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Feature Extraction for Psychophysiological Load Assessment in Unconstrained Scenarios

Hugo Silva[1,2], Ana Fred[1], Susana Eusébio[3], Marco Torrado[3] and Silvia Ouakinin[3]

Abstract— **The relevance of psychophysiological measurements for affective computing and emotion analysis applications has been widely recognized. However, and although several authors have studied the informative content of parameters derived from cardiovascular and other modalities, feature extraction remains an open topic in the field. This is particularly relevant in scenarios where the autonomic nervous system triggering stimuli are unknown. In this paper, we analyze a set of features extracted from multimodal biosignal data, applicable to the assessment of psychophysiological load in unconstrained settings. Experimental evaluation is performed on real world data, collected both from control subjects and subjects with a strong clinical background, in a context of questionnaire-based clinical history reporting. The devised feature set has shown promising properties, making it prone to complement the more tradicional measurements.**

I. INTRODUCTION

Although the application of biosignals to the study of emotion and psychophysiology can be dated back to the early 20th century, there are still few well-established indicators targeted at psychophysiological load assessment over time [1]. Moreover, while cardiovascular and respiratory measurements have been inherited from the medical domain, where they are extensively covered, measurements extracted from other biosignals are still the focus of ongoing research; an example of these are the Skin Conductance Level (SCL) and Skin Conductance Response (SCR), together referred to Electrodermal Activity (EDA) or Galvanic Skin Response (GSR).

In general, feature extraction is still an open topic in the field. This aspect is even more meaningful when researchers are targeting non-intrusive sensing and wearability, and when data is acquired in scenarios where there is little insight about the affective eliciting or triggering stimulus. For example, whereas the ECG can provide highly detailed information on the different waveform complexes P-QRS-T, it introduces constrains in terms of the acquisition setup, as the sensor placement is generally performed at the chest level, and it requires conductive gel or paste [2]. Also, in experiments where the occurrence of the stimulus is known, a fine tuned analysis of the biosignal responses can be performed, which is not always the case.

[1]H. Silva and A. Fred are with the IT - Instituto de Telecomunicações, Instituto Superior Técnico, 1049-001 Lisboa, Portugal. {hsilva, afred}@lx.it.pt

[2]H. Silva collaborates with PLUX - Wireless Biosignals, S.A., 2630-355 Arruda dos Vinhos, Portugal. hsilva@plux.info

[3]S. Eusebio, M. Torrado, and S. Ouakinin are with the Faculdade de Medicina, Universidade de Lisboa, 1649-028 Lisboa, Portugal. {susanaeusebio, marcovtorrado, souakinin}@gmail.com

Over the years several features have been proposed in the literature, and extensively used in psychophysiological studies for Autonomic Nervous System (ANS) activity assessment. The comprehensive review work by [3] and references therein, highlights the autonomic measurements found in studies on emotion, and also the need to find consistent autonomic response indicators. In this paper we present an overview and study, on the applicability of multimodal biosignal feature extraction as an aid for psychophysiological changes evaluation.

Tests are performed in a real-world case of monitoring subjects during questionnaire-based clinical history assessments, which is particularly challenging, since the subjects browse freely through their memoires, resulting in a low traceability between a stimuli and its psychophysiological response. The rest of the paper is organized as follows: Section II details the feature set used in our study; Section III describes the statistical analysis of the application to real-world data; and Section IV outlines the main conclusions.

II. FEATURE EXTRACTION

The ANS activity has contributions from two interconnected components: psychological and physiological. The former is related with the intrinsic behavioral and affective dimensions of the subject; the latter has to do with the physical manifestations generated in response to a change in the affective state of the subject, or perceived when an external affective triggering stimulus occurs [1]. While the psychological component is more difficult to assess *per se*, with wearable and non-intrusive sensing techniques several electrophysiological signals exhibit manifestations related to changes in the subjects' affective state [4], [5], [6].

