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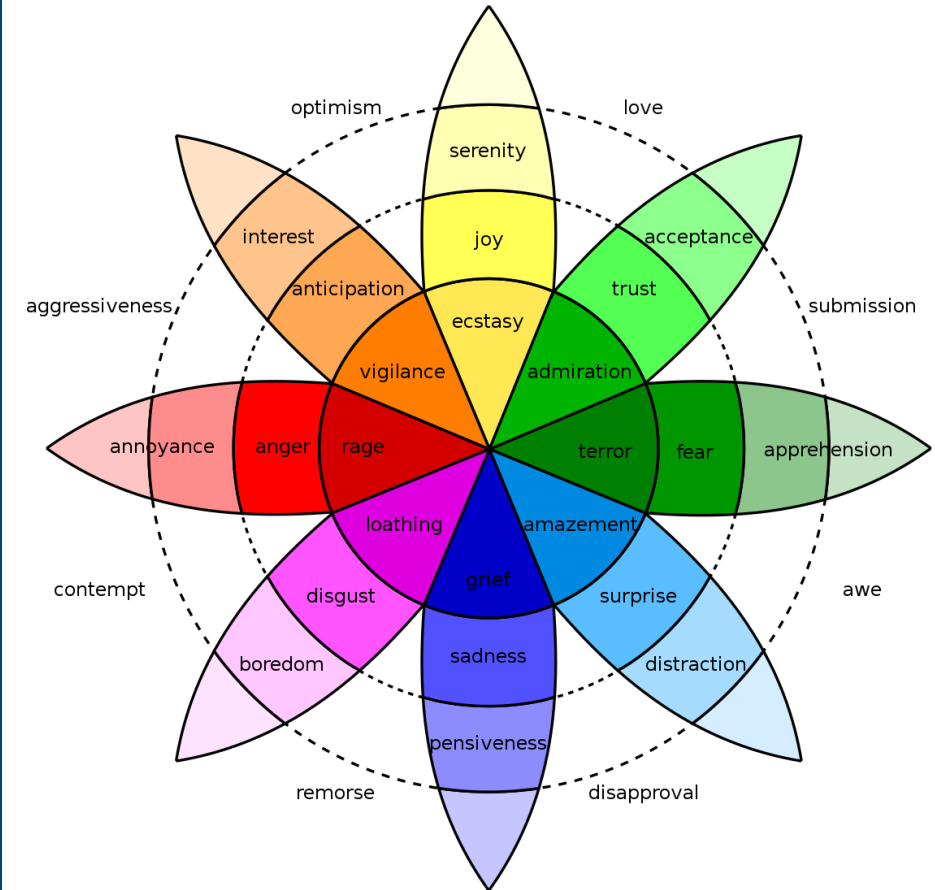
Perception-Comprehension-Action Cycle Enhancement based on Emotions in Human-Robot Interactions

