Analysis of the Electromechanical Activity of the Heart from Synchronized ECG and PCG Signals of Subjects Under Stress

Ana Castro[1], Ali Moukadem[2], Samuel Schmidt[3], Alain Dieterlen[2] and Miguel T. Coimbra[4]

[1]*Faculdade de Engenharia, Universidade do Porto, Porto, Portugal*

[2]*MIPS - IUT, Université de Haute-Alsace, Mulhouse, France*

[3]*Department of Health Science and Technology, Aalborg University, Aalborg, Denmark*

[4]*Instituto de Telecomunicações, Departamento de Ciência de Computadores, Faculdade de Ciências, Universidade do Porto, Porto, Portugal*

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Abstract: In this exploratory study we propose to analyze, in healthy adult volunteers, the heart electrical (electrocardiogram, ECG) and mechanical (phonocardiogram, PCG) activity during exercise. Heart sounds amplitude, frequency content, and RS2, may be important features in the non-invasive assessment of heart activity, such as for the estimation of cardiac output and blood pressure. Nine healthy volunteers were monitored with ECG and PCG simultaneously, under a stress test. After each workload level a 10 s window of signal was collected. PCG first (S1) and second (S2) heart sounds were manually annotated, based on time of QRS complex occurrence. A QRS detector was implemented to detect the QRS complex, and time intervals between electrical and mechanical events. Extracted features were analyzed in relation to heart rate (HR), including RS2, S1 and S2 amplitudes, and high frequency content of S1 and S2. Spearman correlation was used. Changes between baseline and maximum workload stage/HR for each volunteer were analyzed. Significant correlation was observed between HR, and all characteristics extracted ($P<0.01$). There was a clear difference between all variables from baseline to maximum workload level: with increasing workload/HR heart sounds amplitude increased (more pronounced in S1), RS2 decreased, and high frequency content of S2 decreased in relation to the high frequency content of S1, demonstrating that dynamic cardiovascular relations are individualized during cardiac stress and that assumptions for resting conditions may not be assumed.

1 INTRODUCTION

The heart is the center of the cardiovascular system, pumping blood to the pulmonary and systemic circulations, taking oxygen and nutrients to all organs.

During exercise, the muscles need for oxygen and nutrients, leads to an increase in heart activity and respiration rate. It is known that stroke volume (SV) in athletes is superior to the normal person, nonetheless in rest condition the cardiac output (CO) is comparable between the two, since heart rate (HR) tends to be lower in the athletes.

With increasing levels of exercise, oxygen consumption increases, leading to an elevated CO. The CO increases as a function of increased HR (major responsible for this increase), and SV, which tends to stabilize in a plateau (Guyton and Hall, 2006). Also, the blood pressure (BP) during exercise is increased (Sullivan et al., 1989).

Heart function may be monitored through different means, such as electrical activity (electrocardiogram, ECG), and the register of mechanical activity through ecocardiography, or heart sound auscultation (phonocardiogram, PCG). In the PCG, the heart cycle period (S11) is depicted in four main components: the first sound (S1) corresponding to the closure of mitral and tricuspid valves, the systolic period (S12), the second sound (S2) corresponding to the closure of the aortic and pulmonary valves, and the diastolic period (S21) (Guyton and Hall, 2006).

The correct identification of heart sounds allows retrieval of information from each component, including the detection of murmurs and their characteristics, which is very important for cardiovascular pathologies screening. The S2 is described as being composed by two components: the first related to the closure of the aortic valve (A2) and systemic BP, and a second component related to the closure of the pul-

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monary valve (P2) and pulmonary BP (Guyton and Hall, 2006; Xu et al., 2001). Previous studies have demonstrated a relation between S2 characteristics such as amplitude and frequency, and the arterial BP both on the systemic (Bartels and Harder, 1992) and pulmonary circulations (Xu et al., 2001; Smith and Ventura, 2013).

