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Studying LF and HF Time Series to Characterize Cardiac Physiological Responses to Mental Fatigue †

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Abstract: Heart rate variability (HRV) was largely used to evaluate psychophysiological status of Human at rest as well as during cognitive tasks, for both healthy subjects and patients. Among the approaches used for assessing cardiac autonomic control from HRV analysis, biomarkers such as the power in low and high frequencies (LF-HF) are often extracted from short-term recordings lasting 2 to 5 min. Although they correctly reflect the average psychophysiological state of a subject in situation, they fail to analyse cardiac autonomic control over time. For this reason, we suggest investigating the LF-HF biomarkers over time to identify mental fatigue and determine different physiological profiles. The following step consists in defining the set of parameters that characterise the LF-HF time series and that can be interpreted easily by the physiologists. In this work, polynomial models are considered to describe the trends of the LF-HF time series. The latter are then decomposed into decreasing (d) and increasing (i) parts. Finally, the proportion of the i parts of the polynomial trends of the LF and HF powers over time are combined with classically-used metrics to define individual profiles in response to mental fatigue.

Keywords: times series; mental fatigue; HRV

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1. Introduction

When dealing with biosignal processing, physiologists, psychologists, doctors and colleagues working in the field of statistical signal processing often work together, each bringing their own expertise. Usually, a protocol is first defined. This includes the selection of signals that can be recorded (EEG, ECG, EMG, etc.), the types of sensors that can be used, but also the types and durations of the tasks that the volunteers will do, the questionnaires they will answer, etc. Then, the campaign is done and the collected time series are analysed. Various ways exist to address this step: depending on the type of signals, the power in some frequency bands can be computed. Parameters such as the Hurst exponent can be estimated using the detrended fluctuations analysis [1] or their variants such as [2]. The complexity of the signal can be also derived and be based on the eigen complexity [3] or the sample entropy, its variants such as the RCMSE [4] and their multiscale derivations [5,6]. An alternative is to select a model well suited to the time series and to estimate the model parameters. In case of a short memory and wide sense-stationary process, the autoregressive (AR), moving average (MA) or ARMA modelling can be well suited. The AR parameters can be estimated using the Yule-Walker equations [7]. If the data are disturbed by an additive white Gaussian noise, the noise-compensated approaches or the error-in-variable approaches [8] can be used to estimate the model parameters. Projecting the signal on a function basis such as the wavelets and the Legendre polynomials

can be also considered. Finally, the set of parameters that have been obtained can be input of classifiers. Comparing the signal based on the entropy rate is sometimes another way to address the problem [9,10].

Recently, the effects of mental fatigue in terms of cognitive and physical were presented in [11]. This survey also included the way to address the detection of the mental fatigue such as self-reporting questionnaires, attention network test, salivary cortisol levels, saccadic eye movements performance and heart rate variability (HRV) (The functioning of the autonomic nervous system (ANS) relies on dynamic regulations of two distinct branches named sympathetic (activation) and parasympathetic (modulation). Therefore, the inter beat intervals, i.e., RR-intervals, defined as a signal that reflects cardiac autonomic modulation, are continuously modulated according to the evolution of the psychophysiological state. This defines the concept of HRV) . When dealing with HRV [12–14], biomarkers such as the powers in low frequency (LF, 0.04–0.15 Hz) or high frequency (HF, 0.15–0.40 Hz), their ratio but also the root mean square of successive differences (RMSSD) are calculated from RR-intervals signals in the time and frequency domains. They provide information on the psychophysiological state of subjects in situations of rest or cognitive activity and even stress, since they are related to the sympathetic and parasympathetic cardiac autonomic system, but also to the sympatho-vagal ratio, which is an index of cardiac health monitoring.

However, none of the above approaches dealt with biomarkers that change during the same task. Therefore, in the present study, instead of having a single value of a biomarker for one task, we propose to take into account its time-evolution over the task. This is a novelty of the paper from a physiological point of view. From the point of view of signal processing, the main issue is to extract parameters from the LF and HF time series in order to facilitate the interpretation of physiologists. We have decided to choose polynomials to model the trends of the LF and HF time series of each volunteer. Then, the decreasing (d) and increasing (i) parts of each trend are identified and their durations in percentage are deduced. The proportion of the i parts of the polynomial trends of the LF and HF powers over time is then combined with classical cardiac metrics in a clustering analysis to identify individual response to mental fatigue.

