Towards a Standardization in the Use of Physiological Signals for Affective Recognition Systems

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Abstract

The implementation of physiological signals, as an approach for emotion recognition in computer systems, is not a straight forward task. This paper discusses five main areas that lack of standards and guided principles, which have led Human-Computer Interaction (HCI) researchers to take critical decisions about (i) models, (ii) stimulus, (iii) measures, (iv) features and (v) algorithms with some degree of uncertainty about their results. Methodology standardization would allow comparison of results, reusability of findings and easier integration of the various affective recognition systems created. The background theory is given for each of the five areas and the related work from psychology is briefly reviewed. A comparison table of the HCI common approaches of the five discussed areas is presented, and finally some considerations to take the best decisions are discussed. The aim of this paper is to provide directions on which the future research efforts for affective recognition in HCI should be focused on.

Introduction

Physiological signals provide an insight into human feelings, which are not always completely expressed as facial expressions, body movements, voice tone, and not at all captured in questionnaires. Some of their favourable characteristics as an approach to corroborate affective states in HCI include: reliability, validity, sensitivity, real time feedback, and less bias by both the experimenter and the subject [1]. Currently there is a trend to use physiological signals for many different applications and as a new form of computer interaction [2], [3]. Despite the advantages offered by this method for measuring affective reactions, there is no standardized methodology for their use in the development of affective recognition computer systems. An agreement on some conventions and guided principles would facilitate the integration of knowledge and expertise in the research community. Methodology standardization would allow comparison of results across experiments carried out in different labs, reusability of findings, and the integration of various affective recognition systems based on different approaches. We have identified five critical areas that need standardizations, conventions and guided principles, which will be reviewed in the following sections.

Area 1: Emotional Model to be Used

Many different theories about what emotion is have been proposed through the years [4]; unfortunately, there is no universal agreement on its definition or on its nature. With regards to the autonomic nervous system (ANS) activity associated to emotions, researchers still debate on how to establish a definitive model. Some theorists support that discrete emotions originate from distinct autonomic patterns [5], [6]. On the contrary, others argue that it is the perception of undifferentiated physiological arousal that originates them [7]; or that the physiological reactions are determined by the actions required from the emotional challenge [8]. Some criticisms to the physiological emotion-specificity are reported in [9], [10]. Moreover, other researchers propose an alternative dimensional model where all the sets of affective states are originated by two neurophysiological systems (one related to valence and the other to arousal) [11] [12].

Despite the non-existence of a consensus among psychologists; from a HCI perspective, only matters that affective states evoke observable physiological responses that can be identified by a computer-based system. Considering this argument only, two strategies could be considered for the development of emotion recognition systems based on physiological signals.

The first would be a pattern match approach based on proposed models about the relationship between psychology and physiology (e.g. [13]), or based on empirical findings (e.g. [14]). The dilemma is to decide which model, or empirical findings, the system should be based on. A vast number of studies document the autonomic responses to emotions; yet, some inconsistencies remain among their findings, as it can be observed on the compilation of physiological responses to specific emotions in [9].

The second option would be based on algorithms of pattern recognition and machine learning. Researchers in HCI generally follow this strategy and make use of existing, or specially created, models depending on the aim of the application or study conducted. Selecting arbitrarily a set of affective states and training a system to physiologically discriminate those specific emotions, can be seen as a practical solution for a particular problem. Nevertheless, due the nature of this strategy, the comparison of results amongst different studies is difficult as well as the integration of systems based on different approaches (see table 1).

In conclusion, the intrinsic nature of pattern matching presents favourable characteristics for standardization in HCI systems. However, its use of predefined patterns creates a controversy as there are no well-established physiological patterns for affective states so far. This has led the HCI community to privilege the use of pattern recognition and machine learning in affective recognition systems.

Area 2: Stimulus used for the identification of physiological patterns.

One reason for the inconsistency of physiological patterns among different studies might be due to the use of different types of stimulus to elucidate a particular emotion. Among the different methods in literature, one can find: staged manipulations [15], directed facial actions [16], imagery techniques [17], pictures [18], music [19], film clips [20], dyadic interaction [21], etc. When deciding about which stimuli to use for the pattern recognition stage of a HCI application, the following issues need to be taken into consideration:

I. The different types of methods to elucidate affective states offer advantages and disadvantages regarding the ecological validity and experimental control [22].

II. Due to individual differences, the same stimulus might not evoke the same emotional reactions to all participants [23]. For this reason, it is important to verify, directly with the subject, if the stimuli used succeeded to evoke the emotion intended.

III. The emotional and hence physiological reactions to a same stimulus can be different for the same person at different points in time. Multiple exposures can desensitize the subject [24].

IV. The same emotion can be experienced at different intensities depending on the context and type of the stimuli, involving different physiological reactions [25]. Therefore, the stimuli and context chosen for the recognition of patterns should be as similar as possible to the "real" stimuli and context that will be experienced later by the user.

A fundamental step towards the standardization of physiological patterns for affective states concerns the standardization of the stimulus used for their elicitation. Efforts in this direction can be found in [26], [27] and [28] where sets of pictures (IAPS), sounds (IADS) and film clips have been proposed to evoke different affective states. A comprehensive review of the methods and resources used to evoke emotions is available on the Handbook of Emotion Elicitation and Assessment [29]. In HCI, the standardization of the stimulus also needs to take in consideration the context in which the interaction will take place. Two other aspects that require well defined guidelines are: (a) the period of time for which a stimulus needs to be present to trigger a clear physiological reaction, and (b) the time needed for participants to recover from an emotional experience.