Electrical and mechanical time events in the heart cycle have also been explored to better understand cardiovascular function, using pulse transit time (Sola et al., 2011), vascular transit time (Chandrasekaran et al., 2013), RS2 timing (Figure 1) (Zhang et al., 2008) and their relation to BP and CO, in the search for non-invasive estimations of these variables.

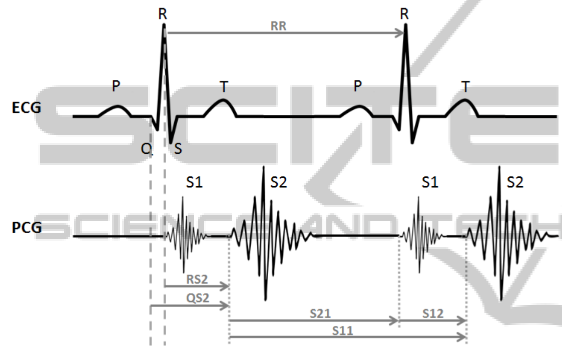

Figure 1: Representation of the heart electromechanical activity as measured by the electrocardiogram (ECG) and the phonocardiogram (PCG), with time intervals of interest.

Individual response to cardiac stress is dependent on baseline conditions and dynamic adaptations during exercise, nonetheless assumptions for resting conditions may not me assumed under cardiac stress. The study of the dynamic relations between electrical and mechanical cardiac events may introduce important information for the non-invasive assessment of cardiac state (CO and BP e.g.) (Zheng et al., 2014). In this exploratory study it was aimed at analyzing, in adult volunteers under different exercise levels, the evolution of the heart electromechanical activity until stress is reached, including RS2 time interval and the amplitude and frequency characteristics of heart sounds, in order to better understand these relations during exercise.

2 MATERIAL AND METHODS

2.1 Data Collection

To study experimentally the variation of some physiological parameters in the ECG and PCG signals under a stress test, data collected from healthy subjects from the department of Health Science and Technology, Aalborg University is used in this paper (Ronved et al., 2011).

Nine healthy subjects were enrolled in the study, four females and five males, with median age 32 (24-36). Informed consent was retrieved from all subjects prior to the exercise test.

A Panasonic microphone was incorporated in a coupler, specially designed by the Department of Acoustics at Aalborg University, Denmark. The microphone detects the mechanical pressure differences in the coupler, caused by alterations of the sound pressure. The microphone records with a sampling frequency of 48000 Hz. The microphone was fitted to the 3rd left intercostal space with a specially designed double adhesive plaster. The heart sound recordings are synchronized with a 3-lead ECG.

Following monitoring, the subject cycled on a Monark Ergometric 894E ergometer bicycle, and the workload was increased by 25 Watt every two minutes, with an initial workload of 25 watt. The subject cycled until subjective maximum endurance was reached. Afterward subjects that did not reach 80% of maximum heart rate defined as 220 minus age$\pm$12 were excluded from the study. One subject did not reach this rate and was therefore excluded from the study. Recordings of heart sounds were made for 10 seconds at the end of each workload level.

An Acarix Data Acquisition System was used for recording the heart sounds and ECG (Hansen et al., 2011).

2.2 Electromechanical Activity Analysis

PCG and ECG signals were visually inspected, and the heart sounds manually annotated based on the point where the variation from the baseline began (Ronved et al., 2011).

For the ECG, a QRS detector based on the wavelet transform was implemented. A zero-phase, Butterworth band-pass filter was applied to the data (10-25 Hz), and the wavelet transform level 8 was obtained. Energy peaks of detail coefficients at levels 7 and 8 were used in a peak-picking algorithm to detect the QRS complex (Kohler et al., 2002; Zidelmal et al., 2012).

Figure 2 presents the collected signals in one of the volunteers in the study, including the manually annotated heart sounds, and detected QRS complexes.

