Guidelines for Affective Signal Processing (ASP): From Lab to Life

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Abstract

This article presents the rationale behind ACII2009's special session: Guidelines for Affective Signal Processing (ASP): From lab to life. Although affect is embraced by both science and engineering, its recognition has not reached a satisfying level. Through a concise overview of ASP and the automatic classification of affect, we provide understanding for the problems encountered. Next, we identify guidelines for ASP: 1) four approaches to validation: content, criteria-related, construct, and ecological, 2) identification of users, 3) triangulation, and 4) signal processing issues. Each of these guidelines is briefly touched upon in this paper. A more exhaustive discussion on these guidelines, in perspective of the invited speakers' experience, will be provided through the session and its accompanying papers.

1. Introduction

In the preface of the Proceedings of the First Affective Computing and Intelligent Interaction (ACII) conference [28], the chairs stated:

Traditionally, the machine end of human-machine interaction has been very passive, and certainly has had no means of recognizing or expressing affective information. But without the ability to process such information, computers cannot be expected to communicate with humans in a natural way.

Over the recent years, a lot of effort has been put into automated recognition of affect. Often this is done through speech or face analysis; see [41] for a recent review. Alternatively, bio- or physiological signals have also shown to facilitate the identification of emotions; e.g., [30, 32, 37] (see also Table 1). This paper, and in fact this entire special session, discusses the latter approach, which we denote as Affective Signal Processing (ASP). Biosignals have the advantage that they are free from social masking and have the potential of being measured by non-invasive sensors; e.g., [8, 36, 37], making them suited for a wide range of applications. In contrast, recognizing facial expressions is notoriously problematic and requires the user to be in front of a camera. Speech is often either absent or suffers from severe distortions in many real-world applications [38, 41].

Hitherto, despite the cumulated efforts and more than a decade of work, the results founded on biosignals are also disappointing. Moreover, both relevant (fundamental) knowledge and results of interest for ASP are scattered throughout virtually all corners of science and engineering, which makes it increasingly hard to obtain a good overview. Therefore, we stress the need for ASP guidelines. This

[‡]Organizer of the special session *Guidelines for Affective Signal Processing (ASP): From lab to life*, which is introduced in this paper.

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could potentiality reduce the repetition of mistakes and, consequently, the waste of valuable research time.

In this introduction to the special session *Guidelines for ASP: From lab to life*, we first provide both an overview and a review of both ASP and the automatic classification of affect. Next, we introduce four guidelines for successful ASP. We end with some conclusions. The invited contributions to this special session will provide more in depth discussions on a number of the issues and topics we raise; we refer to them throughout this introduction. The topics addressed by the invited speakers and the issues denoted in this paper are no complete set of guidelines; nonetheless, we hope that it will be a start and a complete set of guidelines will emerge in time.

2. Affective Signal Processing (ASP)

A broad range of affective signals are used in emotion research. Some important and often used signals are cardiovascular activity [21, 22], electrodermal activity [3, 32, 33], muscle activity [7, 32, 33], skin temperature [13, 33], and respiration [2, 33]. For concise overviews on affective signals, we refer to: [29, 33]. With ASP some general issues have to be taken in consideration:

1. ASP is typically conducted through non-invasive methods to determine physiological signals and, as such, is an indirect measurement. So, a delay between the actual change in emotional state and the signal's change has to be taken into account [29].

2. Physiological changes can evolve in a matter of milliseconds, seconds, minutes or longer. Some changes hold for a brief moment, while others can be permanent. Consequently, the time windows of change are of interest [32, 33]. In particular, since physiological reactions can add to each other, even when having a different origin.

3. Physiological sensors are unreliable: they are sensitive for movement artifacts and differences in body position [22, 27].

4. Most sensors are obtrusive to some extent. This prevents their embedding in real world applications. However, the progress in biodevices must be acknowledged. Throughout the last years, various sensor systems have been launched that allow hardly obtrusive, real-time ASP; e.g., [8, 36].

5. Affective signals are influenced by a variety of factors. Some of them are located internally (e.g., a thought), others are among the broad range of possible external factors. This makes affective signals inherently noisy, which is most pregnant in real world research [11, 22].

6. Humans are no linear time (shift or translation) invariant systems [3], they tend to habituate. This increases the complexity of ASP significantly, since most signal processing techniques rely on this assumption.

7. ASP is subject to large individual differences. Therefore, methods and possibly models have to be tailored to the individual. It has been shown that personal approaches increase the performance of ASP [16, 17].