Area 3: Physiological Measures to be used

Common physiological measures used in research to identify emotions include: cardiovascular, electrodermal, muscular tension, respiration, brain activity and ocular responses. Some studies have reported the relevance of some physiological measures for particular affective states. For instance, Bradley & Lang [30] found in their experiments that facial supercilii muscle activity strongly correlates with the reports of pleasure, while skin conductance strongly covariates with the report of emotional arousal.

Regarding HCI applications, Meehan et al. [31], for example, found that changes in heart rate correlate well when evaluating stressful virtual environments. As it can also be observed in the summary of empirical work by [9] some of the findings suggest that it is possible that some physiological signals behave similarly on different emotions; however a difference in the whole set of physiological responses is appreciated. For this reason, further research is needed to determine which physiological measures provide the best results when identifying a specific emotion.

Area 4: Features to Analyze

Common features extracted from the physiological measures to identify emotions are the mean and standard deviation of the signal. Again, there are no defined guidelines. Most of the researchers in HCI based their selection of features on both previous findings and on the nature of the physiological measures selected. Heart rate, inter beat interval, amplitude, and other heart rate variability parameters, are examples of features that can be extracted from cardiovascular measures due to their underlying nature. Feature extraction methods can be used to generate new features based on transformations or combinations of the original feature. Some of the common methods include: Principal Component Analysis (PCA), Linear Discriminant Analysis, Projection Pursuit, Independent Component Analysis, Kernel PCA, PCA Network, Nonlinear auto-associative network, Multidimensional scaling and Sammon's projection and Self-Organizing Map.

It is important to note that the number of features to process will have an effect on the speed of the classifier and on the use of memory. In order to use only the features that best discriminate among the classes, methods for feature selection can be used. Examples of these include: Exhaustive Search, Branch-and-Bound Search, Best Individual Features, Sequential Forward Selection, Sequential Backward Selection, "Plus t-take away r" Selection and Sequential Forward Floating Search and Sequential Backward Floating Search. Jain et al. [32] present a review on feature extraction and selection methods. All this give the possibility of the use of many different combinations from a wide range of features. Further investigation is also needed in this area to establish which method determines the set of features that best discriminate affective states. Moreover, as the current expectations for HCI applications imply real-time responses; it is consequently highly desirable for the features to be extracted in real time.

Area 5: Models for Pattern Recognition and Classification of Emotions

The last area identified that needs standardization concerns the use of models and algorithms for pattern recognition and emotion classification. The recognition of patterns can be done using machine learning algorithms from a supervised, unsupervised or semi-supervised classification approach. In supervised learning, the training sets are already provided. In contrast, in unsupervised learning, there is no given a priori label of patterns; the system determines itself the classes based on statistical information. A combination of both labelled and unlabelled examples is carried out in semi-supervised learning [33].

There is a vast combination of possible algorithms depending on the approach used to classify the data. However, all the algorithms can be grouped on one of the three basic problems in statistical classification: (i) finding a map from features space to a set of labels; (ii) estimating the class given the training data; (iii) estimating class-conditional probabilities and then produce a class probability. A comprehensive review of common methods used in the various stages of pattern recognition systems can be found in [32]. Regarding the emotional classification in HCI, there are different algorithms that have been used such as: linear discriminant classifiers, neural networks, support vector machines, k-nearest neighbours, Bayesian networks, decision trees, etc. The main unsolved issue in this area is to determine what type of methods and algorithms provide the best results. Table 1 presents a summary of relevant studies in affective recognition for HCI, related to the five areas discussed in this paper.

Conclusion

Despite the lack of consensus among psychologists about the nature, theories, models, and specificity of physiological patterns for each emotion, psychology signals offer a great potential for the recognition of emotions in computer systems. In order to fully exploit the advantages of physiological measures, standardization needs to be established on the five key areas identified in this document. For each area, a review of the research carried out in psychology and in HCI was presented; along with the problems originated by the different methods used; and a discussion to guide further research

Table 1. *Comparison of Studies in Affective Recognition for HCI related to the five areas discussed in the paper.*

Author	Affective states	Stimulus	Physiological measures	Features	Classification	Results
[33]	No emotion, Anger, Hate, Grief, Platonic Love, Romantic Love, Joy, Reverence	Guided imagery technique	EMG, BVP, Electrodermal, Respiration	40	Combination of SFFS and FP methods	81.25% for all 8 emotions
[34]	3 Positive and 3 Negative states (with low, medium and high arousal characteristics)	IAPS	ECG, BVP, EMG, Electrodermal, Respiration, Temperature	13	Neural Net classifier	96.6% Arousal 89.9% Valence
[35]	Sadness, Anger, Fear, Surprise, Amusement, Frustration	Movie clips and math problems	Electrodermal, Temperature	Not specified	DFA, KNN, MBP	KNN: 71%, DFA: 74%, MBP: 83%
[36]	Joy, Anger, Sadness, Pleasure	Music songs chosen by participants	EMG, ECG, Electrodermal Respiration	32	KNN LDF MLP	About 80% for 3 classifiers.
[37]	Engagement, Anxiety, Boredom, Frustration, Anger.	Solving anagrams and playing videogame Pong	ECG, BVP, Electrodermal, EMG, Temperature	46	KNN RT BNT SVM	SVM: 85.81% RT: 83.50% KNN: 75.16% BNT: 74.03%.

SFFS = Sequential Floating Forward Search
FP = Fisher Projection
DFA = Discriminant Function Analysis
KNN = k-Nearest Neighbour algorithm
MBP = Marquardt Backpropagation
LDF = Linear Discriminant Function
MLP = Multilayer Perceptron Network
RT = Regression Tree
BNT = Bayesian Networks
SVM = Support Vector Machines
EMG = Electromyography
BVP = Blood Volume Pulse
ECG = Electrocardiogram

decisions. The paper ends with a table summing up the work carried out on emotion recognition for HCI, related to the five proposed areas.

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