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Detecting Heart Rate From Virtual Reality Headset-Embedded Inertial Sensors: a Kinetic Energy Approach

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***Abstract*— At each cardiac beat, blood flowing through the arterial tree produces micro-movements that can be measured by positioning inertial sensors in contact with the body. The resulting signal is the ballistocardiogram (BCG). The study aims to demonstrate the feasibility to exploit inertial sensors embedded in a virtual reality (VR) headset to estimate heart rate (HR). Eight volunteers were enrolled. 1-minute head BCG signals were acquired in supine, sitting and standing position using the tri-axial accelerometer and gyroscope (f_s=71[71;77] Hz) integrated in a Oculus Quest (Facebook) VR headset. Linear and rotational kinetic energies were computed and used to automatically detect cardiac beats. Inter-beat intervals were extracted and mean HR was computed. In addition, 1-lead ECG signal was acquired and used as a gold standard for HR measurement. The HR values computed from BCG in each posture were compared with the gold standard (Wilcoxon Signed Rank Test, $p<0.05$). Correlation (r^2) and Bland Altman analyses were also performed. Best results were obtained using the rotational kinetic energy derived by the gyroscope, obtaining HRs comparable to the gold standard in both supine and sitting postures, with high correlation, no bias, and acceptable limits of agreement. In standing posture, the balancing movements for body equilibrium maintenance contributed reducing HR estimate accuracy. This is the first study in which HR has been measured using kinetic energy computed from the head-BCG obtained with a commercial VR headset, providing important insights on the possibility to expand the use of inertial units to accurately and non-invasively monitor physiological parameters.**

Keywords—Ballistocardiography; Virtual Reality Headset; Heart Rate; Kinetic Energy; Inertial Sensors.

I. Introduction

At each cardiac beat, blood flowing through the arterial tree produces changes in the center of mass of the body [1]. This phenomenon was first described in [2]. By assuming the cardiovascular system as a Newtonian one, the subtle body vibrations produced by cardiac mechanical activity and blood flow in major vessels are explained as the result of the recoil forces generated by blood ejection and blood flow into the aorta [3]. This is at the foundation of ballistocardiography, a technique that measures cardiac activity by recording such micro-movements of the whole body.

Recent advances in technology brought to the creation of wearable devices embedding Micro-Electro-Mechanical Systems (MEMS). Such miniaturized elements include inertial sensors, and specifically accelerometers and gyroscopes. Although being largely used to monitor daily physical activity (i.e. number of steps, distance walked, time spent in bed), when positioned in contact with the body, these inertial units can sense the subtle body vibrations in response to the cardiovascular activity, thus resulting in the so-called seismocardiographic (SCG) signal [4] or in the ballistocardiographic (BCG) signal [5].

We recently demonstrated the feasibility to measure mean heart rate (HR) and respiratory frequency from the inertial sensors already embedded in a commercial virtual reality (VR) headset [6]. Indeed, at each heart beat, 12 grams of blood flow towards the head from the aorta through the carotid arteries, causing reaction forces in the head and generating cyclic subtle head motion that can be used to derive information about the cardiac activity of the VR user.

The use of VR in the healthcare sector is increasing [7]: it is utilized in medical rehabilitation, creating a simulated environment to provide the patient with effective training [8] as well as in psychiatric treatment for anxiety disorders [9], or even for pain and distress management during medical procedures [10][11][12]. However, the evaluation of the user's quality of experience through monitoring physiological parameters while exposed to the VR environment involves the use of additional sensors and instrumentation, which could affect the evaluation and limit it into the laboratory environment.

Our aim in this preliminary study was to extend our previous observations to propose a method to automatically detect beat-by beat cardiac activity from the head BCG signal obtained through the VR. This would create the bases to evaluate heart rate variability (HRV) parameters able to quantify the sympatho-vagal status of the subject while exposed to a VR scenario, neither using additional sensors nor being confined to a specific laboratory study.

II. Materials and methods

A. Study population and design

Eight healthy volunteers (age: median [25th percentile; 75th percentile], 21[21;21] years) were enrolled. Each participant provided written informed consent to participate in the study, approved by the Ethics Committee of the Politecnico di Milano. Acquisitions were performed in standing, sitting and supine postures. The experimental protocol is schematized in Figure 1, and includes: 1-minute acquisition while standing, 3 minutes of baseline while sitting followed by 1-minute acquisition in sitting position, 3 minutes of baseline while supine followed by 1-minute acquisition in supine position. Baseline periods prior to sitting and supine recordings were adopted in order to allow the stabilization of the HR to the new postural condition. For each subject, this acquisition protocol was repeated three times.