Daniela De Venuto, Giovanni Mezzina, Michele Ruta, Eugenio Di Sciascio

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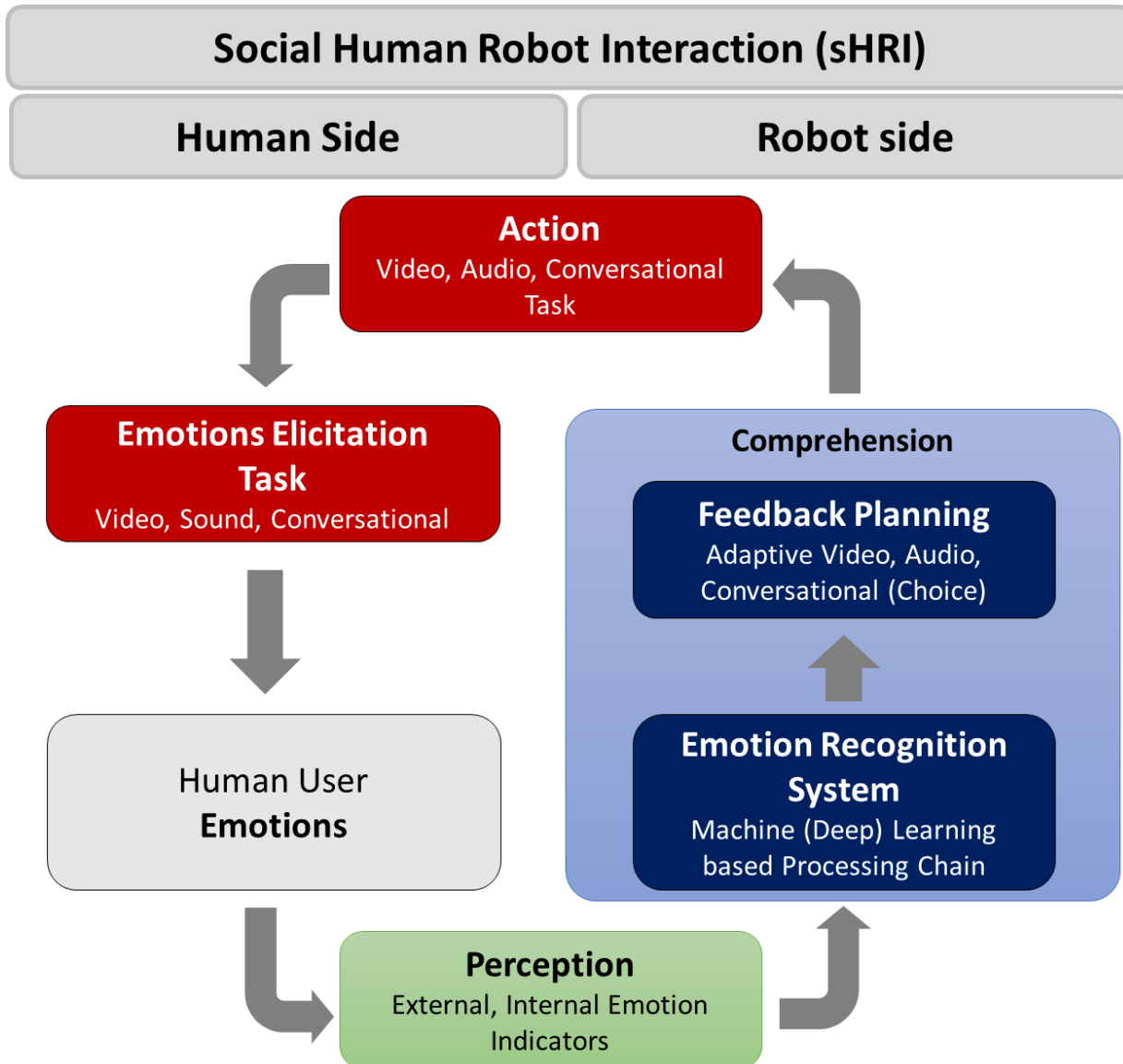
Outline

- ✓ Introduction
- ✓ Motivations and Aims
- ✓ The Architecture
- ✓ Results
 - Dataset
 - System Performance
- ✓ Conclusions



Plutchik, R. The nature of emotions: Human emotions have deep evolutionary roots, a fact that may explain their complexity and provide tools for clinical practice. *American scientist* 2001 89.4: 344-350.

Introduction: Affective Loop



Perception-comprehension-action cycle in Human-Robot Interactions

Perception

- **External Indicators** : Natural Language Analysis, face and body motion
- **Internal Indicators**: Physiological Signals

Comprehension

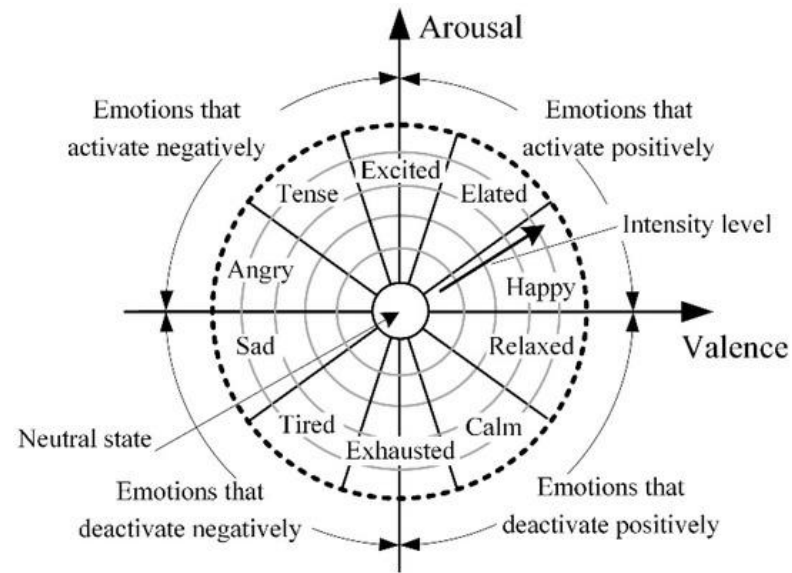
- Semantic-based approach
- **Machine (Deep) Learning approach**

