# Guidelines for biosignal-driven HCI

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## Abstract
Biosignals, peripheral or from the brain, can be used to recognize mental states. Subsequently, these signals can be employed to enhance user experiences. This paper identifies challenges that have to be faced with processing such signals and defines guidelines to tackle them. We pose that these guidelines can initialize a leap forward in the development of real-time biosignal-driven adaptive systems.

## Keywords
Biosignal processing, guidelines, physiological computing

## ACM Classification Keywords
H1.2 User/machine systems, H.5.2 User Interfaces: Input devices and strategies, B.4.2 Input/output Devices: Channels and controllers

## General Terms
Human factors, measurement, standardization, reliability, performance

## Introduction
Technology that enables unobtrusive real-time recording of biosignals has flourished the previous decennium. Such biosignals provide us with important information about a user's psychological state and experience. Consequently, adaptive biosignal-driven man-machine interaction in ambulatory settings has become within reach [5]. For example, as affect can be

derived from biosignals [1], music can be automatically selected to guide the user's state to a predefined goal affective state using music [4]. Additionally, the relation between cardiovascular measures and workload can be used to provide adaptive support to drivers [10]. Biosignals that can be thought of are peripheral (measuring autonomic nervous system activity) and brain signals (measuring brain potentials). Both types of biosignals share some challenges, as they both work with body signals and use the same methodology to assess the same constructs; e.g., workload, stress, affect, or user experience.

Despite recent progress, the performance of biosignal processing techniques still results in recognition rates that are too low for real world applications. This is illustrated in Table 1, which provides a sample of results in the affective computing domain. These studies used a broad range of signals, features, and classification techniques. Moreover, the context in which the studies were conducted differ. All this makes a straight forward comparison between these studies hardly possible. Moreover, no guidelines or structured suggestions for improvements have been put forward.

**Table 1: An overview of eight studies on automatic physiological-driven classification of affect.**

| Information source | Year | Signals | Partici-pants | #of features | Selection, reduction | Classifiers | Target | Classifica-tion result |
|---|---|---|---|---|---|---|---|---|
| Picard et al. | 2001 | C,E,R,M | 1 | 40 | SFS, Fisher | LDA | 8 emotions | 81% |
| Cheng et al. | 2008 | M | 1 | 12 | DWT | ANN, TM | 4 emotions | 75% |
| Kim & André | 2008 | C,E,M,R | 3 | 110 | SBS | LDA | 4 emotions | 70% |
| Yannakakis & Hallam | 2008 | C,E | 72 | 20 | ANOVA | SVM,MLP | 2 fun levels | 70% |
| Katsis, et al. | 2008 | C,E,M,R | 10 | 15 | - | SVM, ANVIS | 4 affective states | 79% |
| Liu et al. | 2008 | C,E,S,M | 6 | 35 | - | SVM | 3 affective states | 83% |
| Lichtenstein et al. | 2008 | C,E,R,M | 40 | 5 | - | SVM | 5 emotions | 47% |
| Chanel et al. | 2009 | C,E,R | 10 | 18 | - | LDA, SVM, RVM | 3 emotions | 51% |

*Signals: C*: cardiovascular activity; *E*: electrodermal activity; *R*: respiration; *M*: electromyogram and; *S*: skin temperature. *Selection:* SFS: Sequential Forward Selection; SBS: Sequential Backward Selection; DWT: Discrete Wavelet Transform; Fisher: Fisher projection; and ANOVA: ANalysis Of VAriance. *Classifiers:* ANN: Artificial Neural Network; ANVIS: Adaptive Neuro-Fuzzy Inference Systems; SVM: Support Vector Machine; RVM: Relevance Vector Machines; LDA: Linear Discriminant Analysis; MLP: MultiLayer Perceptron; and TM: Template Matching.

