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Stress and heart rate: significant parameters and their variations

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Abstract The aim of this paper is to identify heart rate parameters with higher significant values when a set of people are performing a task under stress condition. In order to accomplish this, one computer application with arithmetic and memory activities which lets drive the subjects to different stages of activity and stress has been designed. Tests are formed by initial and final rest periods and three task phases with incremental stressful level. Electrocardiogram is measured in each state and parameters are extracted from it. A statistical study using analysis of variance (ANOVA) is done to see which ones are the most significant. It is concluded that the median of RR segments is the parameter to best determine the state of stress.

Keywords: Electrocardiogram, Heart Rate, Stress, Physiological Computing.

1. Introduction

Nowadays, interaction with most computing systems does not take into account the state of the users operating them, responding identically to different users or their emotional state. Overcoming this obstacle is the goal of Affective Computing (AC) that has been a promising research field since the end of the last century. AC can be defined as using emotional and contextual information of the user, such as facial expression [1], nonverbal features of speech [2], etc., to modify the behavior of an application [3-6]. A subfield in AC is Physiological Computing (PC) based on data from the human body and how it changes to "provide one means of monitoring, quantifying and representing the context of the user to the system in order to enable proactive and implicit adaptation in real-time" [7].

This intelligent technology can be used in many different fields to improve the adaptive capability of a system [8]. PC has been researched as an assistive system for reducing the frustration, arousal states, mental block and workload, for example, in driving [9-12] and regulating a notifications system [13]. It has also been applied to maintain the level of challenge and prevent boredom in computer games [14,15]. In addition, reinforcing positive emotional states or reducing negative emotion is another domain of research of PC; for example, changing music according to the mood of the subject [16] or speeding up the recovery from stress [17] by using biofeedback technique. The main idea in all these systems is to determine the subject's emotional state. Some research has concentrated on identifying these states as anger, happiness, disgust, surprise, sadness and fear [18] or a subset of these [19-24], while others have focused on arousal, stress, workload and/or cognitive-mental load [25-32]. They have tried to establish the effect of various psychological states with diverse physiological elements (many-to-many relationship), to determine how several emotional states affect a unique body measure (one-to-many relationship), or gauge the influence of a psychological state on different physiological data (many-to-one relationship) [33,34]. Thus, when designing an AC system one has to determine how the task modifies body parameters.

This paper attempts to establish a one-to-one relationship focus on heart activity and stress state. An individual feels different situations and levels of psychological pressure in the course of a day. Stress, defined as the organism's psychosomatic response to external influences identified as dangerous, threatening or unpleasant, causing a fight-escape reaction [35], has been identified as the second cause of occupational health problems by the European Foundation for the Improvement of Living and Working Conditions [36]. The most common causes of stress are situations that evoke a negative memory of previous stressful situations. There is a large interest in knowing how stress can be efficiently detected by measuring heart rate variability and/or other additional information such the one collected by filling in a diary [37] or a questionnaire [38]. Putting together all these informations might improve efficiency of a stress classifier. Nevertheless, physiological measurements by themselves, like HRV, usually outperforms diaries [38]. In [37] the diary method improves physiological data, but in that case just one subject took part in the study. Measuring HRV can be accomplished by detecting QRS complex in a conventional ECG or by analyzing the signal from finger plethysmography [39].

This work is framed inside a project whose main goal is the adaptation of an application (game, etc.) to prevent or mitigate stressful situations detected in the user by electrocardiogram measurements. To achieve this goal, on one hand we want to study how this heart rate signal changes under stressful situations and select a subset of parameters extracted from it that allow us to identify such situations in a reliable way. On the other hand, to mitigate stress or induce stress recovery, the environment has to react in some way. Some ideas have been pointed out in different works. One of them is based on reproducing sounds of nature in a virtual reality forest [40]. In the next section, we describe the experimental protocol (Section 2). Sections 3, 4 and 5 present the experimental results, discussions and conclusions.