Action

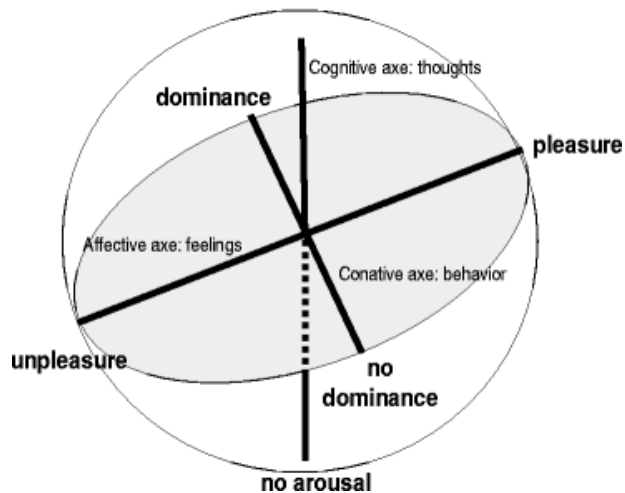
- Adaptive Conversational Task
- Senses Stimulation

Expansion of Personal Care Robots (PCRs) social sphere

Introduction: Emotions Classification



Circumplex model of Affect



Arousal Valence and Dominance model

Emotion Classification

Word –based description:

- Wheel of Emotions (Plutchick [1])
- Seven Primitive Emotions model (Ekman[2])

Quantitative description:

- **Circumplex Model:** 2D model based on Arousal and Valence Parameter [3]
- **Improved Circumplex Model:** 3D model based on Arousal, Valence and Dominance Parameter [3]

[1] Plutchik, R. The nature of emotions: Human emotions have deep evolutionary roots, a fact that may explain their complexity and provide tools for clinical practice. American scientist 2001 89.4: 344-350.

[2] Ekman, P. An argument for basic emotions. Cognition & emotion 1992 6(3-4), 169-200.

[3] Braun, M., Schubert, J., Pfleging, B., and Alt, F. Improving driver emotions with affective strategies. Multimodal Technologies and Interaction 2019, 3(1), 21.

Introduction: State-of-the-Art

Ref.	Classified Emotions	Feature Extraction	Classifier	Accuracy (%)
Gannouni S. et al. 2020	Happy, pleased, relaxed, excited, neutral, calm, distressed, miserable, depressed	Power Spectrum Density (PSD), Sensitive lobes selection, and relevant electrodes selection	10 classifiers Not specified	A: 82.35 V: 79.95 D: 71.14 AVD: 65 (80% max)
Li G. et al. 2017	Excited, relaxed, negative	Wavelet Packet Transform (WPT), Relative power spectrum energy, variance, sample entropy of β band	RBF-SVM	A: 94.1 (max) V: 58.8 (max)
Mohammadpour M. et al. 2019	Fear, sad, frustrated, happy, pleasant, satisfied	Discrete Wavelet Transform (DWT), Statistical features of 4 EEG frequency bands: δ , θ , α , β .	ANN (best results) kNN SVM	AV: 55.58
Barjinder K. et al. 2018	Calm, anger, happiness	Non-stationary and non-linear features with the fractal dimension (FD)	RBF - SVM	AV: 60
Gupta V. et al. 2019	Two binary classifiers (singularly or together): HV/LV and HA/LA	Information Potential (IP) from the flexible analytic wavelet transform (FAWT)	RF	A: 79.95 V: ~80 AV: 71.43
Valenza G. et al. 2020	HA/LA	Time features: peak to peak mean, variance. Frequency features: Hjorth parameters, maximum power spectral frequency, Power Spectrum Density (PSD), and power sum	RF (best results) kNN SVM	A: 62.58

