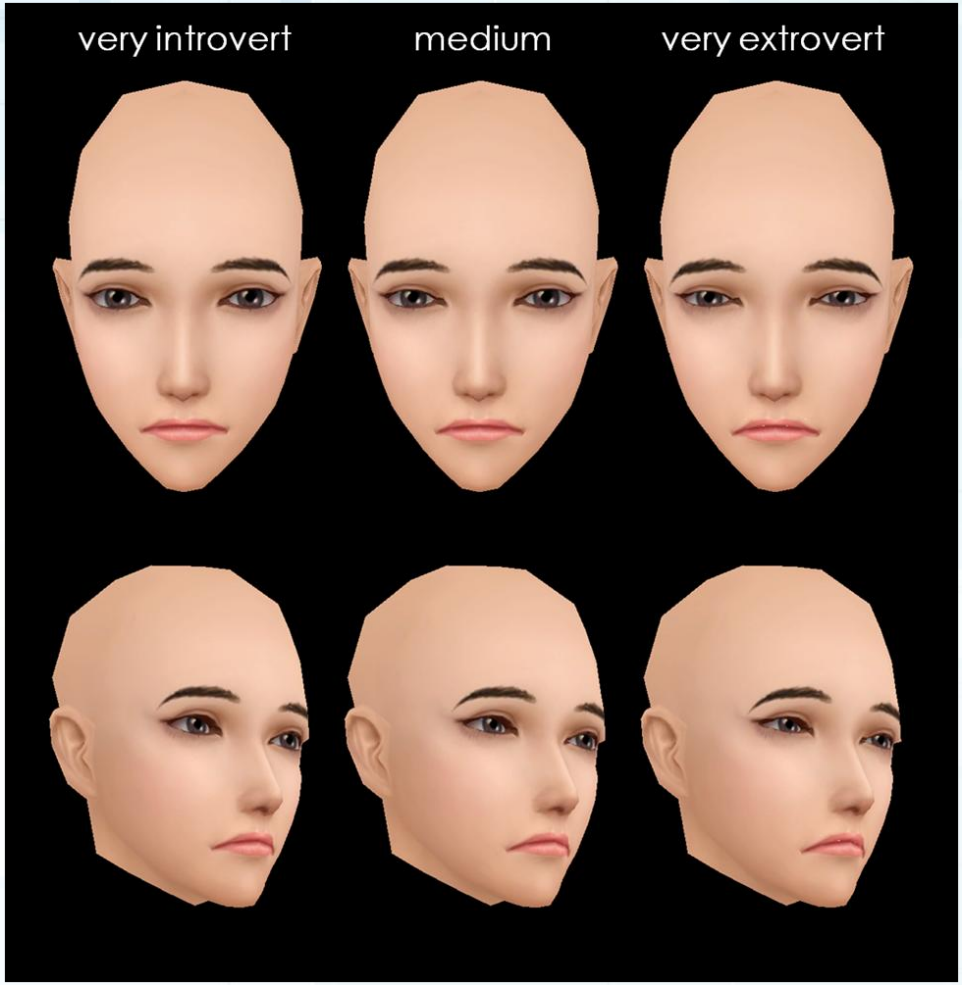
Experimental Results

- **Facial Expressions**
  - Surprise



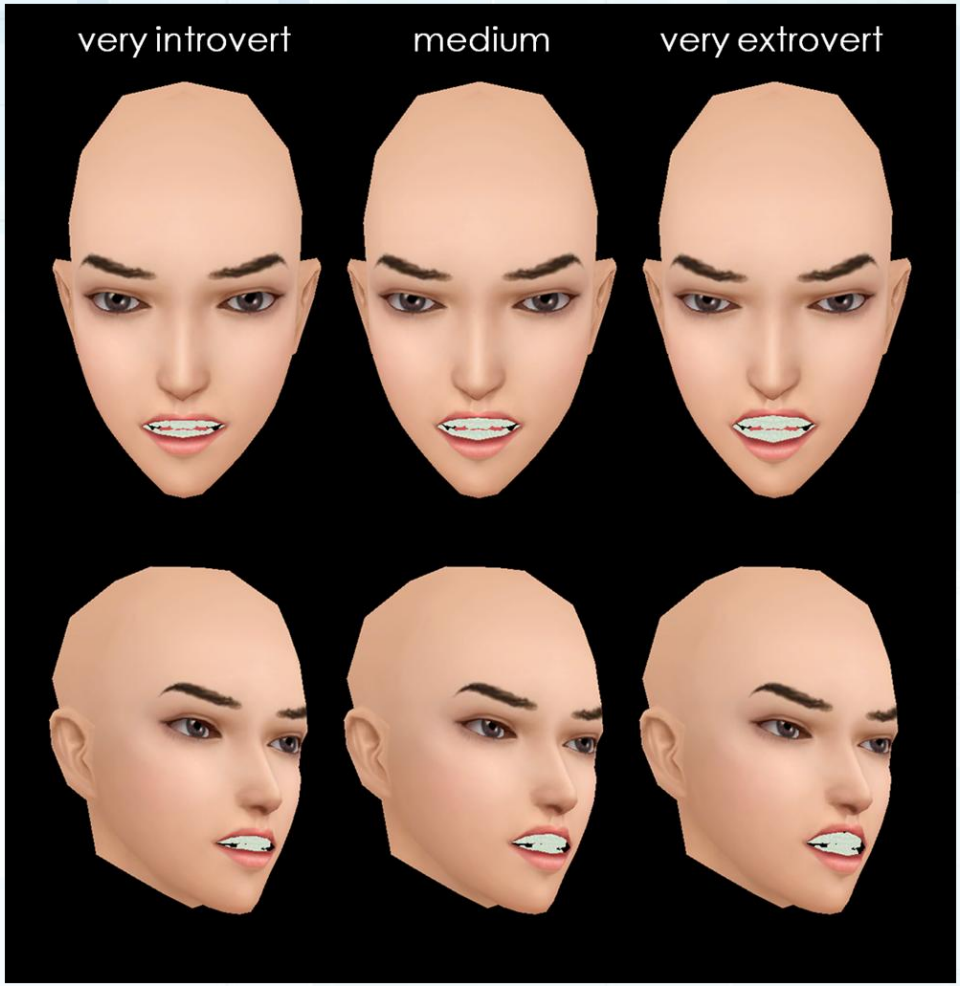
Experimental Results

- **Facial Expressions**
  - Sadness



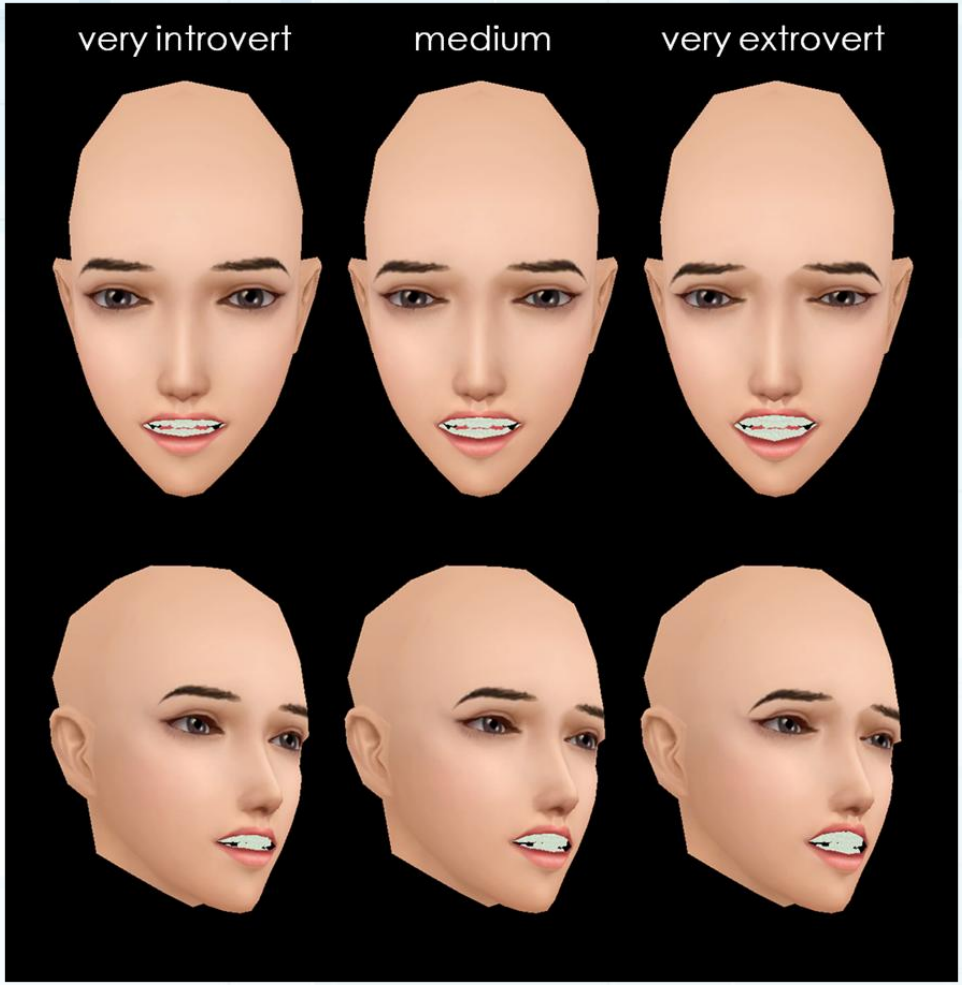
Experimental Results

- **Facial Expressions**
  - Anger



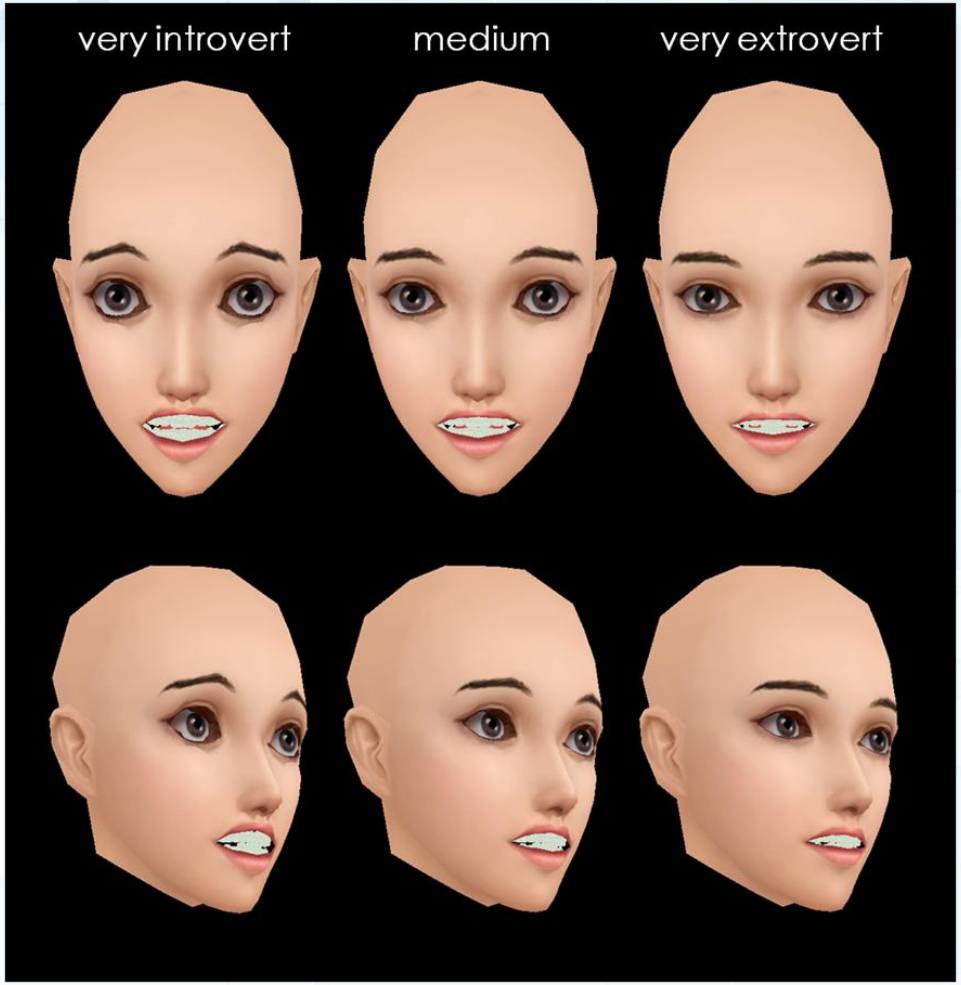
Experimental Results

- **Facial Expressions**
  - Disgust



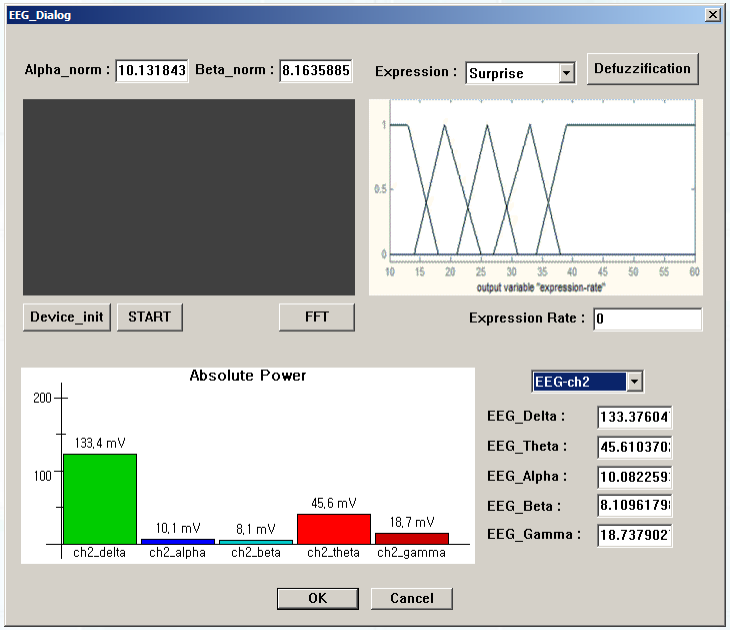
