Generic Tool for Online Classification of Physical and Mental Workload

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Introduction

Physiological signals like the heart rate or the galvanic skin response are used to assess the mental [1] and physical stress of a subject during specific situations and tasks. Similar experiments are used to investigate and recognize emotions [2] and related emotional states of the subject in response to images [3]. Recent developments in the field of human machine [4, 5] and robot interaction require the online measurement and classification of physiological signals and features with respect to emotions and low level intentions in real-time. In the following sections the g.PhysioObserver system and its use for online real-time studies will be presented. The results of an initial test experiment on the detection of the mental and physical loads occurring during four different exercises and their discrimination based on corresponding physiological features and signals will be shown.

Methods

For the evaluation and online classification the g.PhysioObserver™ (Guger Technologies OG, Austria) system, shown in Figure 1, is used, which represents a MATLAB™/Simulink™ (Mathworks Inc, USA) based rapid prototyping system for the simple and thereby flexible design and implementation of study paradigms. The platform allows to record biosignals like the ECG, EEG, respiration (Resp) and galvanic skin response (GSR) signal extract many different physiological parameters and features thereof. It is possible to form application specific feature vectors and classify them with respect to the mental and physical load associated with a specific

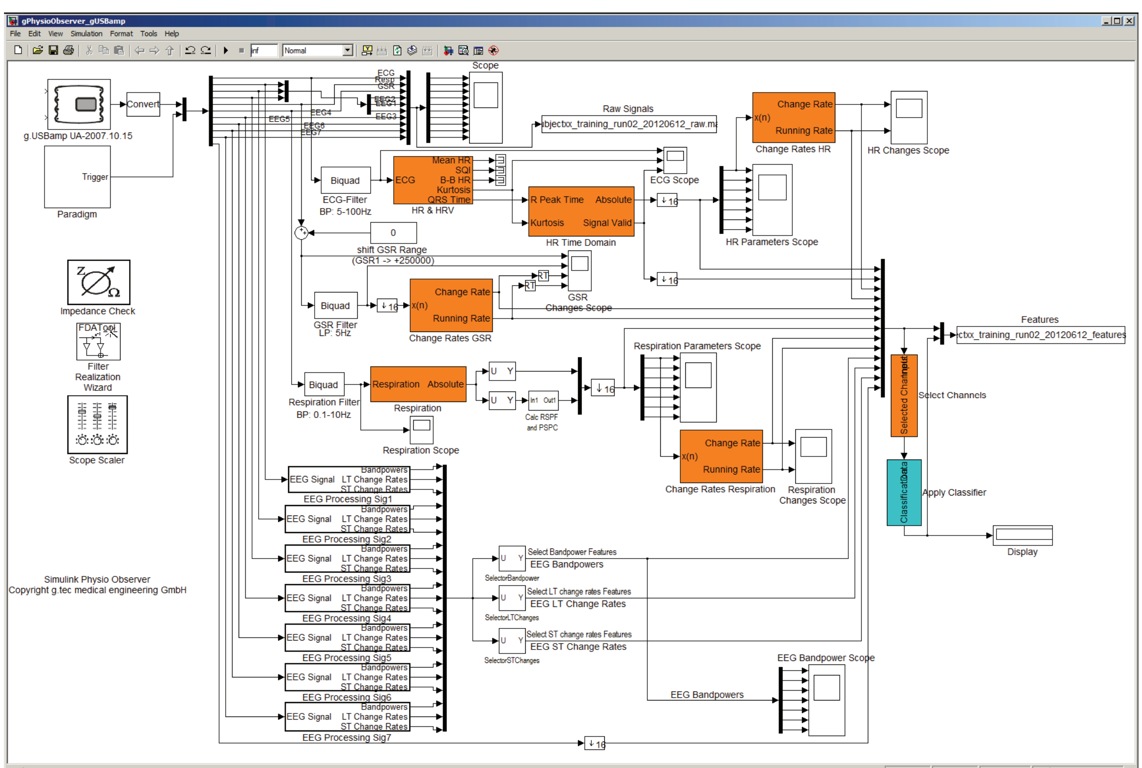

Figure 1. The g.PhysioObserver system allows to assess and evaluate different mental and physical sates of a subject online in real-time based on physiological signals and features extracted thereof.

exercise, mental or emotional state.