Markers from the ECG were crossed with the PCG markers to obtain the electromechanical time intervals, for the different workload levels. For each heart sound cycle manually annotated, the algorithm searched for the corresponding QRS complex (within

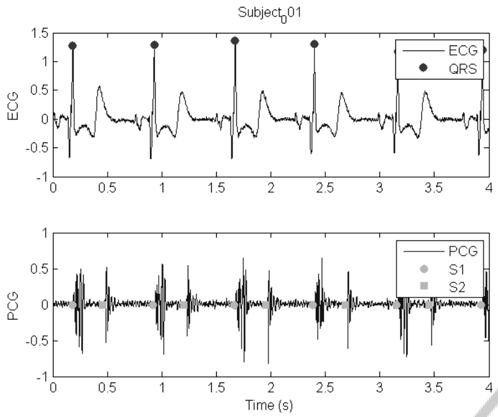

Figure 2: Data from one of the volunteers in the study, at rest condition: on top the electrocardiogram (ECG), and below the corresponding phonocardiogram (PCG) with overlapping markers of the first heart (S1) and second (S2) heart sounds.

a 50 ms neighborhood of S1), and when a match was obtained, the time intervals were registered with the corresponding workload level.

RS2, RR, S12, S21 and S11 time intervals were extracted as the time difference between each marked event as depicted in Figure 2.

For the assessment of the heart sounds' amplitudes the temporal contour envelopes were extracted from each S1 and S2, based on the local maximums and minimums of the signal, and interpolated using a cubic Hermite spline, as may be observed in Figure 3. The contour envelopes were used to estimate the amplitude of heart sounds. The cubic Hermite spline was used since it produces smooth contour envelopes of the signal without overshoot.

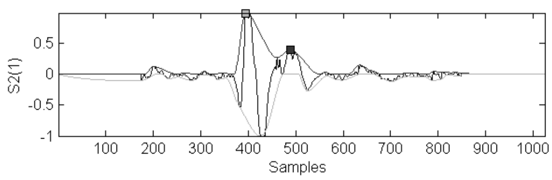

Figure 3: Example of the temporal positive and negative contour envelopes of a S2.

2.3 Assessing the High Frequency Content of Heart Sounds

Besides time analysis the frequency content of S1 and S2 with increasing workload levels/HR was analyzed. As referred earlier, the initial component of S1 is related to the mitral and tricuspid valve closure, due to the contraction of ventricles, thus identifying the onset of ventricular systole and the end of mechanical diastole (Felner, 1990a). The S2 is produced by the aortic and pulmonic valves closing when left ventricular pressure decreases under diastolic aortic pressure. The vibrations of S2 occur at the end of ventricular contraction and identify the onset of ventricular diastole and the end of mechanical systole (Felner, 1990b).

Normally, S2 exhibits higher frequency content than S1, however the intensity and frequency of the S1 are affected by the velocity of the forces responsible to the acceleration and deceleration of the blood masses, which on the other hand are directly related to the HR (Felner, 1990a).

In this paper, the high frequency content of S1 and S2 is assessed and its variation over HR is investigated. The frequency content is calculated from the Stockwell transform (S-transform) which is a time-frequency transform (Stockwell et al., 1996).

The S-Transform originates from two advanced signal processing tools, the Short Time Fourier Transform (STFT) and the Wavelet Transform (WT). It can be viewed as a frequency dependent STFT or a phase corrected WT. The S-transform is becoming a valuable tool applied on many signals and domains as cardiovascular (Moukadem et al., 2013), EEG signals (Assous and Boashash, 2012), geophysics (Pinnegar and Mansinha, 2003), power system engineering (Biswal and Dash, 2013), among others.

Figure 4 presents the heart sound S-Transform for the same volunteer, under two different workload levels.

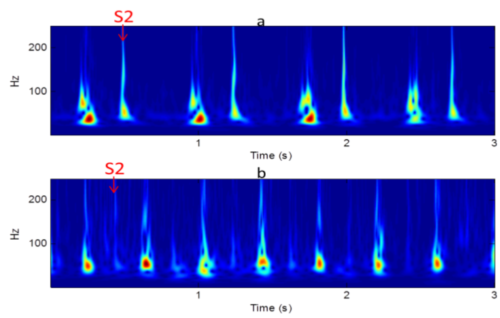

Figure 4: The S-Transform of two sounds corresponding to the same subject and two different heart rates (a: HR=80 bpm, b: 142 bpm) showing the high frequency content of S2 decreases when the heart rate is higher.