We focused on the acquisition of multiple biosignal modalities, and on studying the features typically extracted from them. Due to the non-intrusiveness and usability requirements of our application scenario, a set of wearable sensors for cardiorespiratory and ANS assessment was used, namely: Blood Volume Pulse (BVP); Respiration (RESP); and EDA. The raw BVP signal is bandpass filtered with a $[1-8]Hz$ passband, using a 4^{th} order filter, for SCR analysis, the raw EDA signal is lowpass filtered with a $0.25Hz$ cutoff frequency, using a 2^{nd} order filter, and the raw RESP data is bandpass filtered with a $[0.10-0.35]Hz$ passband, also using a 2^{nd} order filter. For all signals, a Butterworth filter design and a zero-phase digital filter are used [7], [8].

From the filtered BVP data, the instant Heart Rate (HR) is determined as the inverse of the Inter-Beat Interval (IBI), as described in Equations 1 and 2.

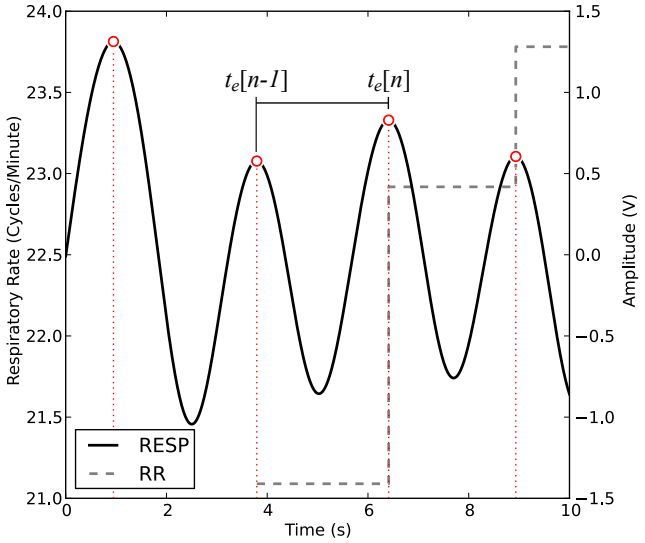

Fig. 1. Respiration sensor data. The filtered RESP signal is presented as a solid line, while the increase of the instant respiratory rate RR corresponds to the dashed line; n denotes the n_{th} respiratory cycle, and $t_e[n]$ denotes the time instant in which the n_{th} expiratory part of the respiration cycle begins.

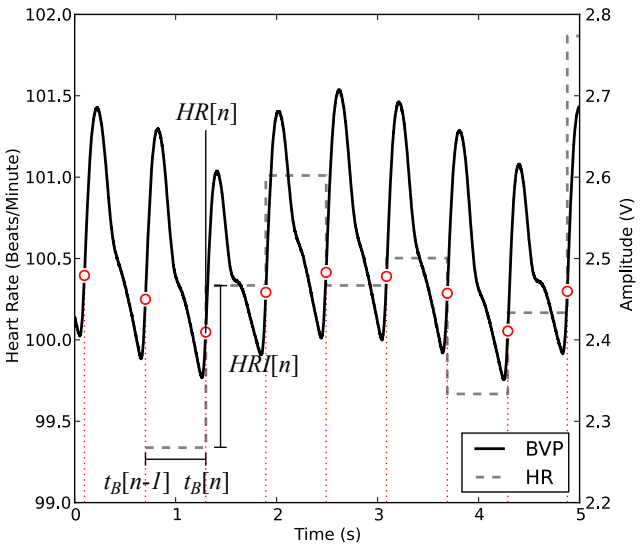

Fig. 2. Blood volume pulse sensor data. The filtered BVP signal is presented as a solid line, while the instant heart rate HR corresponds to the dashed line; n denotes the n_{th} heartbeat event, $t_B[n]$ denotes the time instant in which the n_{th} event occurred, and HRI denotes the heart rate increment between the n_{th} and $n_{th} - 1$ events.

$$HR[n] = \frac{1}{IBI[n]}, \tag{1}$$

where

$$IBI[n] = t_B[n] - t_B[n-1], \tag{2}$$

and $t_B[n]$ is the n^{th} heartbeat time instant. We use HR values to compute the Heart Rate Increment (HRI) as the absolute value of the backward difference (Eq. 3 and 4), which enables us to assess the stability of the heart rate during a time interval of variable length. Figure 2 depicts annotated BVP sensor data for visual reference.