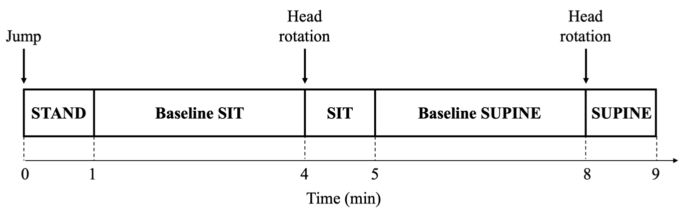

Fig. 1. Schematization of the acquisition protocol.

The continuous BCG signal of the head was acquired using the tri-axial accelerometer and gyroscope sensors embedded in the Oculus Quest (Facebook) VR headset, at a sampling frequency of 71[71;77] Hz. To do so, Softcare Studios Srl (Rome, Italy) developed an "ad-hoc" application which allows the user to start a recording session, at the end of which the samples of linear acceleration (m/s^2) and angular velocity (rad/s) acquired with the triaxial accelerometer and gyroscope are saved.

In addition, continuative 1-lead electrocardiographic (ECG) signal (sampling frequency = 1024 Hz) was acquired by the EcgMove4 sensor (Movisens, GmbH), which was used as a gold standard for HR measurement. To allow the synchronization between BCG and ECG signals, at the beginning of each repetition, the subject performed a small jump. As the EcgMove4 Movisens sensor also embeds a tri-axial accelerometer and a tri-axial gyroscope acquired at 64 Hz, the artifact generated by this movement was used to synchronize in post processing the signal of the VR-embedded sensors with the ECG signal. Moreover, at the beginning of the 1-minute sitting and supine acquisitions, a head rotation movement was performed and used as a start marker.

During the acquisitions, the subjects were asked to maintain their head still, thus avoiding major head motion artefacts which could compromise BCG signal robustness.

B. BCG signal processing

Given the slightly uneven sampling rate, the raw BCG signals acquired from the VR headset were resampled at 100 Hz. Afterwards, a 2nd order band-pass (10–13 Hz) Butterworth filter was applied to each component of both the accelerometer and gyroscope signals [13][6].

The linear (K_{lin}) and rotational (K_{rot}) kinetic energies were then computed from the accelerometer and gyroscope signals respectively, according to the formulae:

$$\boxed{K_{lin} = \frac{1}{2} m(v_x^2 + v_y^2 + v_z^2)} \quad (1)$$

$$\boxed{K_{rot} = \frac{1}{2}(I_{xx}w_x^2 + I_{yy}w_y^2 + I_{zz}w_z^2)} \quad (2)$$

where m is the body mass of the subject, v is the linear velocity derived from the linear acceleration by single-time integration, w is the angular velocity, and Ixx, Iyy and Izz are the orthogonal components of the moment of inertia of the head. These have been computed using the model developed by Hanavan et al. [14], where the head is approximated by a circular ellipsoid having radius r, height 2r and mass m_{head} equal to 7.9% of total body weight. Being the measures of the head unknown, the approximation of the head radius proposed by Weber and colleagues [15], only depending on subject's body mass, was used.

Automated heart beat identification was then performed on the obtained K_{lin} and K_{rot} signals by defining some threshold values: consecutive peaks with a minimum distance of 500 ms, and a minimum amplitude equal to 3 times the standard deviation for K_{lin} and 40% the standard deviation for K_{rot} were considered. For each subject in each position, the mean BCG HR was then computed from the inter-beat intervals series.

C. ECG signal processing

The Pan-Tompkins [16] algorithm is widely used for QRS complex detection which uses a bank of filters to emphasize the rapid heart depolarization. In this study, this method was applied to the acquired 1-lead ECG signal in order to identify the R peaks, from which gold standard measurements of HR were computed as average in each observation period.

D. Statistical analysis

For each posture, the HR values computed from K_{lin} and K_{rot} were compared with the gold standard HR (Wilcoxon Signed Rank test, $p<0.05$). In addition, linear correlation (r^2) and Bland Altman analyses were performed.

III. Results

An example of beat identification on the K_{rot} signal, together with the corresponding ECG, is presented in Figure 2. Noticeably, the peaks on the BCG signal do not manifest at the same timing of the ECG beats, with the BCG peak following the respective ECG peak. This lag is attributable to the physiological transit time between the electrical stimulus of cardiac contraction (visible on the ECG signal) and the arrival of the pulse wave to the head (recorded by the BCG signal) [17].

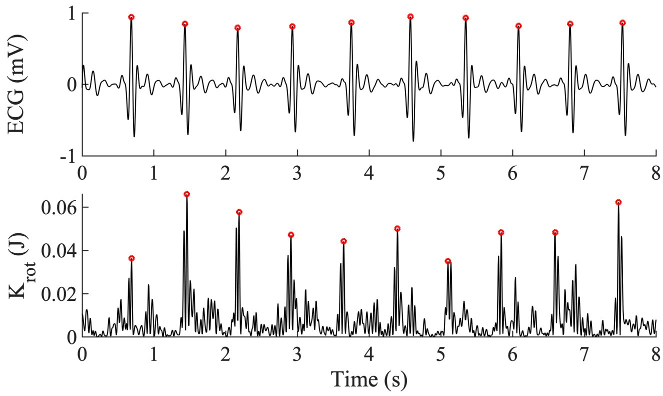

Fig. 2. Example of the results of automatic beat detection on the rotational kinetic energy signal (lower panel) derived from the gyroscope BCG. The identified beats are marked with a red dot. The synchronized reference ECG signal is presented in the upper panel.