2.3.1 The High Frequency Content (HFC)

First, the heart sounds are segmented into S1 and S2 by using the algorithm proposed in (Moukadem, 2013) and the high frequency content is assessed as follows:

$$HFC_x(t) = \int_{-\infty}^{+\infty} S_x(t,f)df \tag{1}$$

where $f \in [50, 250]\,Hz$.

The function HFC_x gives the high frequency content of the given signal x (which is a S1 or S2 sounds in this case). A peak detector algorithm is then applied to assess the frequency content of each segmented sound and the ratio HFC_{S2}/HFC_{S1} (noted $S2/S1$ for simplicity) is calculated.

Figures 5 and 6 show an example of heart sounds selected from the database and the detected peaks on the HFC function which aim to assess the high frequency content of S1 and S2. We may observe that with increasing HR, the HFC of S2 is decreased.

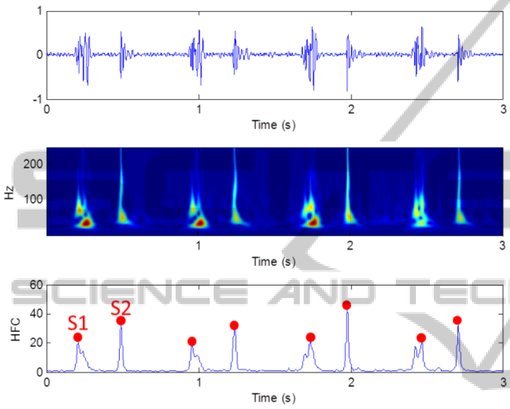

Figure 5: Heart sounds selected form the database (top), the S-transform (middle), the HFC function and the detected peaks where $HFC_{S1} < HFC_{S2}$ (bottom).

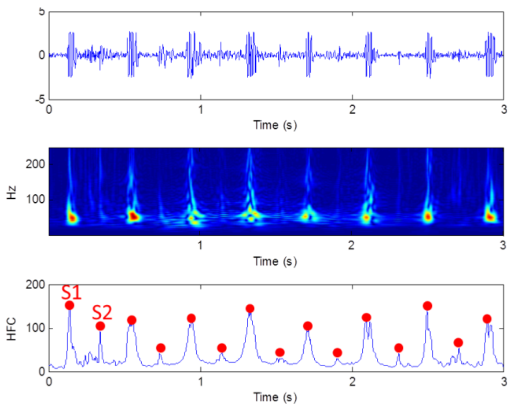

Figure 6: Heart sounds selected form the database (top), the S-transform (middle), the HFC function and the detected peaks where $HFC_{S1} > HFC_{S2}$ (bottom).

2.4 Statistical Analysis

Data collected from nine volunteers was downsampled to 2 kHz, and analyzed for each selected workload level. One of the volunteers was excluded from the analysis due to protocol deviation. The eight volunteers started the experiment with different baseline HR values for the first workload (76±17.6), and reached different workload levels (9, 12, 12, 7, 10, 14, 8, 6).

For each subject four heart cycles are selected at four different stress levels (different HR), then the mean and the standard-deviation of the extracted features are calculated in relation to the HR. Extracted features include HR, RS2, S1 and S2 amplitudes, and S1/S2 HFC ratio.

Features were then analyzed in relation to the HR (Spearman correlation coefficient ρ), for the total data and for each subject individually.

Baseline conditions versus the maximum exercise workload achieved were compared using error bar plots.

3 RESULTS AND DISCUSSION

3.1 Electromechanical Activity of the Heart

It was observed that the RS2 time intervals decreased with increasing workload in all volunteers, as demonstrated in Figure 7. This decrease in time from electrical on-set to mechanical event (aortic valve closure) was accompanied by an increase in heart sounds' amplitude. S1 amplitude had a more pronounced increase than S2 as may be observed in Figure 8.