$$HRI[n] = |\nabla HR[n]|, \tag{3}$$

where

$$\nabla HR[n] = HR[n] - HR[n-1] \tag{4}$$

An analogous calculation is performed for RESP data, where the instant Respiration Rate (RR) is derived as the inverse of the total respiratory cycle duration, as expressed in Equation 5. Figure 1 depicts annotated RESP sensor data for visual reference.

$$RR[n] = \frac{1}{t_e[n] - t_e[n-1]}, \tag{5}$$

where $t_e[n]$ is the n^{th} expiratory cycle time instant.

From the SCR data, we determine the nonspecific skin conductance response rate (nSRR), as the inverse of the SCR events interval, as described in Equation 6:

$$nSRR[n] = \frac{1}{t_{SCR}[n] - t_{SCR}[n-1]}, \tag{6}$$

where $t_{SCR}[n]$ is the onset time of the n^{th} SCR event. The SCR events are detected as zero-crossing transitions from negative to positive, as expressed in Equation 7):

$$t_{SCR} = \{n \in \mathbb{N} : \nabla sgn(\nabla SCR[n]) == -2\}, \tag{7}$$

$$t_{SCRp} = \{n \in \mathbb{N} : \nabla sgn(\nabla SCR[n]) == 2\}, \tag{8}$$

with t_{SCR} being the SCR onset time, t_{SCRp} being the SCR peak time, and

$$sgn(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{if } x = 0 \\ -1 & \text{if } x < 0 \end{cases}. \tag{9}$$

From these measurements, typically reported in the literature [3], additional features are extracted. Namely, from the SCR events we extract the rise time $SCRt_r[n] = t_{SCRp}[n] - t_{SCR}[n]$ as the difference between the peak and onset times of the n^{th} SCR event, the skin conductance event amplitude (SRA) as the difference between the SCR amplitudes at the onset and peak time instants (Eq. 10), the overal maximum $SRA\uparrow$ and minimum $SRA\downarrow$, SRA values, and the difference $SCR\updownarrow$ between the absolute maximum and minimum values of the SCR signal. Finally, we determine the SCL trend $SCL\pm$ (Eq. 11), which provides an indicator of wether an aroused or relaxed trend was predominant. Figures 3 and 4 depict annotated SCR sensor data for visual reference.

$$SRA[n] = SCR[t_{SCRp}[n]] - SCR[t_{SCR}[n]], \tag{10}$$

$$SCL \pm (n) = \begin{cases} 1 & \text{if } t_{SCR\uparrow}[n] > t_{SCR\downarrow}[n] \\ -1 & \text{if } t_{SCR\uparrow}[n] < t_{SCR\downarrow}[n] \end{cases} \tag{11}$$

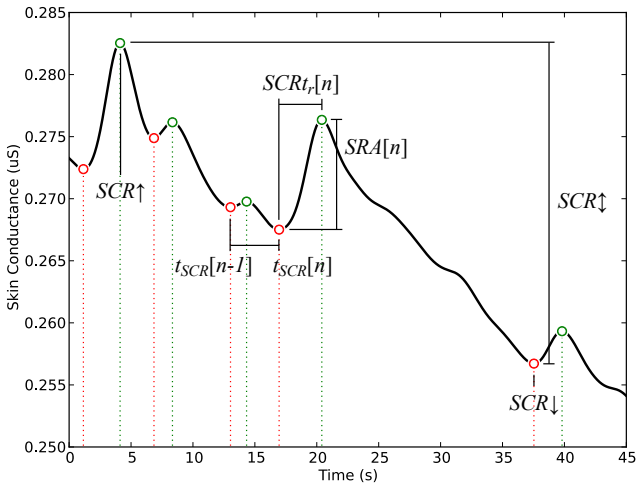

Fig. 3. Skin conductance response data. The filtered EDA data is presented as a solid line; n denotes the n^{th} skin conductance event, $t_{SCR}[n]$ denotes the onset time of the n^{th} event occurred; the description for the remaining events can be found in Table I.

