Multimodal Measure of User Experience

Towards the automatic recognition of affective states

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Abstract

In the field of *Human Computer Interaction* the experience of the user during the interaction is of great interest. Therefore the automatic recognition of the affective state, or emotion, of the user is one of the big challenges. Recent endeavours to do so can be summarised under the newly created domain of *Affective Computing* (Picard, 1997).

In this project we focus on the affect recognition via physiological and neurophysiological signals. Long-standing evidence from the psychophysiological research and more recent research in affective neuroscience suggest that both, body and brain physiology, are able to indicate the current affective state of a subject.

Below the field of affect classification by (neuro-) physiological signals is introduced and some basic principles and procedures discussed in the state-of-the-art report are outlined. Then the experiment design, created according to the above mentioned principles, and the hypotheses are presented.

Introduction

A definition of emotion: An emotion is person's state in reaction to an internal or external event, associated with a subjective feeling. Emotions can be contrasted with moods in that they are direct, involuntary responses that last only for minutes or hours, whereas moods have no specific object and spread over longer periods as hours or days.

Furthermore are changes in emotions often accompanied by changes of physiological and neurophysiological changes. Since 100 years psychophysiological studies are dedicated to find the characteristic correlates of affective states. The interest in the structure of affect was one of the main motivations for those studies.

The research efforts have produced two main types of models. The idea of *basic emotions* proposes a number of discrete emotions, i.e. happiness, anger, surprise, fear, disgust, and sadness, that are universal, and thus cultural independent. Each of these emotions has its idiosyncratic physiological substrates and differing behavioural equivalents.

Dimensional models propose a continuous affective space, spanned by two or more affective dimensions. One of the most popular dimensional models is the circumplex model of Russel (1980). It assumes that any emotion can be localised on a plane spanned by the axes of valence and arousal (Figure 1). This type of model has the advantage that is inherently takes care of the possibility that affective states are not always clearly assignable to one of several basic emotions. In this model mixed emotions could be represented by being located between two or more clearly ascribed emotions.

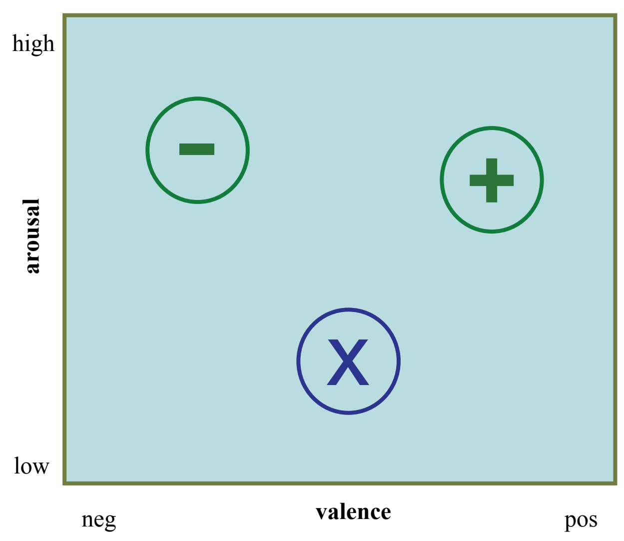

Figure 1. The emotion plane and 3 regions marked as negative-exciting, positive-exciting, and calm-neutral states.

Both model types, discrete and continuous, are compatible with the idea that different affective states can be discerned via their (neuro-)physiological and behavioural "fingerprints". Several studies showed that this is indeed possible. These were reviewed in a state-of-the-art report and used to design a new study on affect classification.

State of the art

To get an overview over the methods and techniques used to automaticly classify emotion 17 studies were reviewed. 13 studies used diverse physiological sensors (e.g. electromyogram, electrocardiogram, galvanic skin response, resperation), 2 employed EEG and further 2 employed EEG and physiological sensors. The table below gives an overview over the designs and methods employed by each of the studies.