Table 1 presents the Spearman correlation coefficient values between the different metrics extracted from the PCG and ECG, and the workload levels/HR.

Table 1: Correlation between workload, HR and the variables extracted from the PCG and ECG, for the total dataset, and the average for each subject individually (* P<0.01).

	Total (ρ)	**Average Individual (ρ)**
RS2	-0.88*	-0.86
S1 Amplitude	0.47*	0.63
S2 Amplitude	0.12	0.29
S2/S1	-0.70	-0.88

We may observe that RS2 presents the highest correlation values for the total data set. This was also observed within each subject data. RS2 has been linked to blood pressure, which is also increased during exercise. This may configure a good indicator of cardiovascular changes during exercise, such as CO, BP, pre-ejection period (PEP), and the left ventricle ejection time (LVET) (Paiva et al., 2009; Carvalho et al., 2010; Sola et al., 2011; Sola et al., 2013). RS2 values present a high correlation with HR, both using the total data, as the individual changes, which indicates that this variable was similar among subjects (baseline values and evolution with HR).

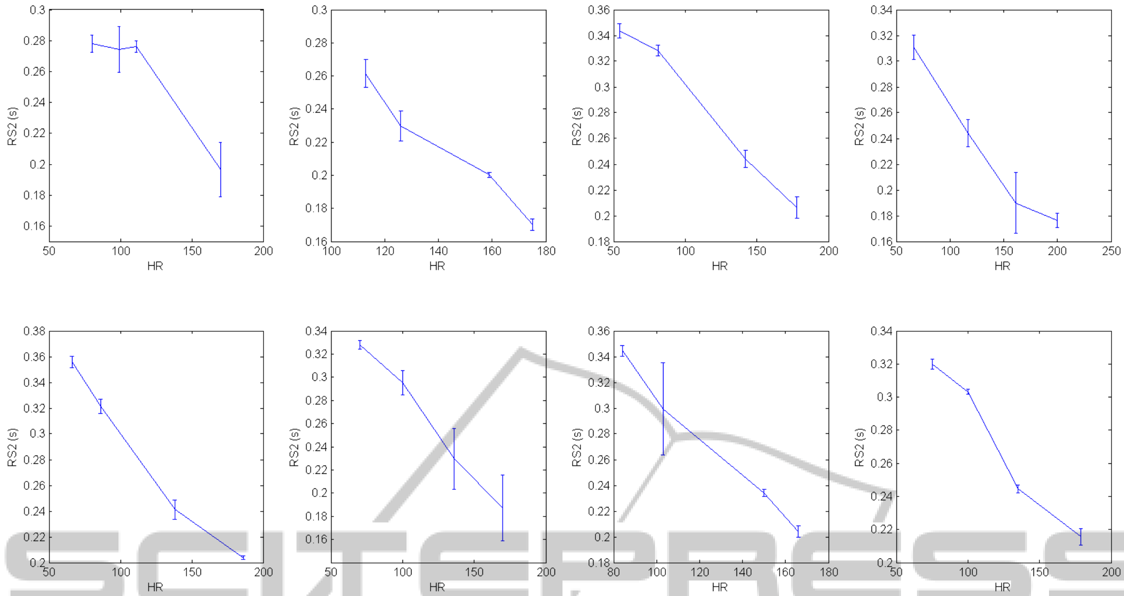

Figure 7: Variation of the RS2 interval over the HR for all subjects.

S1 amplitude also presented a good correlation with the workload/HR, however we should highlight that heart sound amplitudes are highly dependent on the acquisition conditions. Heart sounds amplitudes are known to vary with subjects' biotype, as well as microphone positioning and gain, representing a bias in the comparison of values for different subjects (subject 3 on Figure 8 e.g.). This was confirmed by the lower correlation for the total data set, when compared to the individual assessment.