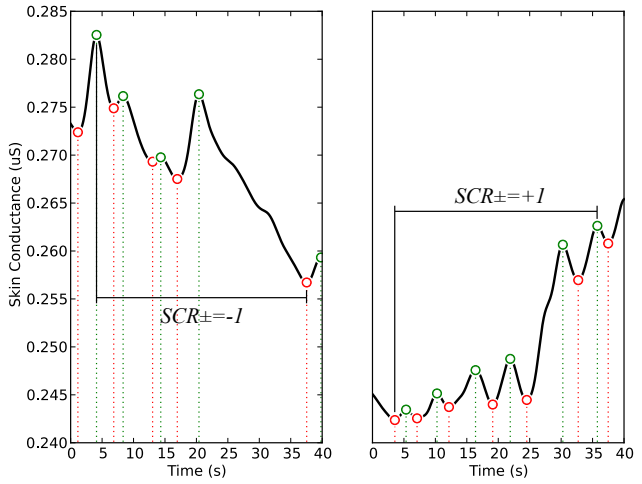

Fig. 4. Skin conductance trend. The filtered EDA data is presented as a solid line; n denotes the n_{th} skin conductance event, and $SCR\pm$ denotes the skin conductance trend as described Table I

Table I summarizes the full feature set, together with the corresponding units.

III. RESULTS

We performed a statistical evaluation of the extracted features on real-world data collected in a context of clinical assessment based on questionnaires, with the purpose of detecting changes between parts of the questionnaire with different psychophysiological load. This is a particularly challenging scenario for techniques normally found in the literature, as the subject does not have any constrains during the completion of the task, and therefore there are several unknown aspects, such as the time for completion is not defined, and a clear indication of the occurrence of any triggering stimulus that might change the affective state of the subjects. The data was collected on two groups of subjects: one clinical group with a severe clinical background; and a control group without any known, highly charged, clinical history.

TABLE I

FEATURES EXTRACTED FROM THE MULTIMODAL BIOSIGNAL DATA.

Modality	Feature	Units	Description
RESP	RR	cycles/minute	Instant respiratory rate
BVP	HR	beats/minute	Instant heart rate
	HRI	beats/minute	Heart rate increment
EDA	$nSRR$	events/minute	Instant SCR event rate
	$SCRt_r$	seconds	Difference between the SCR onset and peak time instants
	SRA	nS	SCR signal amplitude difference between the onset and peak time instants
	$SCR\uparrow$	uS	Maximum SCR amplitude
	$SCR\downarrow$	uS	Minimum SCR amplitude
	$SCR\updownarrow$	uS	$SCR\uparrow$-$SCR\downarrow$
	$SCL\pm$	n.a.	Skin conductance level trend

A total of 34 control subjects and 15 subjects with a strong clinical background participated in the experiment, where they were asked to respond to a questionnaire administered by a psychologist. The questions were organized to provide three distintive moments: a neutral phase, where the subject would provide general characterization information such as age, gender, work status, throughout seven questions (moment 1); a provocative phase, where a mathematical problem of numerical subtraction was placed (moment 2); and a clinical background report phase, where the differentiated emotional responses were expected, and which consisted in seventeen questions related to medication, reaction to the diagnosis, life events, among others (moment 3). The neutral phase targeted the definition of a baseline for the different measurements, while the provocative phase targeted the comparison between a stimuli period that was not related to the clinical history reporting, and the psychophysiological reactions arising from the clinical history reporting itself.

Prior to start responding to the questionnaire, the subjects were instrumented with the measurement apparatus; the BVP sensor was placed on the middle finger, while the EDA sensor was placed on the third phalange of the index and ring fingers, both on the non-dominant hand. The RESP sensor was placed around the thorax and fastened to a point where it would be tight to the subject's chest without causing discomfort. The sensors have embedded signal conditioning circuitry and amplification, and the analog-to-digital conversion was performed with a wireless data acquisition unit. Additional information about the sensors and acquisition hardware can be found at the manufacturers website [9].