Acronyms: N.A.: RBF- radial basis function; SVM – Support Vector Machine; ANN: Artificial Neural Network; RF: Random Forest; kNN: k-Nearest Neighbour; H(L)V - High(Low) Valence; H(L)A - High Low Arousal

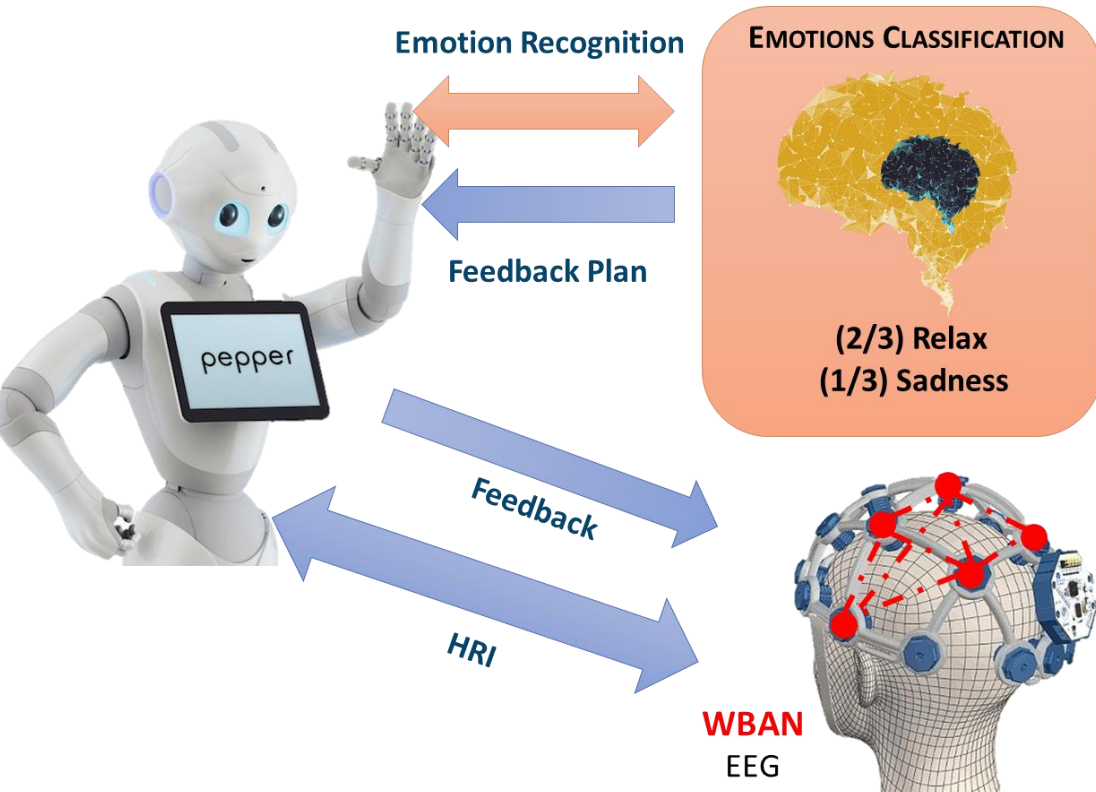
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Li G. et al. 2017	Excited, relaxed, negative	The use of the AVD model permits to increase the number of detectable emotions	RBF-SVM	A: 94.1 (max) V: 58.8 (max)
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Valenza G. et al. 2020	HA/LA	Time features: p Frequency features: Hjorth parameters, maximum power spectral frequency, Power Spectrum Density (PSD), and power sum		(best results) kNN SVM

An increment in the **overall accuracy** is necessary to plan a proper feedback. **Must be maximized.**

Acronyms: N.A.: RBF- radial basis function; SVM – Support Vector Machine; ANN: Artificial Neural Network; RF: Random Forest; kNN: k-Nearest Neighbour; H(L)V - High(Low) Valence; H(L)A - High Low Arousal

Motivations and Aims



Proposed Architecture Workflow

The work proposes the **design** and **test** of an **EEG-based emotion recognition system** that ensures:

- **low-memory** usage and **low-complexity** operations
- Suitability for embedded electronics and congested PCR cores
- **High** emotion recognition **accuracy** (>70%)

METHOD

Using a **grid-search routine** based on a **multi-objective optimization** of the **features extraction** stage.