The remainder of this paper is organized as follows: In Section 2, we first present the experimental protocol that has been defined. Then, in Section 3, the processing chain of the bio-signals is presented. In Section 4, results are provided. Finally conclusions and perspectives are given.

2. Experimental Protocol: Our First Contribution

The following psychophysiological protocol was developed to both induce mental fatigue and collect HRV during the cognitive task. See Figure 1. This protocol was set up by taking into account previous works such as [15–17]. However, the protocols mentioned above were not necessarily very stimulating for the participants. In the present study, a gamification-inducing protocol was developed to keep the subject engaged over time. The protocol itself is therefore new.

Fifty-two volunteers (27 males and 25 females, Age = 20.7 ± 2.9 years) gave their written informed consent to participate in the present study that was part of their academic curriculum and for which they received credits. The institutional review board "Faculte des STAPS" approved the procedure that respected all ethical recommendations and followed the declaration of Helsinki.

None of the participants reported neurological and physiological disorders as well as uncorrected vision problems. Participants were asked to avoid alcohol and caffeinated beverages for the 24 h preceding the experiment, but also to abstain from heavy physical activity.

The experiments were carried out in a quiet room with the same level of brightness (ambient temperature, 20–21 °C). During the whole experiment lasting around 40 min, participants remained quietly seated on a chair, at a viewing distance (more or less equal to

23-inch) of the 17-inch screen of a laptop, whose keyboard was used to respond during the cognitive task.

After a 5-min rest period, subjects performed a 20-min continuous vigilance task (CVT). The CVT was specifically developed to induce a mental fatigue by imposing a high continuous attention demand. For 20 min, red or blue boats appeared randomly on a horizon line with a time interval ranging from 5 to 15 s. Participants were instructed to press the keyboard space bar as quickly as possible when seeing the red boat and to inhibit their reaction when the boat was blue. Note that there can be only one boat at a time, the size and speed being always the same. The task consisted of more or less 120 successive stimuli, depending of the reaction times of the subject, including 70% of red boats and 30% of blue boats presented in an unpredictable manner. All reaction time and inhibition failures were collected.

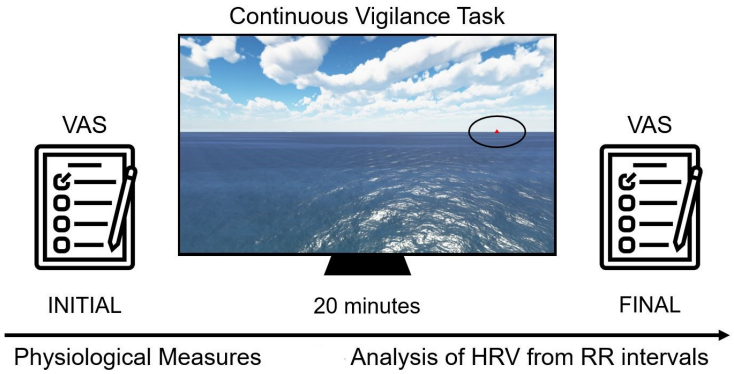


Figure 1. Experimental protocol. INITIAL: Mental Fatigue perceived (VAS); FINAL: Mental Fatigue Perceived (VAS) and Workload perceived (NASA_TLX).

A visual analogue scale (VAS) rated from 1 to 10, corresponding respectively to an "absence of mental fatigue" and an "extreme level of mental fatigue", was used to collect the mental fatigue perceived before and after the 20 min of the CVT. In addition, NASA-TLX [18] was used to collect workload after the CVT. The ECG signal was acquired at a sampling frequency equal to 1000 Hz by using three electrodes linked to an Amp integrate in PowerLab 26T. After a pre-processing carried out on the Software Labchart Pro 8.1.17 about 1200–1400 successive RR intervals were recorded over 20 min of the CVT. The exact length of the RR interval time series depends on the average heart rate of each participant. All computations were performed with Matlab using available functions and custom-designed routines. The raw data of heart rate variability (HRV and RR interval time series) were inspected for artefacts. Occasional ectopic beats (irregularity of the heart rhythm involving extra or skipped heartbeats such as extra-systole and consecutive compensatory pause) were visually identified and manually replaced with interpolated adjacent RR interval values. Due to corrupted data, 5 participants were discarded.