Table II outlines the statistical outcomes for the extracted features in each phase of the questionnaire. As we can observe, the more traditional measurements such as RR and HR have shown little inter-/intra-group informative content; in general, the measurements derived from the SCR signal, as the SRA and $SCR\pm$ have shown more significant outcomes, as well as the HRI. The control group has shown higher

TABLE II

EXPERIMENTAL RESULTS FOR THE EXTRACTED FEATURES ($\mu \pm \sigma$).

Group	Moment	*RR*	*HR*	*HRI*	*nSRR*	*SCRt$_r$*	*SRA*	*SCR*$\uparrow$	*SCR*$\downarrow$	*SCR*$\updownarrow$	*SCR*$\pm$
Control	**1**	13.165± 0.745	84.563± 10.015	12.869± 8.863	7.457 ± 2.575	5.064 ± 1.699	28.939± 16.320	0.068 ± 0.052	0.005 ± 0.009	0.151 ± 0.128	−0.212± 0.977
	2	12.318± 0.954	86.219± 10.796	12.248± 8.328	7.272 ± 1.963	3.890 ± 1.774	26.501± 21.388	0.065 ± 0.075	0.005 ± 0.009	0.158 ± 0.118	0.500 ± 0.866
	3	12.754± 0.418	84.671± 9.097	12.739± 8.017	6.975 ± 2.374	6.185 ± 3.607	27.402± 14.217	0.079 ± 0.052	0.003 ± 0.006	0.160 ± 0.107	−0.182± 0.498
Clinical	**1**	13.199± 0.474	79.000± 6.397	6.561 ± 6.065	6.658 ± 1.733	5.400 ± 2.252	16.886± 9.126	0.056 ± 0.042	0.001 ± 0.005	0.117 ± 0.078	−0.125± 0.992
	2	12.075± 0.695	81.545± 3.950	4.304 ± 6.408	6.834 ± 1.414	3.715 ± 1.315	18.739± 9.135	0.039 ± 0.031	0.005 ± 0.009	0.120 ± 0.098	0.250 ± 0.968
	3	12.719± 0.457	80.348± 7.929	8.060 ± 5.908	6.559 ± 1.714	6.826 ± 2.327	28.994± 6.993	0.077 ± 0.035	0.011 ± 0.023	0.171 ± 0.084	−0.065± 0.518

HRI throughout the different moments when compared to the clinical group, furthermore, between moments 2 and 3, the clinical group shows a more stable trend, while the control group exhibits a higher variation.

On average, the SRA has revealed a consistent increase throughout the different moments in both groups, although on the clinical group the SCR events are on average of lower amplitude. Another interesting finding was the $SCR\updownarrow$ feature, which enables us to see that in both groups, the moment 3 was the one that led to higher SCR amplitude variations throughout the test. Furthermore, combined with the $SCR\pm$ feature, it allows us to conclude that while for the control group, moment 3 is a strongly low arousal period (highly negative $SCR\pm$), for the clinical group it is typically still a high arousal period.

IV. CONCLUSIONS

Feature extraction is currently a highly active research topic in the field of biosignals, with the purpose of obtaining additional insight about the subjects both in the physical and psychological dimensions. In the field of psychophysiology, there are multiple modalities and features already well described in the state-of-the-art, generally applicable to specific experiments and well defined laboratory settings. Questionnaire based assessments are still an important assessment instrument in psychological evaluation and profiling; however, unlike well-defined settings, in this case the triggering stimuli are not easy to identify, and the administration has a highly unrestrained nature.

This poses several problems related to the analysis of the typically used features. Our work describes a statistical analysis and evaluation of a feature set extracted from wearable biosignal measurement sensors, with the goal of determining which features could be more promising to assess the subjects psychophysiological load while participating in questionnaire based assessments. We have analyzed a subset of standardized features commonly found in the literature, and evaluated also an additional set of derived features derived both from cardiac an electrodermal activity data.

Experimental results performed with a control and a clinical group in a real-world setting have shown that, while some of the standard measurements do not exhibit clear distinctive trends between both groups, some of the features addressed in our work are able to provide additional informative content. Future research work will focus on further validating the described features, and on their clinical interpretation within a psychophysiological framework.

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