2. Methodology

2.1 Procedure

The experimentation took place in a room with artificial lighting which was kept at a comfortable temperature. Subjects were seated on a padded chair placed 50 cm away from a 17" monitor with a resolution of 1280x1024 pixels and 32 bits of color. Each subject was asked to attend two 22-minute sessions with one week elapsing between each session. Subjects were randomly grouped into two subsets. Subset 1 performed the arithmetic task in the first week and the memory task in the second, while subset 2 performed the tasks the other way round.

Similar to other experiments conducted to analyze stress [30,41], each session consisted of 5 parts: the initial and final rest periods of 5 minutes and three 4-min phases (Figure 1) in which the task had to be completed. Subjects became accustomed to the task in the first phase, and the level of difficulty and stress were increased in the following phases. Phase 3 should have the greatest level of stress.

Two questionnaires based on the standard State-Trait Anxiety Inventory (STAI) were filled in at the beginning of each relaxation phase [42], where the subject relaxed reading a magazine. The range of results of testing was between 0 and 60 with the minimum and maximum values indicating total stress/anxiety and complete relaxation.

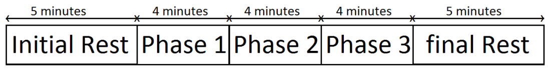

Figure 1.Timing of trials.

A Java application was developed to implement the different tasks the subjects had to carry out. The application contains two activities (memory and arithmetic) with different difficulty levels (Figure 2. The application screen has four areas: time bar, performance bar with two indicators (correct answers and comparison to population), answer panel that shows 1 out of 3 messages (correct/non-correct/time out) and a task panel showing the activity.

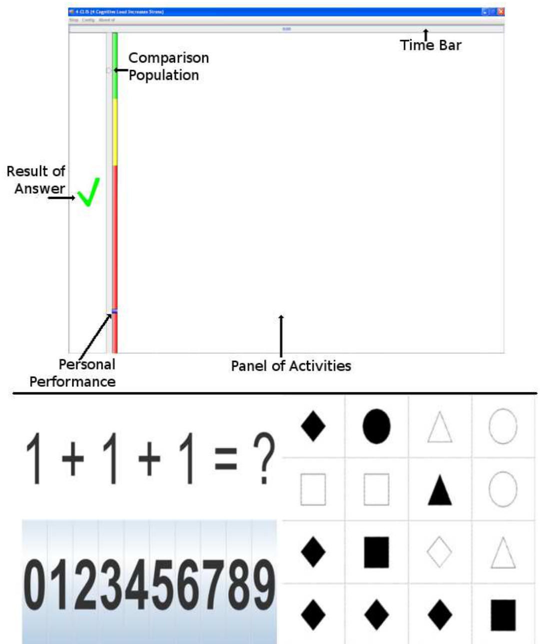

Figure 2. On the top: the Main Application Window, showing the panel for memory and arithmetic activities. In the down-left, the arithmetic panel and on the down-right, the memory panel.

The arithmetic task is based on the Montreal Imaging Stress Task (MIST) [26] where the subjects perform basic math operations (add, subtract, multiplication) whose results are always in the range between 0-9.

The memory activity consists of a matrix where each cell contains a black or white geometric figure (circle, square, triangle, diamond). The individual must memorize the geometric figure, its color and position and then fill in an empty 2x3 matrix [25].

A timer is incorporated to limit the answer periods and set a timeout interval for all phases. The timeout decreases by 10% after 3 consecutive correct answers and increases by 10% when the subject accumulates 3 incorrect responses or/and exhausted timers. The purpose of the timer is to prevent success in the task and to increase stress. Timing in the memory task is greater than in the arithmetic task to allow subjects to finish it properly.

The answer panel shows the result of the subject's (correct or incorrect) answer or a timer timeout. A personal score increases by one unit after a correct answer, otherwise it decreases by two.