Study	Sensors	Subject number	Elicitation method	Emotions elicited	Trial number	Trial length	Feature number	Feature selection	Feature reduction	Classifier
Collet et al., 1997	GSR,R,T	30	imagine	A, D, F, J, S, Su	6 * 1	60 sec	8			uni-variate
Picard et al., 2001	fEMG,GSR, BVP,R	1 over weeks	relive	N, A, H, G, PL, EL, J	8 * 1	180 sec	up to 30	SFFS	Fisher projection	kNN, MAP, quadratic classifier
Scheirer et al., 2001	GSR,BVP, behav.	24	game and mouse failure	Fr	7 * 3	10 sec	5			HMM
Nasoz et al., 2004	ECG,GSR, T,SR	29	movies, math	S, A, F, Fr, Su, Am	6 * 1	70 to 231 sec	3 3			kNN, DFA, NN
Haag et al., 2004	EMG,ECG,R, GSR,BVP,T GSR,BVP,T	1	IAPS	lo/med/hi arousal * pos/neg val	5 * 6	2 sec	7			NN
Wagner et al., 2005	EMG, ECG, GSR, R	1	chosen songs	lo/hi arous pos/neg val	4 * 30	160 sec	32			LDF, kNN NN
Kim et al., 2004	ECG,GSR, T,SR	50 children 7-8 years	multimodal stories	S, A, Su, St	4 * 1	50 sec	6 - 7			SVM
Rainville et al., 2006	ECG,R,SR	43	relive	A, F, S, J	2 * 2	90 sec	18		PCA	SDA
Kreibig et al., 2007	fEMG, ECG GSR, R	34 (37)	movies	F, S, N	3 * 2	600 sec	23			PDA
Benovoy et al., 2008	ECG,GSR, BVP,R,T,SR	1	acting, singing, imagine	A, S, P, J and mixture	4 * 25	60 - 300 sec	225	greedy SFS	Fisher projection	LDA
Kim et al., 2008	EMG,ECG, GSR,R	3 over weeks	chosen songs	4 quadrants	4 * 30	160 sec	110	SBS		LDA (EMDC)

Study	Sensors	Subject number	Elicitation method	Emotions elicited	Trial number	Trial length	Feature number	Feature selection	Feature reduction	Classifier
Kim et al., 2005	EMG,ECG, GSR,R,V,A	3	Wizard of Oz game	4 quadrants	60	10 - 115 sec	26	SFS		SVM
Kapoor et al., 2007	GSR,V, P,M	24	puzzle game	Fr	1	150 sec	14			kNN, SVM GP, SVM+GP
Chanel et al., 2005	EEG,GSR, BVP,R,SR	4	IAPS	low/high arousal	2 * 50	6 sec	24	literature		Naive Bayes, FDA
Chanel et al., 2006	EEG,GSR, BVP,R,SR	1	relive	neg/pos excited,N	3 * 100	8 sec	16726		fast correlation based filter	LDA, SVM
Musha et al., 1997	EEG	7	imagine	A, S, J, R	4 * 1	5.12 sec	135		ESAM	by scale value
Choppin, 2000	EEG,SR	12	IAPS,IADS, and combi	4 quadrants	3 * 32 per stim.type	6 - 10 sec	4 - 5	EEG analysis		LR, NN

Overview over studies using physiological and neurophysiological sensors to classify affective states.
Sensors: *A* audio recordings, *BVP* blood volume pulse, *ECG* electrocardiogram, *EEG* electroencephalogram, *EMG* electromyogram, *fEMG* facial electromyogram, *GSR* galvanic skin response, *R* respiration, *SR* self report, *T* temperature, *V* video recordings; *Emotions:* *A* anger, *Am* amusement, *F* fear, *Fr* frustration, *H* hate, *J* joy, *N* neutral, *R* relaxed, *S* sadness, *Su* surprise, *St* stress; *Trial number:* per subject *(different emotions * repetitions)*; *Feature selection:* , *SBS* sequential backward selection, *SFFS* sequential forward floating selection, *SFS* sequential forward selection; *Classifiers:* *FDA* Fisher discriminant analysis, *GP* gaussian process classification, *HMM* hidden markov model, *kNN* k nearest neighbor, *LDA* linear discriminant analysis, *LR* linear regression, *MAP* maximum a posteriory , *NN* neural network, *PDA* predictive discriminant analysis, *SDA* stepwise discriminatory analysis, *SVM* support vector machine.

The SOTA gives background information about the concepts involved, the measured modalities, and introduces methods and techniques used throughout these studies. Key points are:

- Elicitation of emotions: *What methods assure a greatest possible naturalness of the induced emotion?*
- Ground truth construction: *How can affect labels be assigned to the signals in a confident way?*
- Sensor modalities: *How do physiological and neuro-physiological signals differ and what are the consequences?*
- Modality fusion: *How and when can the multiple modalities be integrated?*
- Feature selection and reduction: *Which techniques are used to reduce the dimensionality of the feature space?*
- Classification: *What accuracy rates have been achieved with subject-dependent, -independent, and time-independent classifiers?*

Conclusion

Studies using physiological measures repeatedly reached very good classification accuracies in several elicitation contexts. However, while neurophysiological classification approaches have also reached accuracies far above chance level, there is clearly room for exploration, especially with regard to subject- and time-independent classifiers, and improvement.