The system currently extracts from the ECG the Heart Rate, Heart Rate Variability, Root Mean Square of Sample Differences (RMSSD) or the RR interval, the percentage of consecutive RR intervals which vary by more than 50ms (pNN50) and the HR/RRMSD ratio. From the Resp signal it extracts the respiration rate (RespR), the duration and depth of the inspiration and expiration phases and a signal corresponding to the beaks during inspiration and expiration. The latter is indicated by a saddle point in the Resp signal exposing a zero value in its first and second derivative. The so called respiration stop signal is converted into a signal corresponding to the average number of breaks per minute and the number of breaks per respiration cycle. For any of the signals and Features it is possible to compute long term and short term changes rates. The long term rate indicates the overall change of the signals compared to an initial baseline segment at the beginning of the experiment. The short-term rate captures relative changes between the current evaluation period and its preceding period. Further it is possible to include measures like the power in the alpha-band, beta-band and theta band from up to 7 EEG channels.

An experiment consists of at least two phases, a training run and an online real-time classification and feedback run. During the training run all data required for computing a classifier are collected. This classifier is used during the online classification run to identify the current mental or physical state of the subject or to identify the exercise executed by the subject. Both runs can fully be controlled through two text files defining the corresponding paradigm. The first file defines the exercises the user has to execute along with the list of tasks to be accomplished for each exercise. Alternatively an external HTML page may be specified defining and controlling the tasks of the experiment. The second file determines the total number of trials and assigns each of them to one single exercise. The duration of one single trial, the amount of time the subject should be engaged in each exercise and the duration of breaks between distinct exercises can be freely defined through experimental parameters. The extracted feature signals are sampled at 16 Hz and stored independently from the raw biosignals which are acquired with a sampling frequency of 256 Hz. Thereby it is possible to keep the amount of data stored for each experiment at reasonably low levels, without losing any relevant information.

Experimental setup

The described experiment tries to identify the physical and mental load of the subject based on the ECG, GSR, Resp and 7 EEG signals only. The ECG signal is based on the bipolar derivation between the right shoulder and the Wilson lead V5. In the discussed preliminary result a thermistor based air flow sensor (SleepSens, S.L.P. Inc , USA) was used to record the respiration signal. Alternatively a piezzo based respiration belt sensor can be used. The EEG signals were recorded from the FCz, Cz, P3, Pz, P4, PO7 and PO8 positions of the international 10-20 system. For acquiring the GSR single two metal electrodes of the g.GSRsensor2™ were mounted on the medial phalanx of the subjects left index and middle finger.

For both, the recording of the EEG signals and the ECG signals active electrodes connected to a g.GAMMAbox were used to reduce undesired artefacts and to improve signal quality. The common ground electrode was placed on the AFz position of the international 10-20 system and the common reference electrode was attached to the left ear lobe. The initial experiments consisted of four distinct exercises of 5 Minutes duration each. In the first exercise (REST) the subject had to sit still and relax. During the second exercise (D2-Test) the subject had to perform a D2-Attention test. For this test the subject has to mark all symbols which show a d character annotated by exactly 2 short lines. During the remaining two exercises, SLEEP and SPORT, the subject had to lay down and sleep and bend the knees respectively. Each of the exercises was split into 5 consecutive trials of one minute duration.

Results

The data recorded during the training run was used to compute a Linear Discriminant Analysis (LDA) based classifier for discriminating the REST, exercise, from D2-TEST, SLEEP and SPORT. The feature signals used to generate the LDA classifier were selected by applying the distinction sensitive learning vector quantization

(DSLVQ) feature weighting method to a set of 192 trials recorded for 4 individual subjects. The resulting set of features included the minimum, mean and maximum HR, the inhalation depth and stops per cycle the long- and short-term change rates of GSR the power in the α-band of the EEG signals recorded from the positions P3, Pz and P4 and the power in the b-band of the positions P4, PO7and PO8. The resulting classifier was used in an online real-time evaluation run to identify, which exercise the subject was performing. In this run the order and duration of each exercise to be accomplished predefined by the paradigm equal to the training run.

Figure 2 depicts the classification errors estimated by the LDA for each time point within all trials of one specific class. The plots indicate the classification error for all four different exercises, (REST class 1, D2-Test class 2, SLEEP class 3 and SPORT class 4) individually and the average overall error achieved. In this first experiment an error of 0% could be achieved at any time point of each of the exercises. The resulting classifier was than tested during the online validation run. In this run each sample consisting of an individual set of values for the selected features was analyzed and assigned to one of the exercise. In case the probability that a specific sample belonged to the class selected by the classifier was below 95 % it was assigned to the virtual zero class instead. Figure 3 shows the average classification error (blue curve) over all error achieved for all four exercises. This classification error was computed by comparing the class assignment of each individual sample recorded during the online evaluation run with the class expected for the trial the sample was recorded for. In the depicted experiment an average classification error of 5 % was achieved through out all experiments. In addition to the classification error the rate of false positive classifications which was approximately 5 % is shown.