The performance bar only compares the correct answers with 1.5 times the average of results for other subjects. For the first subject we used data obtained from application testing. A red color (0-60%) shows bad performances, yellow (60-80%) mediocre and green (>80%) very good performances.

Finally, the population mark, on the left of the screen, shows 90% of the average for all individuals who have taken the test since it was first implemented.

In Phase 1, or accommodation period, the subjects grew accustomed to the task. This phase is free of pressure and the performance bar is not shown. The average of the results for the population was calculated with the correct answers for this period (the subjects were not aware of this) to determine the population comparison indicator (Figure 1).

In Phase 2, each subject was asked to try and exceed the population result indicator, being told that otherwise the data could not be used to compute the average for other individuals. The mental stress and arousal were therefore higher in this phase.

In Phase 3, the researcher introduced stressors by telling the subject that the data from the last phase was useless because he/she had not achieved the goal, unlike the rest of the subjects who had passed the phase correctly. Even more stress was added by asking questions such as "Did you sleep well?", "Do you have personal problems?", etc. and making comments such as "You've got it wrong", "You must concentrate", "Time's running out".

2.2 Subjects

The trials were conducted with 13 healthy subjects aged between 26-56 (mean 37.86; sd 9.93), two of them were women and eleven men. All of them are voluntary and they work in our same site.Twelve subjects completed the arithmetic task, while eleven performed the memory task. We should also mention that the ethics committee of the University of Seville approved this research.

2.3 Equipment

The biosignal was recorded using bioamplifier model gtec gUSBamp, and version 2.0 of the BCI2000 software [43]. The sample rate of the bioamplifier was set at 256 Hz, with a notch filter (48, 52)Hz to delete electrical power signals. A bandpass filter of 0.5, 100 Hz was applied.

Auto-adhesive Ag/AgCl Electrodes with conductive gel were used.

The offline data analysis was done with version 7.6.0.324 of Matlab.

2.4 Data Acquisition

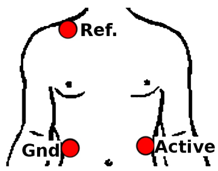

Figure 3. Electrode assembly.

The Electrocardiogram (ECG) signal was recorded using monopolar assembly. The reference was set on the right clavicle whereas the ground electrode was fixed below the right floating rib and the active sensor was placed below the left floating rib (Figure 3).

2.5 Parameters extracted from ECG

In this section we will explain how ECG was processed and what features were extracted from it. Also, the outlier values were avoided in our analysis using the interquartile-range method, that is, the values out of [Q1 - 1.5(Q3 - Q1), Q3 + 1.5(Q3 - Q1)] were eliminated, where Q1 and Q3 are the lower and upper quartiles respectively.

The RR segments are obtained from the ECG signal through the Pan-Tompkins algorithm [44]. Different parameters are extracted from HR and they may be classified in two groups: information based on temporal analysis and that based on frequency analysis [45]. The more common calculated parameters of the first group are the standard deviation of RR intervals (SDNN), the square root of the mean squared difference of successive RR segments (RMSSD), the proportion of RR intervals that differ by more than 50ms (pNN50), the width of the minimum square difference triangular interpolation of the highest peak of the histogram of all RR intervals (TINN). The other group is based on calculating the power spectrum density (PSD) of the HR. Normally, the PSD is divided in 4 parts: frequency from DC to 0.003Hz (Ultra Low Frequency - ULF), from 0.003 to 0.04Hz (Very Low Frequency - VLF), from 0.04 to 0.15Hz (Low Frequency) and from 0.15 to 4Hz (High Frequency - HF). One additional parameter is the ratio between LF and HF (LF/HF). The influence of each band on the PSD is calculated as the sum of the PSD of the band divided by the sum of all PSD. The SDNN, RMSSD and TINN are used to determine the variability over a short time period to obtain the influence of Parasympathetic Nervous System (PSNS). Important information about quick random changes of heartbeat is extracted from pNN50. The frequency bands can inform about different pathologies, such as the thermoregulatory system (ULF band), blood pressure (LF) and breath (HF). Also, the HF band is connected with the parasympathetic system, whereas the sympathetic system is linked with LF. Thus, the LF/HF ratio is associated with the Autonomic Nervous System (ANS), so that an increase in sympathetic activity causes its value to rise, while an increase in parasympathetic activity causes its value to fall.