Many of the issues raised above are discussed in more detail in this special session by Healey [10].

2.1. Classification of Affective Signals

To enable processing of the signals, in most cases comprehensive sets of features have to be identified for them after throrough preprocessing. To extract these features, the affective signals are processed in the time (e.g., statistical moments), frequency (e.g., Fourier), time-frequency (e.g., wavelets), or power (e.g., periodogram and autoregression) domain. The merits and flaws of different approaches to this are discussed in depth by De Waele, De Vries, and Jäger [6] and Stuiver and Mulder [27] in this special issue.

The features obtained from the affective signals are fed to pattern recognition methods that can be classified as: template matching, syntactic or structural matching, and statistical classification; e.g., artificial neural networks (ANN). Statistical pattern recognition distinguishes supervised and unsupervised (e.g., clustering) pattern recognition; i.e., respectively, with or without a set of (labeled) training data.

In the field of ASP, several studies have been conducted, using a broad range of signals, features, and classifiers; see Table 1 for an overview. Nonetheless, both the recognition performance or the number of emotions among which is discriminated are disappointing. Moreover, a comparison between studies is problematic because of the different settings the research was applied in, the emotion triggers used, the target states to be discriminated, and the affective signals and features employed. This illustrates the need for a set of guidelines for ASP. This need is an explicit topic for the panel discussion of the special session. Below, we present our input for this discussion.

3. Guidelines

Although a vast amount of literature on biosignals and their relation to emotions is present, a concise set of guidelines is missing;. Hitherto, most guidelines that were presented did only into account lab research; e.g., [2, 3, 7, 21, 26]. Exceptions on this are [22] and [29]. However, with the introduction of small wearable devices that enable (real-time) ASP [8, 36], the need for guidelines for ASP in real

Table 1. An overview of 14 studies on automatic biosignal-driven classification of emotions of the last 5 years. In addition, the seminal work of Picard et al. [23] is provided as a baseline.

information source		year	signals	#part.	#feat.	classifiers	#classes	result
[23]	Picard et al.	2001	$\mathcal{C}$,$\mathcal{E}$,$\mathcal{R}$,$\mathcal{M}$	1	40	LDA	8 emotions	81%
[35]	Wagner et al.	2005	$\mathcal{C}$,$\mathcal{E}$,$\mathcal{R}$,$\mathcal{M}$	1	32	kNN, LDA, MLP	4 emotions	92%
[40]	Yoo et al.	2005	$\mathcal{C}$,$\mathcal{E}$	6	5	MLP	4 emotions	80%
[5]	Choi & Woo	2005	$\mathcal{E}$	1	3	MLP	4 emotions	75%
[11]	Healey & Picard	2005	$\mathcal{C}$,$\mathcal{E}$,$\mathcal{R}$,$\mathcal{M}$	9	22	LDA	3 stress levels	97%
[20]	Liu et al.	2006	$\mathcal{C}$,$\mathcal{E}$,$\mathcal{M}$,$\mathcal{S}$	14	35	RT	3 anxiety levels	70%
[25]	Rani et al.	2006	$\mathcal{C}$,$\mathcal{E}$,$\mathcal{M}$,$\mathcal{S}$,$\mathcal{P}$	15	46	kNN, SVM, RT, BN	3 emotions	86%
[42]	Zhai & Barreto	2006	$\mathcal{C}$,$\mathcal{E}$,$\mathcal{S}$,$\mathcal{P}$	32	11	SVM	2 stress levels	90%
[14]	Jones & Troen	2007	$\mathcal{C}$,$\mathcal{E}$,$\mathcal{R}$	13	11	ANN	5 arousal levels	31 / 62%
							5 valence levels	26 / 57%
[18]	Leon et al.	2007	$\mathcal{C}$,$\mathcal{E}$	8	5	ANN	3 emotions	71%
[19]	Liu et al.	2008	$\mathcal{C}$,$\mathcal{E}$,$\mathcal{M}$,$\mathcal{S}$	6	35	SVM	3 affect states	83%
[15]	Katsis et al.	2008	$\mathcal{C}$,$\mathcal{E}$,$\mathcal{R}$,$\mathcal{M}$	10	15	SVM, ANFIS	4 affect states	79%
[39]	Yannakakis & Hallam	2008	$\mathcal{C}$,$\mathcal{E}$	72	20	SVM, MLP	2 fun levels	70%
[16]	Kim & André	2008	$\mathcal{C}$,$\mathcal{E}$,$\mathcal{R}$,$\mathcal{M}$	3	110	LDA, DC	4 emotions	70 / 95%
[4]	Chanel et al.	2009	$\mathcal{C}$,$\mathcal{E}$,$\mathcal{R}$	13	11	ANN	2 emotions	66%
							3 emotions	51%