In Figure 8 it is observed that S1 and S2 amplitudes present an increasing tendency with increasing stress levels (except subject 2), but with different baseline values for each subject. It is also observed that the amplitude ratio between S1 and S2 amplitudes are different at baseline, which may be a result of microphone positioning and subjects' biotype, as referred earlier. This however does not diminish the information contained in these signals on the mechanical activity of the heart under stress tests, if one considers an individual calibration, as suggested in (Bartels and Harder, 1992). Heart sounds amplitude and frequency content have been used in previous studies to estimate systemic and pulmonary BP (Bartels and Harder, 1992; Smith and Ventura, 2013; Dennis et al., 2010), and results in this preliminary study indicate that they also reflect the known cardiovascular changes during exercise (increased CO).

The observed changes in the electromechanical events and heart sound characteristics are the result of the heart effort to pump more blood to reach the tissues with increasing muscular effort. It is known that the heart morphology varies with increasing exercise (left ventricle diameter e.g.), and depending on the type of physical activity (Pluim et al., 2000), this results in different baseline and stress adaptations from the cardiovascular system, which may explain the difference between volunteers regarding the baseline values observed, and maximum workload achieved.

The different features extracted may convey important information on the assessment of the cardiovascular system, and allow for the better understanding of these changes during a stress test.

3.2 Assessing the High Frequency Content of Heart Sounds

To show experimentally the relation between the frequency content of heart sounds and the HR, the HFC of S1 and S2 is estimated as described earlier. Results for the eight subjects in the experiment considering $S2/S1$ are presented in Figure 9.

The results in Figure 9 show clearly the direct relation of the frequency content of the heart sounds and the heart rate. Normally, S2 has a higher frequency content than S1 ($S2/S1 > 1$) except for subject 5. When the heart rate increases, the high frequency content of S2 decreases which decrease the ratio $S2/S1$, also observed in Figures 5 and 6.

The red line in Figure 9 indicates when the frequency content of S1 exceeds the frequency content of S2. The HFC ratio (S2/S1) presented a very good correlation with the workload/HR (-0.88). However, a lower correlation results for the total data set is ob-

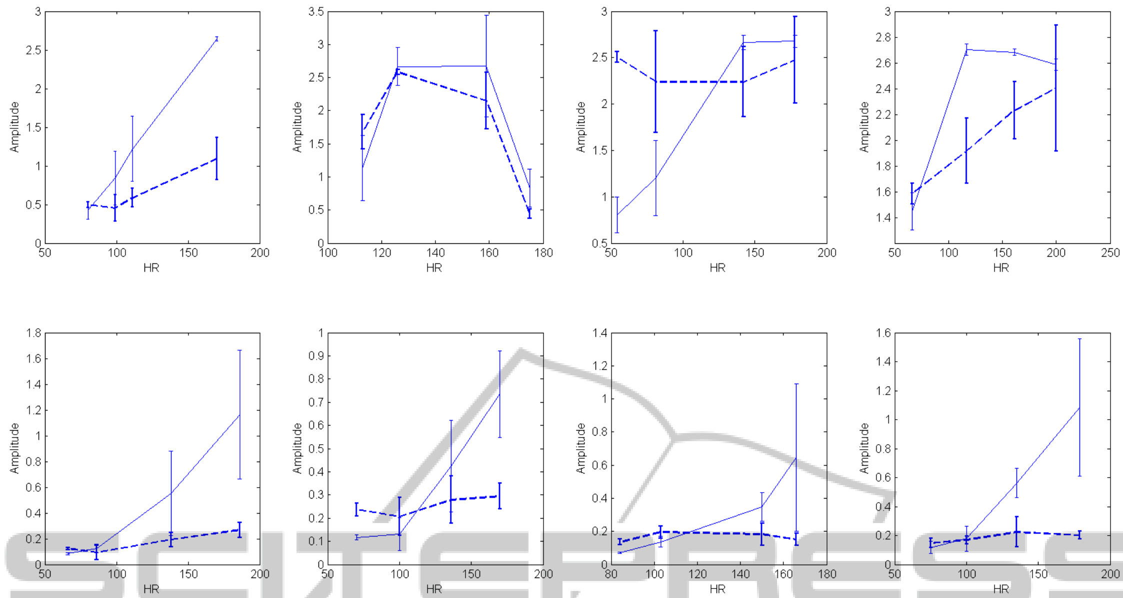

Figure 8: Variation of the S1 (solid line) and S2 (dashed line) amplitudes over the HR for all subjects.