Additionally, we obtained the main frequencies of each band (fmVLF, fmLF, fmHF), by applying equation (1), main frequency (fm) is calculated as the average weighted spectral frequencies with energy spectrum density (ESD).

$$fmb = \left(\sum_i f(i) \cdot ESD(i)\right) \Big/ \sum_i ESD(i) \quad \text{(Eq. 1)}$$

The median of RR segments (Mrr), was obtained too. This measure is based in the histogram too, it is simple but not as common as the other measures based in HR.

3. Results

We are not just interested in discovering how the different features change through the phases for a specific subject, but also in choosing the best features for detecting the onset of a stressful situation for a population as a whole. After obtaining the features for the set of subjects in each phase we studied the ANOVA test for the variations of such features through the different phases in order to select the ones with statistical significance. The variations between phases were obtained by applying the equation (2), where ΔJ^i_{ref} is the variation of the parameter *J* in the phase *i* with phase *ref* as refline; ΔJ^i and ΔJ^{ref} are the values of the parameter *J* in the phase *i* and *ref* where $i \neq ref$.

$$\Delta J^i_{ref} = 100 \cdot \left(\left(J^i / J^{ref}\right) - 1\right) \quad i \neq ref \quad \text{(Eq. 2)}$$

The expected behavior for the change from the initial-rest period to the first task phase is a change resulting from a higher-induced stress level, since the subject passes from an initial relaxed state to a mental-activity period and because the individual does not know how the task and the control of the application work. Thus, the stress level is confirmed if these variations occur in the other activity phases compared to the initial rest time. So, a significant difference between task phases and rest periods is the a priori expected behavior (PEB), making it possible to distinguish between the activity and relaxed states. This is the goal of the first analysis (A1). The parameters which do not show those changes must be rejected as correct indicators of stress level, even if one of the phases has a significant change.

Passing from one phase to the next means an increase in what a subject is required to do in an activity. In fact, from rest to the performance period (or viceversa) means moving from relaxed (or arousal) to arousal (or relaxed) state, because the individual goes from reading a magazine to answering different mental operations without having the pressure of an aim. In addition, the second activity phase raises the stress level, in that the subject must achieve a target, and the third phase increases the arousal state because the subject did not succeed in the previous phase. This is the focus in the second analysis (A2). The desired behavior is a significant change from one phase to the next, with the stress level being higher in an activity phase and lower in the relaxed periods.

The arousal of the first activity phase is the induced initial stress level. Taking this phase as baseline, the expected behavior of the parameters is a significant variation from their values in rest periods. Also, the other activity phases must maintain or increase stress levels. Thus, we expect results to include significant changes for the start and finish relaxed phases, and significant variations or not depending on whether stress levels are similar or vary. Therefore, the target of the third analysis (A3) is to distinguish between the stress level and arousal produced by the task.

The three analyses mentioned above were carried out using a one-way analysis (ANOVA). The A1 analysis was performed using the initial rest phase as reference, so that the changes due to the task could be observed. The A2 analysis compared one phase to the previous phase (ref line). This showed the differences between phases, and made it possible to determine whether there was an incremental stress effect. The A3 analysis was done with the first activity phase as refline. The first performance period was used because the subject grew accustomed to the task without pressure. Using this phase as triger line made it possible to calculate the variations caused by the stress level.

Outliers were dismissed beforehand because the ANOVA is very sensitive to them, although we did not find more than 3 outliers in the worst case.