Signals: $\mathcal{C}$: cardiovascular activity; $\mathcal{E}$: electrodermal activity; $\mathcal{R}$: respiration; $\mathcal{M}$: electromyogram; $\mathcal{S}$: skin temperature; and $\mathcal{P}$: pupil diameter.
Classifiers: MLP: MultiLayer Perceptron; RT: Regression Tree; BN: Bayesian Network; ANN: Artificial Neural Network; SVM: Support Vector Machine; LDA: Linear Discriminant Analysis; kNN: k-Nearest Neighbors; ANFIS: Adaptive Neuro-Fuzzy Inference System; and DC: Dichotomous Classification.
Additional abbreviations: #: number of; part.: participants; feat.: features; and result: classification result.

life emerged. This section will briefly touch four key notions, which are proposed as guidelines for real world ASP.

3.1. Four approaches to validition

In the pursuit to trigger emotions, a range of methods have been applied: introspection, movements [1], acting, images (e.g., IAPS), sounds (e.g., music) [13, 16, 33, 34], light and color [1], (fragments of) movies [30,32,37], speech [31,41], commercials [24], games, agents / serious gaming / virtual reality [18, 37], reliving of emotions [4, 31], and real world experiences [10, 11, 37]. However, do these methods trigger true emotions? This question addresses the validity of the studies conducted. Validity can be obtained through:

1. Content validity refers to a) the agreement of experts on the domain of interest; b) the degree to which a signal's feature represents a construct; and c) the degree to which a set of features adequately represents the domain. For instance, employing skin conductance level (SCL) for ASP will result in a weak content validity when trying to measure emotion, as SCL relates to the arousal component of an emotion, not to the valence component. However, when trying to measure arousal, measuring only SCL may form strong content validity.
2. Criteria-related validity handles the quality of the translation from the preferred measurement to an alternative. Emotions are preferably measured at the moment they occur. However, measurements before (predictive) or after (postdictive) the particular event are sometimes more feasible; e.g., through questionnaires. The quality of these translations is known as predictive or postdictive validity. A third form of criteria-related validity is concurrent validity: the reliability of measurements related to a standard; e.g., a ground truth.
3. Construct validation aims to develop a ground truth through a nomological network, an ontology, or semantic network, build around the construct of interest. This requires theoretically grounded, observable, operational definitions of all constructs and their relations. The lack of construct validity is a pregnant problem of ASP. For example, frequently emotions are denoted where moods (i.e., longer object-unrelated affective states with very different physiology) are meant. This is highly relevant, as it is known that moods are accompanied by very different physiological signals than emotions [9, 33].
4. Ecological validity refers to the context of measure-

ments. Let us denote two major issues: 1) Natural occurring emotions are sparse. Hence, it is hard to let participants cycle through a range of affective states, in a limited time frame. 2) Affective signals are easily contaminated by contextual factors. So, using a similar context as the intended ASP application for initial learning is of crucial importance. Emotion measurements are often done in controlled laboratory settings, which makes their results poorly generalizable to real-world settings [30].

3.2. Identification of users

Throughout the field of affective computing, an ongoing debate is present on generic versus personal approaches to emotion recognition. This issue is thoroughly addressed by Kim, André, and Vogt in this special session [17].

It is generally accepted that we, as human beings, are all unique but also share characteristics with others. These characteristics are far from unraveled. However, in general, groups can be made of those who share more characteristics or share more dominant characteristics. The applicability of an ASP pipeline is determined by the amount of people on which it is applied and on the characteristics of them.

The identification of users has implications for the ASP pipeline. We propose three distinct categories, among which research in affective science could choose:

1. *all*: generic ASP; e.g., [30, 32]

2. *group*: tailored ASP; e.g., [5]

3. *individual*: personalized ASP; e.g., [11, 23]

Although attractive from computational point of view, the category *all* will probably not solve the mysteries concerning affect. As is long known in neurology and psychology, special cases can be of great help in improving ASP.