Discussion

The relatively high rate of false positive classifications compared to the average classification error may be explained by the low number of only 5 trials per class used to compute the classifier. Thereby it was necessary to use the same data for computing and testing the classifier which may be over fitted to the training data. The results obtained during the initial tests show that the presented system allows to extract a large variety of physiological features and use them to discriminate the mental and physical loads of user defined exercises.

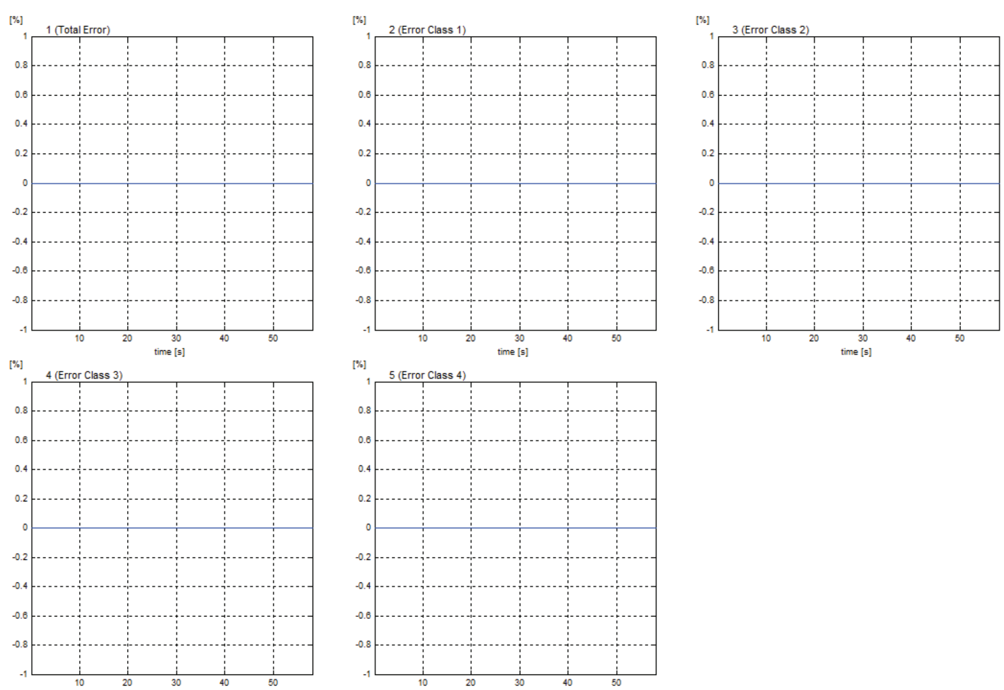

Figure 2. Classification error for discriminating the four exercises Rest, D2-Test, Sleep and Sports. The break between the exercises was set to 90s.

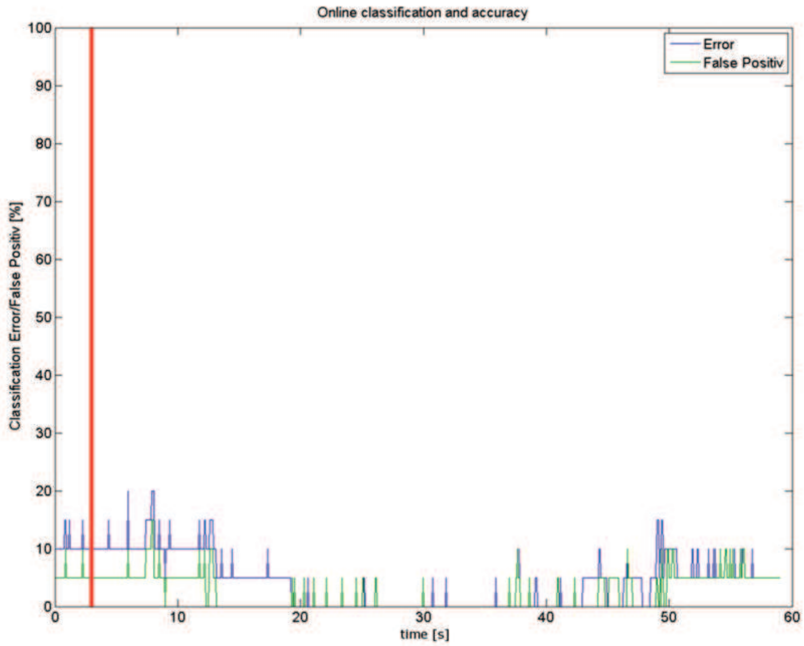

Figure 3. Online classification error and false positive rate achieved by the subject during the feedback session.

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