It consists of **assessing - together** - the **easiness of implementation**, memory usage, and **classification performance**

The Architecture

Offline Subjectively Grid Search for Arousal, Valence or Dominance Parameters

Complexity Assessment
(Feature Extraction Methods)

Feature Extraction Methods DB

C scripts assessment on quality software metrics

Complexity-based Selected Features C1 .. Cn

Score

Accuracy Assessment
(Selected Feature Extraction Methods)

C1	0,1	0,3	0,5	...	0,1
⋮	...				
Cn	1	12	6	...	4

Accuracy

	Score	Acc.
C1	0.1	75
C2	0.9	72
...		
Cn	0.4	78

Target:
Ci with
Max(Acc.)
Min (Score)

Feature Selection

f1	0,1	0,3	0,5	...	0,1
⋮	...				
fN	1	12	6	...	4

Weight

Feat

f1	0,1	0,3	0,5	...	0,1
⋮	...				
fM	1	12	6	...	4

M < N

Train & Test
(Classification Committee)

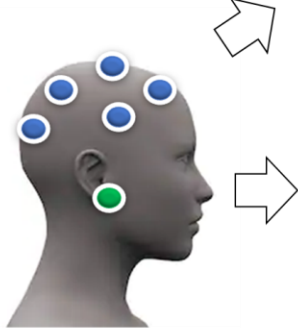
f1	0,1	0,3	0,5	...	0,1
⋮	...				
fM	1	12	6	...	4

M > N

Naive Bayes

K-NN

SVM



EEG
 i^{th} channel

Feature Extraction

f1	0,1	0,3	0,5	...	0,1
⋮	...				
fM	1	12	6	...	4

M < N

Arousal **Valence** **Dominance**

Classifiers Committee

F(x)

Online Emotion prediction

Results

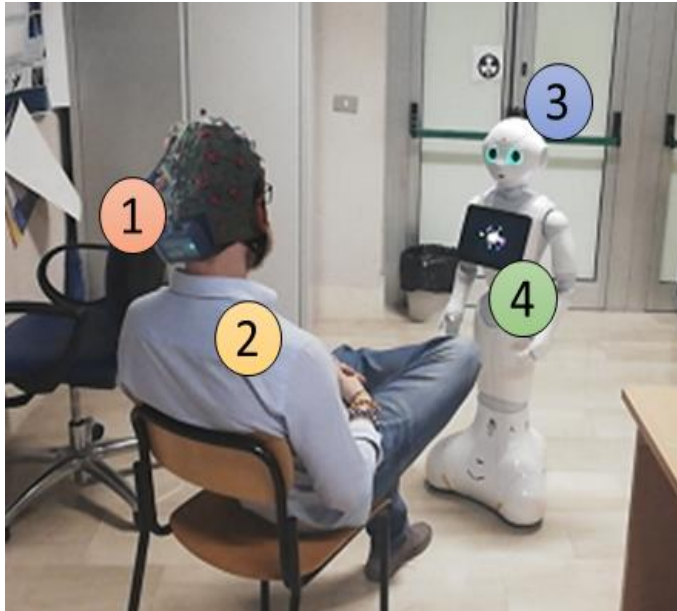
Algorithm Design, Validation and Test:

DEAP Dataset: <https://www.eecs.qmul.ac.uk/mmv/datasets/deap/readme.html>

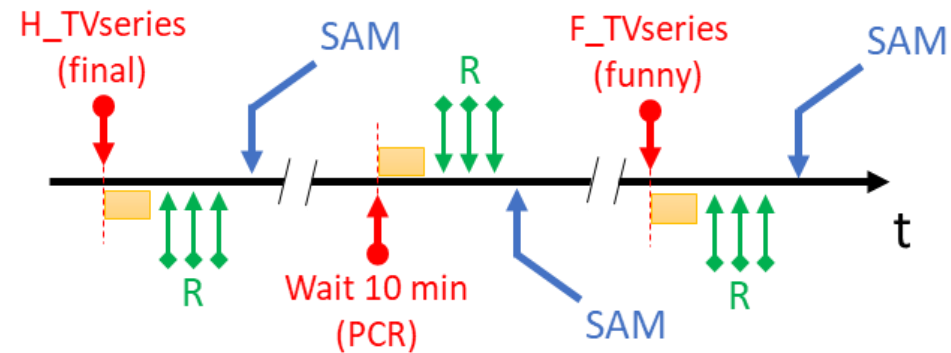
32 Subjects (range: 19-37 years old) watching at 40 1-min long music videos.