For both categories *group* and *individual*, the following subdivision can be made:

1. Specific, dominant characteristics; e.g., autism [19] and post-traumatic stress disorder [31].

2. Personality [30]

3. Other characteristics; e.g., based on age, culture, and/or context [30].

This subdivision is based on the ASP research done so far. However, it is also arbitrary to some extent. For example, one could pose that context should be the fourth category instead of assigning it to other characteristics. In addition, it is important to take into people's activities (e.g., office work [13], driving a car [11], and running [10]) when processing biosignals. In [10], Healey shares her experiences on ASP during various activities.

So far, comparisons are solely made between classification results of individuals and groups (i.e., a set of individuals). However, other approaches should be explored as well. Such experiences can substantially contribute to the further development of ASP, as has been seen in other sciences; e.g., biology, psychology, and medicine.

3.3. Application of triangulation

We adopt Heath's (2001) definition of triangulation: *the strategy of using multiple operationalizations of constructs to help separate the construct under consideration from other irrelevancies in the operationalization* (p. 15901). Triangulation provides several advantages:

1. Validation (see also Section 3.1): Signals can be validated against each other;

2. Reliability: Multiple data sets can be analyzed, providing more certainty. In addition, results that defy from other results can be identified as errors; and

3. Ground truth (see also Section 3.1): A more solid ground for the interpretation of signals can be obtained when multiple perspectives are used.

A few studies [4, 11, 30] successfully employed triangulation. We advise to employ at least three indicators, using ASP, for each construct under investigation.

Another directive is the incorporation of qualitative and subjective measures in research on ASP; e.g., questionnaires, video recordings, and/or interviews [11, 16, 30, 37]. See also Section 3.1. Kim, André, and Vogt [17] as well as Healey [10] will discuss this issue.

3.4. Signal Processing Issues

The majority of research on ASP is conducted by psychology, physiology, medicine, HCI, and AI. Consequently, signal processing expertise is often missing [29]. Some of the issues on which improvement can be made are:

1. Filters tailored to the specifications of ASP sensors and to applications could significantly boost the performance of ASP [29]. De Waele, De Vries, and Jäger [6] and Stuiver and Mulder [27] provide insights on this aspect in this special issue.

2. It is recommended to determine the relation between sample frequency and signal loss / distortion. So far, this has not been done for ASP and guidelines are provided founded on weak assumptions. For example, for all signals, the Nyquist frequency should be determined and taken into account in ASP [29].

3. An ASP benchmark would enable objective performance measurements of ASP and pattern recognition

techniques. Three benchmarks methods would be possible: 1) open source standard database; 2) a standard method to synthesize labeled sets of signals; and 3) standardized research setups; e.g., IAPS. Triangulation (see Section 3.3) could be exploited using it and the generic applicability of techniques could be tested. Signals and/or apparatus can be compared with each other. Consequently, it could be explored whether or not these could substitute each other; i.e., concurrent validation (see also Section 3.1). In addition, in various other ways concurrent validation could be applied.

A range of other issues is also of importance. However, an exhaustive discussion of them falls beyond the scope of this paper. For this we refer to [6, 27].

4. Conclusion

This introduction provided both an overview and a review of ASP and tried to explain the lack of success of ASP. Four guidelines were introduced from which ASP is expected to benefit significantly. These guidelines also form the starting point for the rest of this special session. Healey's contribution [10] is primarily concerned with validity issues besides giving a thorough overview of the different affective signals. Kim, André, and Vogt [17] focus on the issue of user identification. De Waele, De Vries, and Jäger [6] and Stuiver and Mulder [27] provide filters and algorithms tailored to ASP, and as such, concentrate on signal processing issues. Although the focus of these valuable contributions differs, they all consider each of our guidelines. In turn, this makes it possible to bridge the gaps between the different problems and fields involved, which is necessary to reach truly successful ASP.

With these guidelines and the more in depth discussion in the session papers, we hope to provide a strong base from which to continue the development of ASP. The future holds great promises and we envision ASP embedded in various professional and consumer settings, as a key factor of our every day life. We strongly believe that ASP will lead to many valuable innovations that augment our lifestyle and health. This will mark a new, biosignal-driven, era of intelligent interaction.

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References

[1] L. S. S. Bialoskorski, J. H. D. M. Westerink, and E. L. van den Broek. Mood Swings: An affective interactive art system. *Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering (Intelligent Technologies for Interactive Entertainment)*, 9:181–186, 2009.

[2] F. A. Boiten, N. H. Frijda, and C. J. E. Wientjes. Emotions and respiratory patterns: Review and critical analysis. *International Journal of Psychophysiology*, 17(2):103–128, 1994.