Experimental Results

- **Facial Expressions**
  - Fear



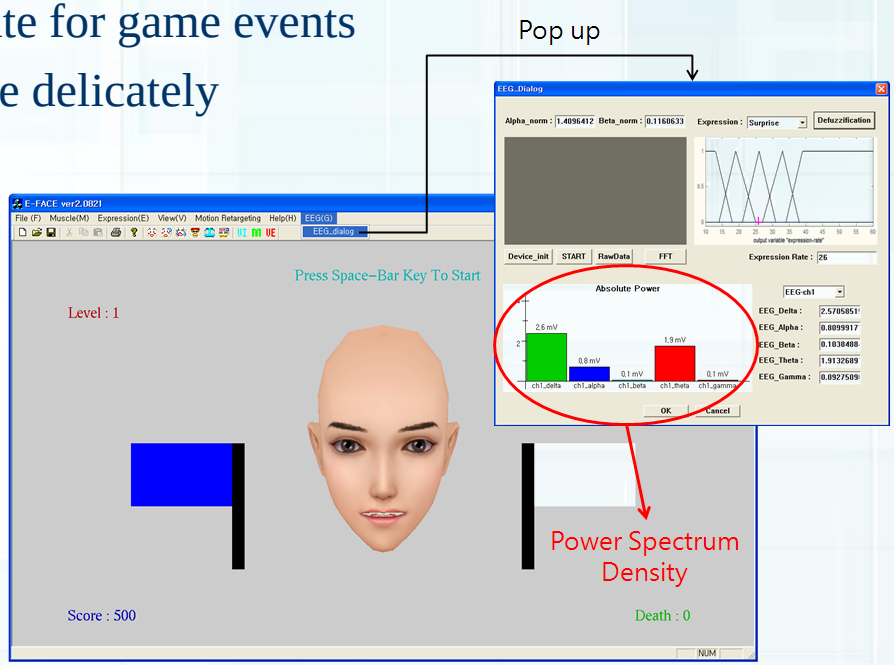
Experimental Results

- **Applications**
  - Fuzzy-EEG system
    - Get user's EEG and classify the personal-trait in real-time
    - Display PSD and Expression rate with Fuzzy Model



Experimental Results

- **Applications**
  - Flag up
    - Game application based on Fuzzy-EEG and E-FACE
    - Before game starts, it recognizes user's personal-trait
    - It shows facial expressions appropriate for game events
    - The intensity of facial expressions are delicately different by users' personal-traits



Conclusion

- We extracted personal traits and expression rates from genuine sources such as EEG and photograph to make facial expression of 3D face model more similar with users.
- We set EEG fuzzy models and EI fuzzy models to calculate expression rates delicately.
- All these algorithms were realized in a system level and were implemented by a game application.
- Entertainment applications including gaming and virtual environments using BCI have drawn attention of healthy users.
- The distinctive facial expressions of individual avatar that shows users' personal-trait well is crucial for more intuitive and realistic communication.

Thank-you

Acknowledgement

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