Arousal Valence and Dominance evaluated via **self-assessment manikin** (SAM) rating scale

Real Life Scenario Application:



Experimental setup for the emotion recognition system application in a real-life scenario.



Legend:



Stimulus Onset (with characteristics)



Stimulus (video clip or vocal command)

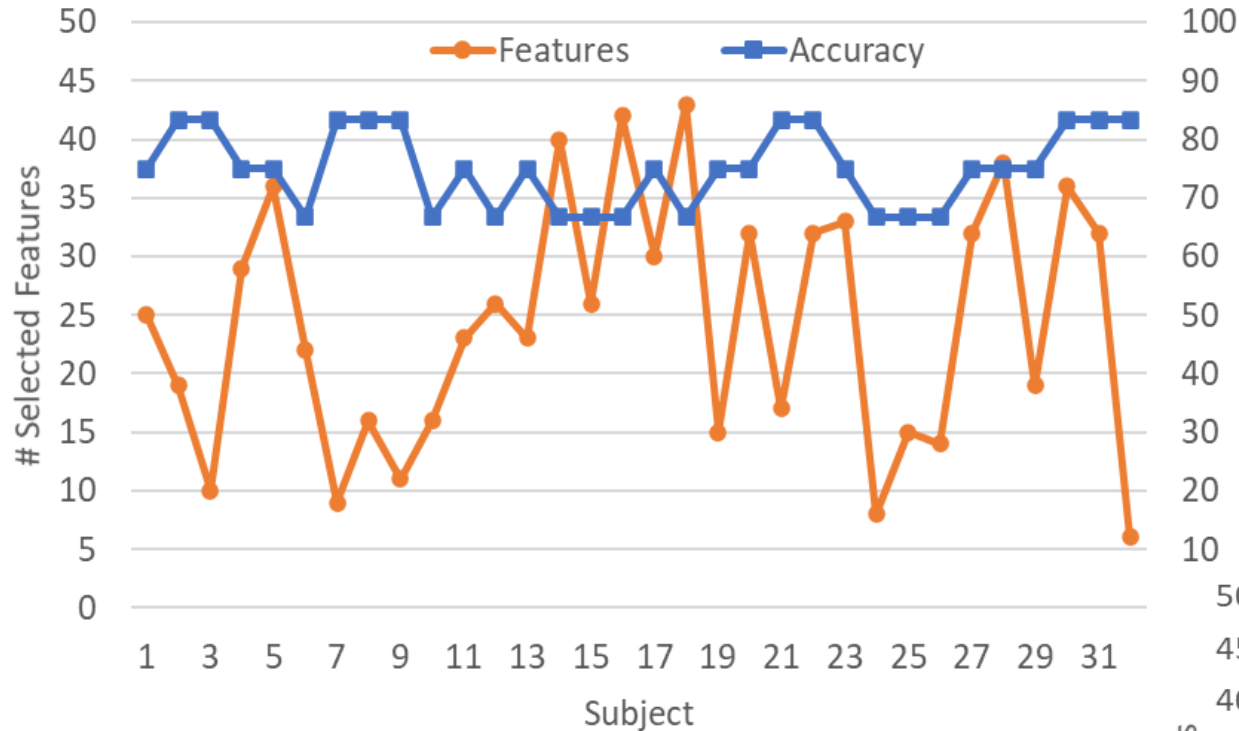


Emotion Recognized

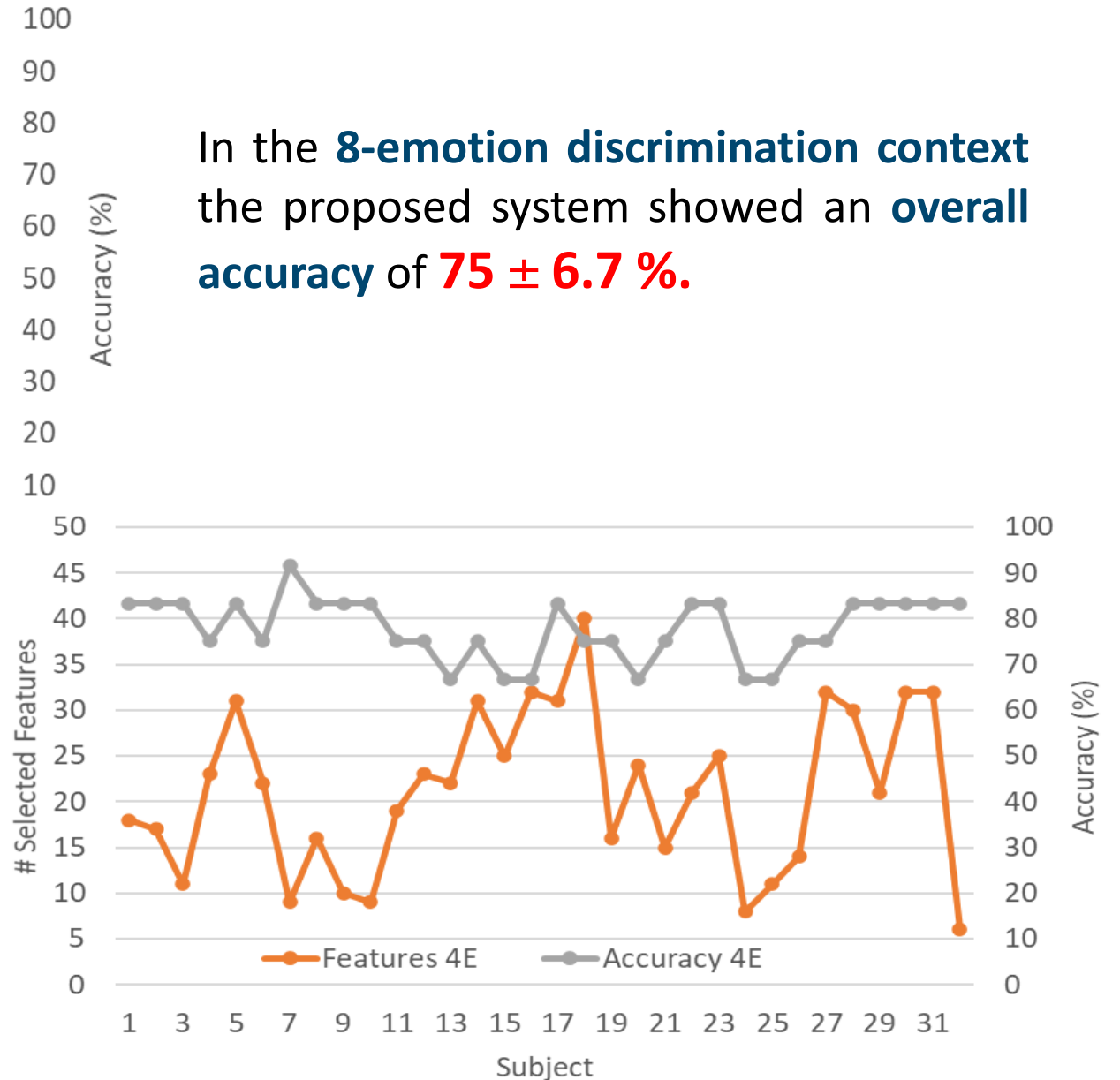


Self-Assessment Manikin rating

Results: Classification Performance



In the **4-emotion discrimination context** the proposed system showed an **overall accuracy of $77.86 \pm 6.89 \%$**



In the **8-emotion discrimination context** the proposed system showed an **overall accuracy of $75 \pm 6.7 \%$** .

Conclusions

This work focused on the **design**, and **test** of a novel emotion recognition system for the perception-comprehension-action cycle improvement in HRIs.

The proposed system exploits **EEG signals** to find a **direct connection** between the **brain activity** and the **arousal-valence-dominance model**.

The system uses a **multi-objective optimization** of the features extraction stage, which consists of **assessing - together** - the **easiness of implementation** and **classification performance**.

The system performance have been validated on an online dataset (DEAP) and in a real-life scenario.

The system can reach an **overall accuracy** of **75%** on **8 emotions** discrimination and **~77%** on **4 emotions**.