[3] W. Boucsein. *Electrodermal activity*. New York, NY, USA: Plenum Press, 1992.

[4] G. Chanel, J. J. M. Kierkels, M. Soleymani, and T. Pun. Short-term emotion assessment in a recall paradigm. *International Journal of Human-Computer Studies*, 67(8):607–627, 2009.

[5] A. Choi and W. Woo. Physiological sensing and feature extraction for emotion recognition by exploiting acupuncture spots. *Lecture Notes in Computer Science (Affective Computing and Intelligent Interaction)*, 3784:590–597, 2005.

[6] S. de Waele, G.-J. de Vries, and M. Jäger. Experiences with adaptive statistical models for biosignals in daily life. In *Proceedings of the IEEE 3rd International Conference on Affective Computing and Intelligent Interaction, ACII*, volume [this], 2009.

[7] A. J. Fridlund and J. T. Cacioppo. Guidelines for human electromyographic research. *Psychophysiology*, 23(5):567–589, 1986.

[8] H. Gamboa, F. Silva, H. Silva, and R. Falcão. PLUX – Biosignals Acquisition and Processing, 2009. URL: `http://www.plux.info` [Last accessed on June 30, 2009].

[9] G. H. E. Gendolla and K. Brinkman. The role of mood states in self-regulation: Effects on action preferences and resource mobilization. *European Psychologist*, 10(3):187–198, 2005.

[10] J. A. Healey. Affect detection in the real world: Recording and processing physiological signals. In *Proceedings of the IEEE 3rd International Conference on Affective Computing and Intelligent Interaction, ACII*, volume [this], 2009.

[11] J. A. Healey and R. W. Picard. Detecting stress during real-world driving tasks using physiological sensors. *IEEE Transactions on Intelligent Transportation Systems*, 6(2):156–166, 2005.

[12] L. Heath. *Triangulation: Methodology*, pages 15901–15906. Elsevier Science Ltd.: Oxford, UK, 1 edition, 2001. ISBN: 978-0-08-043076-8.

[13] J. H. Janssen, E. L. van den Broek, and J. H. D. M. Westerink. Personalized affective music player. In *Proceedings of the IEEE 3rd International Conference on Affective Computing and Intelligent Interaction, ACII*, volume [this], 2009.

[14] C. M. Jones and T. Troen. Biometric valence and arousal recognition. In B. H. Thomas, editor, *Proceedings of the Australasian Computer-Human Interaction Conference (OzCHI)*, pages 191–194, Adelaide, Australia, 2007.

[15] C. D. Katsis, N. Katertsidis, G. Ganiatsas, and D. I. Fotiadis. Toward emotion recognition in car-racing drivers: A biosignal processing approach. *IEEE Transactions on Sys-*

tems, Man, and Cybernetics–Part A: Systems and Humans, 38(3):502–512, 2008.

[16] J. Kim and E. André. Emotion recognition based on physiological changes in music listening. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 30(12):2067–2083, 2008.

[17] J. Kim, E. André, and T. Vogt. Towards user-independent classification of multimodal signals. In *Proceedings of the IEEE 3rd International Conference on Affective Computing and Intelligent Interaction, ACII*, volume [this], 2009.

[18] E. Leon, G. Clarke, V. Callaghan, and F. Sepulveda. A user-independent real-time emotion recognition system for software agents in domestic environments. *Engineering Applications of Artificial Intelligence*, 20(3):337–345, 2007.

[19] C. Liu, K. Conn, N. Sarkar, and W. Stone. Physiology-based affect recognition for computer-assisted intervention of children with Autism Spectrum Disorder. *International Journal of Human-Computer Studies*, 66(9):662–677, 2008.

[20] C. Liu, P. Rani, and N. Sarkar. Human-robot interaction using affective cues. In *Proceedings of the 15th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN06)*, pages 285–290, Hatfield, UK, 2006. IEEE Computer Society.

[21] M. Malik and A. J. Camm. *Heart Rate Variability*. Armonk, NY, USA: Futura Publishing Company, Inc., 1995.

[22] L. J. M. Mulder. Measurement and analysis methods of heart rate and respiration for use in applied environments. *Biological Psychology*, 34(2–3):205–236, 1992.

[23] R. W. Picard, E. Vyzas, and J. Healey. Toward machine emotional intelligence: Analysis of affective physiological state. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 23(10):1175–1191, 2001.

[24] K. Poels and S. Dewitte. How to capture the heart? Reviewing 20 years of emotion measurement in advertising. *Journal of Advertising Research*, 46(1):18–37, 2006.