To deal with the challenges to measure, preprocess, and interpret biosignals, we suggest the use of a set of 5 guidelines to improve mental state recognition from biosignal processing for adaptive devices. We hope that this provides a starting point to bring these fields closer together, so that they can learn from each other.

## Guidelines for biosignal processing

*Theoretical specification and validation*

Actuators can trigger several mental states which again cause changes in several biosignals. To help dealing with this many-to-many relationship between psychological constructs and biosignals three methods are suggested: 1) Specification of the theoretical relation between construct of interest and biosignal to make sure the most suitable biosignals and time windows are chosen; e.g, emotions are short and need a time window of seconds, while moods changes slowly over minutes to hours, 2) involving context information to explain noise in the data, 3) and using multiple classifier systems to integrate different constructs.

Furthermore, psychological states can be triggered by different actuators. As such, different methods have been used to enhance user experiences: e.g., music, images, movies, etc. However, the induced state has to be validated to ensure it was actually induced. Validity can be obtained in different manners; content, criteria-related, construct, and ecological validation. For detailed information on these validation methods see Van den Broek et al. [2].

*Triangulation and integration of biosignals*

Triangulation is defined as the strategy of measuring one construct, using several biosignals simultaneously. This strategy has the advantage that distinct signals can be used to validate each other, to provide higher certainty, and to provide a more solid ground as multiple signals are integrated. By integrating features from two or more biosignals into one feature, more noise can be explained. Three steps are involved in this process, 1) a theoretical relationship between multiple biosignals has to be identified, 2) an appropriate model to integrate both has to be selected, and 3) data has to be gathered and the model has to be trained. An example can be found in the respiration sinus arrhythmia (RSA), related to relaxation, which shows the variation in the heart rate due to breathing. RSA is most often calculated by correcting the heart rate for the respiration cycle.

*Identification of users*

Different users respond differently to stimuli and systems. Hence, tailoring recognition systems to specific groups or users will probably improve the performance. Subdivisions can, for instance, be made on specific characteristics, psychological traits, demographics, and contexts. For example, Picard et al. [12] tailors biosignal-driven HCI to autistic persons. She uses biosignals to develop unobtrusive therapist intervention models.

*Biosignal characteristics*

Different physical characteristics of sensors and the environment have different implications on signal processing. Criteria for physical characteristics of the sensors vary per application. Therefore the following choices should be carefully considered: finding the best combination of the sensitivity and reliability versus conductivity of the sensors, the electrode type (e.g., dry / wet), and the position of the sensors. Moreover, day-to-day differences in temperature and humidity, and sensor placement, need to be dealt with.

One way to approach this challenge is to standardize the measurements using baselining for each session. The specification of the baseline should consider the correction method (e.g., z-transformations or difference scores) and the selection period of the baseline. This selection period is used to calculate the parameters of the correction method, which are mostly extracted from a moving window over time.

*Temporal construction*

Three classes of temporal aspects in physiological signals have to be taken into account for biosignal processing: psychological, biosignal, and signal processing. The psychological aspects cover the fact that people habituate to stimuli in the environment. When habituation occurs, responses to a stimulus decrease every time the stimulus is presented. As a result, the user gets insensitive to that stimulus. First, it has to be acknowledged that the annotation of the events of interest is difficult, as the duration it takes from stimulus to biosignal reaction differs per signal. Secondly, as mental states show different temporal characteristics with signals, this should also be taken into account. As such, the window selection for each signal separately is important. Last, the law of initial values is important for signal processing, as it influences the physiological reactions to an event; biosignals tend to move to a stable level over time. Regression can be used to compensate for this issue.

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## Conclusion

This paper showed the complexity of biosignal processing (i.e., physiological and BCI signals) and processing to enhance biosignal-driven HCI. We identified a set of guidelines to better coordinate the use of biosignals for real life applications. There is a long way to go, but we are confident that, when these guidelines are employed, automated mental state prediction can be significantly improved. These guidelines improve the fruitful use of biosignal technologies, leading to valuable new applications and interactions.

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