3. Processing Chain Taking into Account the Time-Evolution of the Biomarkers: Our Second Contribution

In the following, we present the whole processing chain we considered. It operates with the following three steps:

Step 1. Analysing the power in the LF band and the HF band

The time series are processed using a sliding window whose duration corresponds to 5 min and whose shift corresponds to 5 s. The power spectrum or the Welch periodogram based on the fast Fourier transform and a zero-padding can be computed for each frame. Finally, the power in each frequency band is deduced using the trapezoidal rule. As an alternative, a wavelet transform [19] or an empirical mode decomposition [20,21] can be considered.

Step 2. Characterising the resulting LF and HF power time series by a set of parameters

This step was done in agreement with the physiologists as their main difficulty is to *a posteriori* give an interpretation to the parameters and the clustering results. As our motivation is to extract different classes of profiles that can be related to individual physiological status, the LF and HF time series have been modelled by polynomials. Our idea is to describe how the trends evolve over time because it can be interpreted from a physiological point of view. Therefore, the *d* and *i* parts of each trend are identified. The next step is to deduce their durations. As the LF and HF time series of the volunteers do not have the same length, the percentages with respect to the global duration are considered. The next step is to sum the *i* parts on the one hand and the *d* parts on the other. As the sum is necessarily equal to 1, only the *i* parts of the polynomial trends of LF and HF powers over time are considered. In the following, theses markers will be denoted as iLF and iHF respectively corresponding to the proportion of LF and HF increase during the CVT task. See Figure 2.

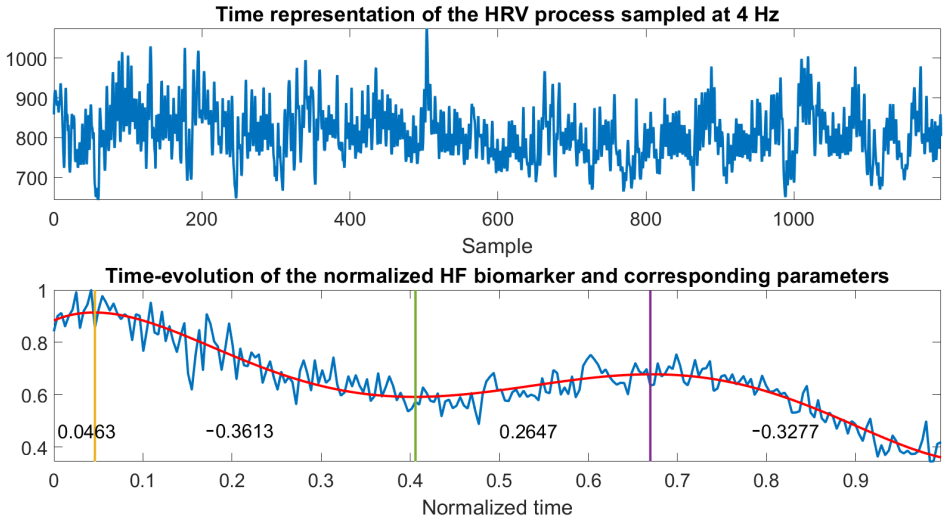


Figure 2. Illustration of the approach with patient 29. The HF process (in blue) modelled by a 5*th*-degree polynomial (in red) and resulting signed parameters: $iHF = 0.311$. The sign $-$ is added before the value of the percentage to express the fact that it is a decreasing trend.

Step 3. Classification step/Clustering

Both indices iLF and iHF are combined with the following classically-used metrics calculated during the first 10 min and last 10 min: average RR, RMSSD, LF power, HF power, LF/HF ratio and RCMSE [4]. This leads to 14 markers of the CVT used as input to perform a K-means analysis [22].

4. Results and Comments

4.1. Preamble: Comment on Initial and Final VAS

First we noticed that mental fatigue appeared after the CVT. Indeed, the individual scores of self-perceived fatigue (corresponding to the VAS introduced in Section 2) are significantly higher in all but one subject after CVT, as shown in Figure 3. This result suggests that the level of mental fatigue increases as the task progresses, but with strong heterogeneity between the subjects, as evidenced by the strong variations in the VAS. This result reinforces our willing to classify subjects in function of their individual responses, by describing the time-dependent changes of the biomarkers (LF and HF). For the above reason, let us now apply the clustering approach.