[25] P. Rani, C. Liu, N. Sarkar, and E. Vanman. An empirical study of machine learning techniques for affect recognition in human-robot interaction. *Pattern Analysis & Applications*, 9(1):58–69, 2006.

[26] M. B. I. Reaz, M. S. Hussain, and F. Mohd-Yasin. Techniques of EMG signal analysis: detection, processing, classification and applications. *Biological Procedures Online*, 8(1):11–35, 2006.

[27] A. Stuiver and L. J. M. B. Mulder. On artefact-free real-time computation of cardiovascular measures. In *Proceedings of the IEEE 3rd International Conference on Affective Computing and Intelligent Interaction, ACII*, volume [this], 2009.

[28] J. Tao, T. Tan, and R. W. Picard. *Affective Computing and Intelligent Interaction*, volume 3784 of *Lecture Notes in Computer Science*. Berlin/Heidelberg, Germany: Springer-Verlag, 2005.

[29] E. L. van den Broek, J. H. Janssen, J. H. D. M. Westerink, and J. A. Healey. Prerequisits for Affective Signal Processing (ASP). In P. Encarnação and A. Veloso, editors, *Biosignals 2009: Proceedings of the International Conference on Bio-Inspired Systems and Signal Processing*, pages 426–433, Porto – Portugal, 2009.

[30] E. L. van den Broek, M. H. Schut, J. H. D. M. Westerink, and K. Tuinenbreijer. Unobtrusive Sensing of Emotions (USE). *Journal of Ambient Intelligence and Smart Environments*, 1(3):287–299, 2009.

[31] E. L. van den Broek, F. van der Sluis, and T. Dijkstra. Therapy Progress Indicator (TPI): Combining speech parameters and the subjective unit of distress. In *Proceedings of the IEEE 3rd International Conference on Affective Computing and Intelligent Interaction, ACII*, volume [this], 2009.

[32] E. L. van den Broek and J. H. D. M. Westerink. Considerations for emotion-aware consumer products. *Applied Ergonomics*, 40:[in press; online available], 2009.

[33] M. D. van der Zwaag and J. H. D. M. Westerink. Physiological differentiation between positive and negative moods. [submitted for publication].

[34] M. D. van der Zwaag, J. H. D. M. Westerink, and E. L. van den Broek. Deploying music characteristics for an affective music player. In *Proceedings of the IEEE 3rd International Conference on Affective Computing and Intelligent Interaction, ACII*, volume [this], 2009.

[35] J. Wagner, J. Kim, and E. André. From physiological signals to emotions: Implementing and comparing selected methods for feature extraction and classification. In *Proceedings of the IEEE International Conference on Multimedia and Expo (ICME)*, pages 940–943, Amsterdam, The Netherlands, July 6–8 2005.

[36] J. Westerink, M. Ouwerkerk, G.-J. de Vries, S. de Waele, J. van den Eerenbeemd, and M. van Boven. Emotion measurement platform for daily life situations. In *Proceedings of the IEEE 3rd International Conference on Affective Computing and Intelligent Interaction, ACII*, volume [this], 2009.

[37] J. H. D. M. Westerink, M. Ouwerkerk, T. Overbeek, W. F. Pasveer, and B. de Ruyter. *Probing Experiences: From Academic Research to Commercial Propositions*, volume 8 of *Philips Research Book Series*. Springer: Dordrecht, The Netherlands, 2008.

[38] J. Whitehill, G. Littlewort, I. Fasel, M. Bartlett, and J. Movellan. Towards practical smile detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 31:[in press], 2009.

[39] G. N. Yannakakis and J. Hallam. Entertainment modeling through physiology in physical play. *International Journal of Human-Computer Studies*, 66(10):741–755, 2008.

[40] S. K. Yoo, C. K. Lee, J. Y. Park, N. H. Kim, B. C. Lee, and K. S. Jeong. Neural network based emotion estimation using heart rate variability and skin resistance. *Lecture Notes in Computer Science (Advances in Natural Computation)*, 3610:818–824, 2005.

[41] Z. Zeng, M. Pantic, G. I. Roisman, and T. S. Huang. A survey of affect recognition methods: Audio, visual, and spontaneous expressions. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 31(1):39–58, 2009.

[42] J. Zhai and A. Barreto. Stress detection in computer users through noninvasive monitoring of physiological signals. *Biomedical Science Instrumentation*, 42:495–500, 2006.