None of the studies, however, looked at the generalisation of classifiers over several affect-inducing modalities. While this might be less of an issue with physiological sensors it can be expected to play an important role for EEG signals.

To study the classification of affect via both, EEG and neurophysiological sensors, especially with regard to the generalization over modalities, we designed the following experiment.

Experiment design

The currently prepared experiment is designed to study the capability to automatically classify affective states and their "modality of origin". To elicitate the affective states we therefore make use of *affective multimodal stimuli* (Figure 2), that is pictures from the *International Affective Picture Stimuli database* (Lang et al., 2005) and sounds from the *International Affective Digital Sounds Stimuli database* (Bradley and Lang, 2007). These are combined in a way that allows us to tag the trials according to :

- *Valence* value of affective state (positive/negative valence)
- *Arousal* value of affective state (low/high activation)
- *Modality* of affect origin (affect value in visual/auditory)

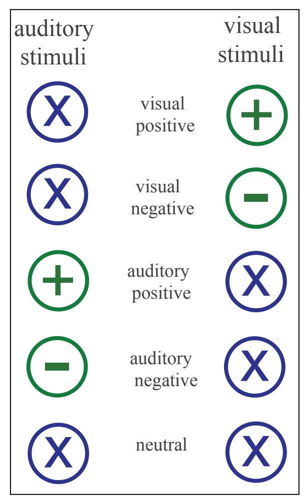

Figure 2. The audiovisual stimuli combinations used.

Additionally to the normed affective values of the stimuli datasets subjects have to judge their affective state after each stimulus presentation, providing more reliable subject-specific labels for the classifier training (Figure 3).

After the acquisition of the signals and their labels a time-frequency analysis will explore possible features that discriminate affective states and elicitation modalities.

Taking the outcome of this analysis into consideration several feature selection/reduction and classification methods will be applied to gain the highest possible classification accuracy.

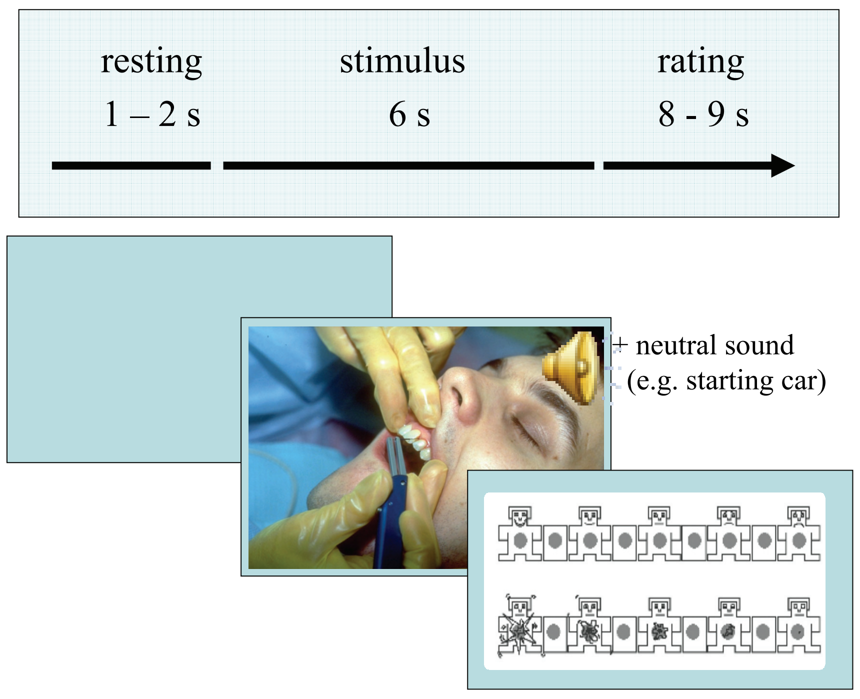

Figure 3. Trial structure. A multimodal affective stimulus is preceded by a resting period of several seconds and the rating of the own affective state.

Furthermore we plan to use computer games to elicitate emotions in a natural context. In gaming environments subject-relevant events, e.g. loss and gain of points, lead to life-like emotional involvement with a high frequency.

References

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