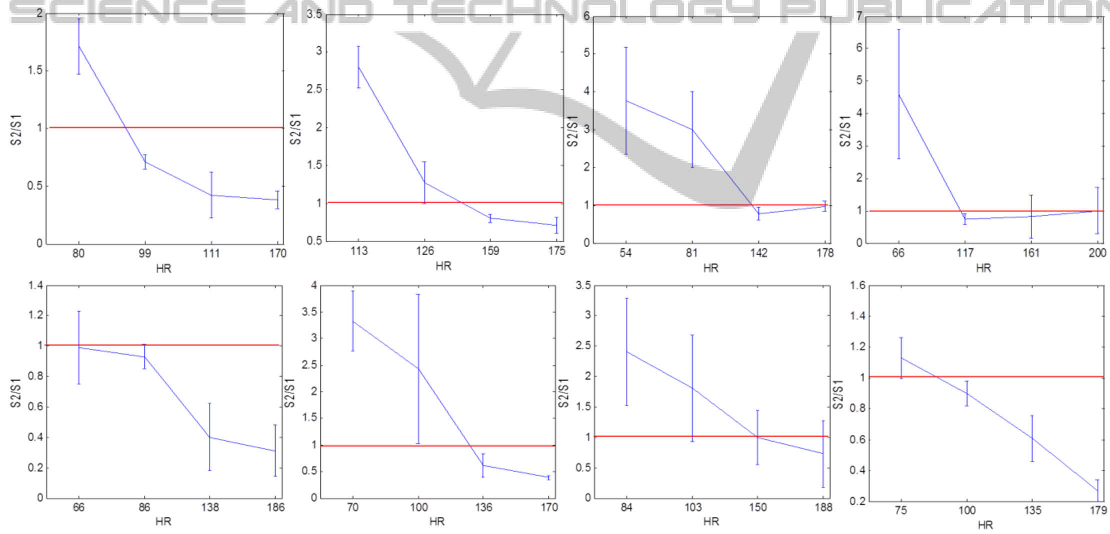

Figure 9: Variation of the high frequency content ratio ($S2/S1$) over the HR for all subjects. The red lines indicate when the high frequency content of S2 become lower than S1.

tained (-0.7). The frequency content of S1 and S2 is also related to the biotype which makes the HFC measure more sensitive when compared between diffirent subjects.

4 CONCLUSIONS

Investigating unobtrusive monitoring is of paramount importance due to the society demands for long-term monitoring in several scenarios from athletes assessment, to the monitoring of the elderly at home (Zheng et al., 2014). In this study a framework for the analysis of the cardiovascular electromechanical events during exercise is proposed.

Several features from the ECG and PCG were studied in adult volunteers during a exercise test including the RS2 time interval, heart sounds amplitude and HFC. All analyzed characteristics were related to the increase in cardiac stress. Different baseline values were observed between subjects which may be determined by their fitness and biotype.

RS2 was comparable between subjects, both for the baseline and maximum stress achieved, with a good correlation both individually and for the total data set. The assessment of the RS2 may be useful for the non-invasive assessment of PEP and LVET during exercise. Heart sound amplitude was also observed to be increased with stress, the result of the cardiovascular response to the extra need for oxygenated blood in the muscles during exercise, leading to an increase in CO, HR and BP.

$S2/S1$ was decreased with increasing exercise, and although HFC of S2 tend to be higher than of S1, in this study we observed that during a stress test this relation may be altered, leading to the need of different features in the discrimination of S1 and S2 than those usually proposed.

The description of these features allows a more comprehensive assessment of the cardiovascular system, and the dynamic changes that occur during a stress test, paving the way for future studies, including the assessment of these variables with blood pressure measurement and simultaneous pulse wave amplitude analysis (vascular transit time).

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