3.1 Test STAI

As we mentioned earlier, the subjects were given two stress tests during the initial and final rest phases for arithmetic and memory tasks. The difference between the final and initial STAI scores gave us information about whether or not the task was stressful. Negative differences indicated that the task was stressful, whatever the experimental situation for both tasks. Specifically, in the arithmetic task, the average difference was -7.5 with a standard error of 2.18%, and in the memory task this difference was -5.0 with a standard error of 1.46%. An ANOVA analysis applied to the initial and final STAI tests confirmed that such differences were significant (arithmetic p= 0.004, memory p=0.05)

3.2 Electrocardiogram

Table 1 contains the maximum p-value obtained using A1 analysis for each parameter and task in no significant cases. Exceptions are ΔpNN50 and ΔHF band in the memory task as shown below.

	Arithmetic	Memory
ΔSDNN	0.97	0.78
ΔRMSSD	0.25	0.13
ΔTINN	0.88	0.67
ΔVLF	0.39	0.51
ΔLF	0.65	0.91
ΔLF/HF	0.81	0.21
ΔfmVLF	0.51	0.93
ΔfmLF	0.69	0.71
ΔfmHF	0.79	0.68

Table 1. Maximum p-value in task phases for A1 analysis.

Although the averages of most parameters applied to subjects were not statistically significant, there were changes in heart rate for all of them. In Figure 4 we can see the histogram in both the two phases of rest and the three of activity for one of the subjects who performed the test. It can be observed that RR intervals changed significantly throughout the experimental task. The maximum for the histogram shifted to the left when the subject went from rest period 1 to phase 1. This implies a reduction in the RR interval or, equivalently, an increase in heart rate. One can also see how, even in the most stressful phase, phase 3, this histogram shifted even further to the left. The final period, rest 2, caused the histogram to shift to the right and go back to the initial position. Hence, a parameter exhibiting the shifting of the histogram through the different phases and showing robustness against outliers is needed. The median of RR segments (Mrr) was not sensitive to outliers and adjusted fairly well to the shifting of the histogram, so this might be a good choice.

A first approximation of the performance of this parameter is shown in Figure 5. The horizontal axis contains all the experimental subjects, with the vertical axis showing the ΔMrr parameter according to the experimental phase. The expected behavior for phase 1 was that the position of the median would decrease from the refline (rest 1) and continue to drop even further as the experimentation moved into phase 2 and 3. This behavior was observed for most subjects in both tasks. Subjects 4, 5, 7, 8 and 10, in the arithmetic task, and 2, 8 and 11, in the memory task, showed a sequential decrease in Mrr values through the phase. In the memory task, subjects 1, 4, 5, 6, 7, 9, and 10, and 2, 9 and 11 in the arithmetic task exhibited a lower value in the third performance than in the second. The final rest period had a higher value in 13 cases (6 arithmetic / 7 memory) than in the initial rest time and in 5 cases they were almost the same.

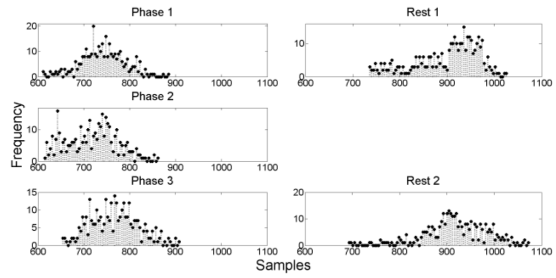

Figure 4. RR interval Histogram for a subject in different phases.

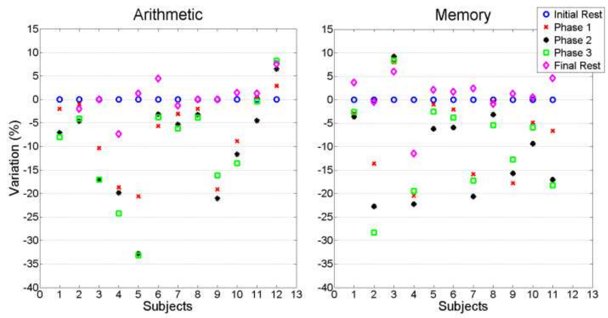

Figure 5. Median variations for subjects.