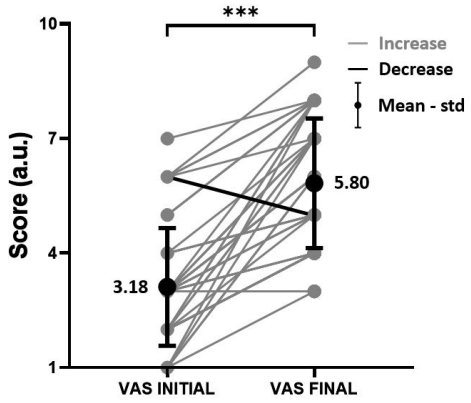


Figure 3. Evolution of perceived mental fatigue before and after CVT. Score 1: "absence of mental fatigue"; Score 10: "extreme level of mental fatigue"; ***: p-value < 0.001.

4.2. Application of Our Approach

The optimal number of clusters is determined using the "elbow" method. Because the data set contains more than two variables, the variables chosen to represent the original data on each dimension (Dim1 and Dim2 on Figure 4) is calculated by applying a Principal Component Analysis (PCA).

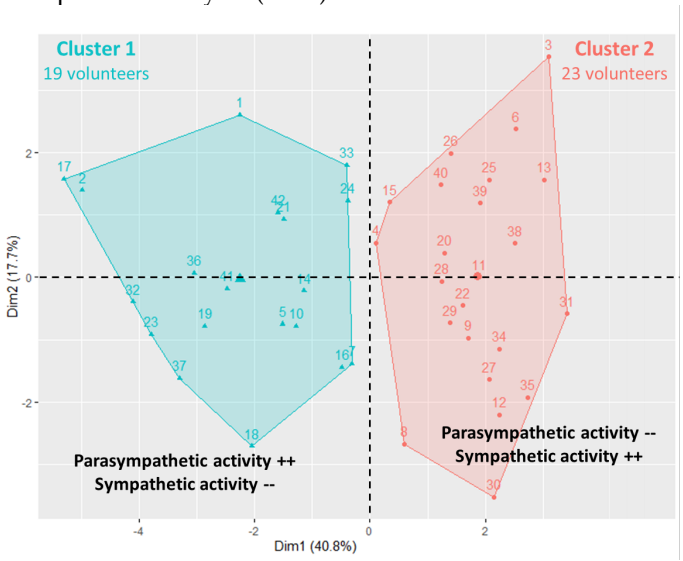


Figure 4. K-means clustering performed on a dataset of 42 volunteers from the average of RR, RMSSD, LF power, HF power, LF/HF ratio, and RCMSE calculated over the first 10 min and last 10 min of CVT, combined with the time course markers *iLF* and *iHF*. For the sake of simplicity, we represent the clusters with their respective characteristics with respect to each dimension (Dim1 and Dim2).

The K-means clustering algorithm applied on physiological metrics previously described partition the subjects into a set of 2 groups, as shown in Figure 4. The resulting clusters have similar levels of mental fatigue (VAS) and perceived workload (NASA-TLX). However, Cluster 1 is characterised by a better performance during CVT (p value = 0.04). In addition, this cluster is characterised by a lower sympathetic activity, with a significantly lower RMSSD (p-value <0.001), HF power (p-value < 0.001), and *iLF* (p-value = 0.005) indices. It also differs from cluster 2 with a higher sympathetic activity, with higher LF power (p-value < 0.001), and logically enough, an higher mean RR (p-value < 0.001) and LF-HF ratio (p-value < 0.001).

5. Conclusions and Perspectives

So far, biomarkers such as LF and HF powers have been averaged over the whole task in the protocol. However, they are known to vary along time in response to stimuli. In this

paper, we suggest adding markers describing the time evolution of the LF and HF power during the task. The choice we made is the proportion of increasing parts of the polynomial trends of the LF or HF powers over time. Both indices bring a real added value to the study of individual signatures to mental fatigue since they allow a more precise characterisation of individual profiles over time.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The dataset generated and analyzed during the current study is available from the corresponding author on a reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AR	Autoregressive
ARMA	Autoregressive moving average
CVT	Continuous vigilance task
ECG	Electrocardiogramm
EEG	Electroencephalogram
EMG	Electromyography
HRV	Heart rate variability
LF	Low frequency
HF	High frequency
MA	Moving average
PCA	Principal component analysis
RCMSE	Refined composite multiscale entropy
RMSSD	Root mean square of successive differences
VAS	Visual analogue scale

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