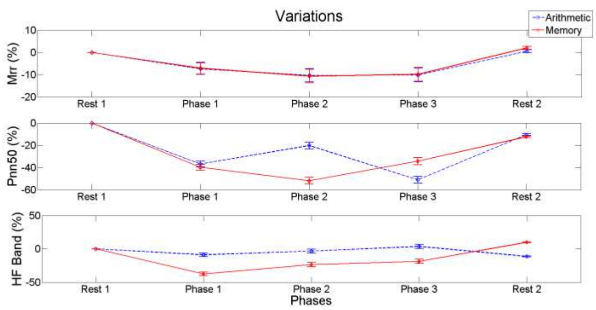

Figure 6. ΔMrr, ΔPnn50 and ΔHF-band averages.

Figure 6 shows the ΔMrr averages for all phases and tasks based on analysis A1. One can see that for both tasks its behavior was very similar. For phase 1 ΔMrr fell showing that the RR interval decreased, and for phases 2 and 3, when more stress was applied, the ΔMrr dropped again close to -10% (±3%) but it is not easy to distinguish phase 3 from the previous one. As the task ended and the subject went to the final rest period, the median rose up to the refline. The ANOVA test confirmed what we can see in Figure 6 ΔMrr was very significant for the A1 analysis in which the p-value was lower than 0.01 for all phases and tasks, excluding the final rest period, and the p-value for phase 3 in analysis A2 and A3 was not significant.

The ΔpNN50 did not behave as expected as we can see in Figure 6. In the arithmetic task, this parameter drew a w-shape, going down in phase 1, then up in phase 2, and so on to the end. The ANOVA test (Table 2) showed this feature was not significant in the A1 analysis (p=0.25 in phase 2). This situation was similar for this parameter and the memory task, where the curve it described was not PEB compliant but the A1 ANOVA test was significant (p<0.01 for phases 1-3).

		Phase				
		Rest 1	Phase1	Phase2	Phase3	Rest 2
A1	ΔMrr		<0.01a 0.02m	<0.01a <0.01m	<0.01a <0.01m	0.31a <0.01m
	ΔpNN50		<0.01a <0.01m	0.25a <0.01m	<0.01a <0.01m	0.33a 0.14m
	ΔHF		0.52a <0.01m	0.81a 0.05m	0.80a 0.05m	0.79a 0.43m
A2	ΔMrr		<0.01a 0.02m	0.02a 0.02m	0.21a 0.39m	<0.01a <0.01m
	ΔpNN50		<0.01a <0.01m	0.07a <0.01m	0.27a 0.46m	0.05a <0.01m
	ΔHF		0.52a <0.01m	0.73a 0.78m	0.12a 0.12m	0.50a 0.15m
A3	ΔMrr	<0.01a 0.02m		0.02a 0.02m	0.10a 0.30m	<0.01a <0.01m
	ΔpNN50	0.37a 0.04m		0.07a <0.01m	0.15a 0.33m	0.13a <0.01m
	ΔHF	0.54a 0.03m		0.73a 0.78m	0.90a 0.17m	0.87a 0.02m

Table 2. ANOVA Analysis of ECG. a=arithmetic, m=memory.

ΔHF showed PEB in the arithmetic task but not in the memory task. Focusing on the first task, the ANOVA test was not significant either for activity or stress detection. The significance in this feature only appeared as an indicator of activity in the memory task.

4. Discussion

During the development of a stressful activity changes occur in the homeostasis of the human body which can be detected because several regulatory variables modify their resting values. The progressive increase in the level of stressors during the subject's task would determine the dependence of the analyzed variables with the degree of induced stress. The analysis conducted in this study aimed to identify such dependencies and profile a subset of these variables which would be suitable for stress detection in a population. To achieve this goal we have to take into account, on the one hand, that a variable is suitable for detecting stress when it is significant from a statistical point of view. Due to the variability in resting values in a population, the statistical analysis requires, on the other hand, changes in these variables to be processed subject by subject before they can be used in a statistical study, otherwise the results could be irrelevant.

The trials were designed to increase the stress level in each activity phases. However, observing the ANOVA results and parameter's variation charts could be concluded the subjects were less arousal in the third task period, where it had to be the most stressful performance. This fact may be caused by the users tried relax and concentrate because they previously did twice the operations and their nervousness level made that they failed. Furthermore, it should also take into account that the main difference between the third and second phase were the questions of the person driving the experiment. The desired stress increase could not be achieved.

It is important in this study to identify an activity period from a rest phase, differentiate properly an unstressful activity from a stressful one, and check variable dependency on stressor intensity. To achieve these goals, we carried out three types of analysis. In analysis A1, we wanted to calibrate the changes in the set of values of the physiological variables when the task (or stressful task) was performed compared to the rest state and thus determine how the activity and stress affected them. In the second analysis, A2 and A3, we identified stress by erasing the effect the activity had over the analyzed variables.

Finally, to confirm that the proposed tasks were stressful, the STAI test was given to subjects at the beginning and at the end of each trial. The results confirmed that the tasks subjects performed did produce stress.

Most of the typical features widely used in ECGs are not suited to showing clearly the shifts in the RR- histogram even if the outliers are deleted. Their sensitivity to extreme values may be the cause. However, the median of RR segments was less sensitive to outliers and was better for showing the histogram shift between phases.

The value of the median, ΔMrr, in the arithmetic and memory tasks decreased significantly during phases, while it was similar in rest periods. Furthermore, the changes from one phase to the next showed that the stress level was the cause of this variation. The phase 3 showed a behavior indistinguishable from the others two task periods (analysis A2 and A3 show that), in spite of changes of this feature (Figure 3.2.3) drew similar values of average and standard error respect to phases 1 and 2. This can be due to the fact that the subjects knew the operations and they tried to get relaxed. We conclude that this feature is appropriate for being used as a stress detector.

On the other hand, the ΔpNN50 and ΔHF band only exhibited relevance in the memory task. A low pNN50 meant that the variability of the RR segment was also low, so the PSNS activity was lower and thus subjects were more aroused. The HF band was also linked to PSNS, so low values in this band represented a reduction in activity in PSNS, meaning individuals were more overexcited.

5. Conclusions

The goal of this research was to determine the statistical significance of the effect of stress levels in parameters related with HR and verify the results with a subjective psychological questionnaire. To do this, these biosignals were recorded, processed and analyzed. The STAI test confirmed that the significant parameter changes were caused by increased stress levels during task periods, since the results showed lower values after activity periods than before they had started. Some features extracted from biosignals changed depending on the task and their variations were significant during the arithmetic tasks while others were significant during the memory activity task. A summary of significant parameters is shown in Table 3.

The most interesting parameters were those that made it possible to distinguish activity and stress situations in both memory and arithmetic tasks. This was the case of ΔMrr in ECG.

ΔpNN50 and ΔHF of ECG also showed effects in both tasks but only weakly.

PHYSIOLOGICAL SIGNAL	PARAMETER	ACTIVITY INDICATOR	STRESS INDICATOR
ECG	ΔMrr	both tasks	both tasks
	ΔpNN50	both tasks	both tasks
	ΔHF	both tasks	both task

Table 3. Significant parameters.

In future work, we will analyze stressor effects on others biosignals as a result of the tasks described in this paper, examining the best features for detecting such a situation. When significant physiological variables are detected, they should all be combined into a system capable of deciding about the state of the subject and acting accordingly, so as to lead the subject towards a less stressful state.

6. Acknowledgements

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