The results of the heart rates computed from the ECG as well as from the K_{lin} and K_{rot} signals are summarized in Figure 3. Specifically, in sitting position, the mean HR values computed from K_{lin} and K_{rot} appeared not different from the gold standard, as well K_{rot} In the supine position. Conversely, in standing both K_{lin}- and K_{rot}-derived mean HR were significantly different from the gold standard HR.

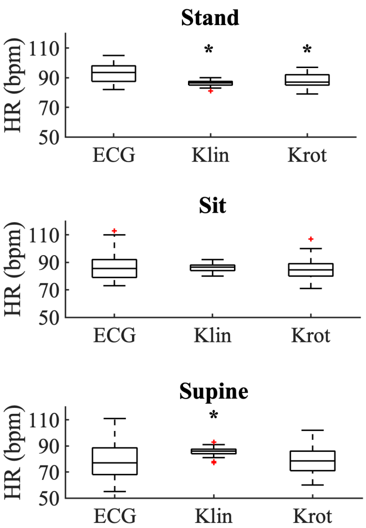

Fig. 3. Results of the mean HR obtained by K_{lin} and K_{rot} compared to the gold standard ECG. *: Wilcoxon Signed Rank test vs HR_{ECG}, $p<0.05$.

Correlation analysis resulted in low determination coefficients for K_{lin} in all positions (Standing: $r^2=0.01$; Sitting: $r^2=0.11$; Supine: $r^2=0.24$), while a good correlation was obtained from the K_{rot} in both sitting ($r^2=0.82$) and supine ($r^2=0.90$), but not in standing ($r^2 = 0.10$). Correlation and Bland Altman analyses relevant to the K_{rot} in supine and sitting postures are presented in Figure 4. Bland Altman analysis for K_{rot} showed no bias (Sitting: -0.85 bpm; Supine: +1.4 bpm) and acceptable limits of agreement (Sitting: [-9.6;+7.9] bpm; Supine: [-9.5;+12] bpm).

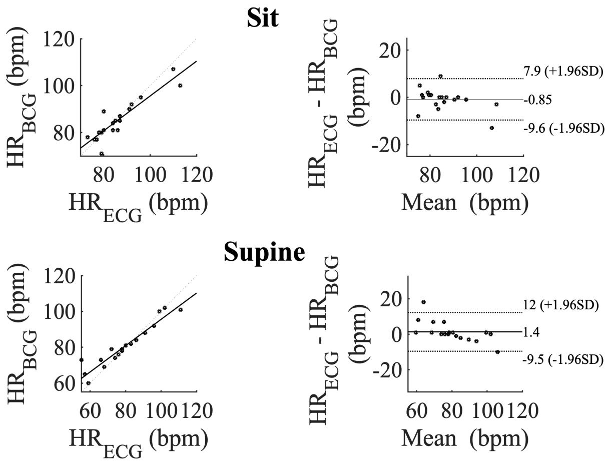

Fig. 4. Resuls of the correlation and Bland Altman analyses relevant to mean HR obtained by the K_{rot} compared to the one extracted by the ECG in supine and sitting postures.

IV. Discussion

Our results showed for the first time the possibility to extract reliable beat-by-beat information from the VR headset by exploiting subtle head movements synchronous with the heart beat.

Differently from our previous study [6], where the mean HR was obtained by applying frequency domain methods to the tri-axial accelerometer and gyroscopes signals acquired using an Oculus Go (Oculus, Microsoft, USA) headset, the present study explored the possibility to detect single heart beats by thresholding the linear and rotational kinetic energy signals computed from the accelerometer and gyroscope signals, respectively.

In our experimental protocol, the keeping of a still head position during the acquisitions was crucial for a good HR estimation, as major body or head movements would have introduced high amplitude noise into the BCG signal [18], thus reducing the signal-to-noise ratio, and generating potential artifacts in the HR computation. This observation could explain the critical results that were obtained for the standing posture, in both this and the previous [6] study. Indeed, while standing, the balancing movements relevant to keeping the body equilibrium introduce a noise component to the BCG signal, thus resulting in poor automated HR estimations.

Our results confirm previous observations [6] that the gyroscope signal is able to provide better HR estimation compared to the accelerometer signal. In sitting position, the obtained accuracy is comparable to that previously obtained in 30 subjects [6], while in supine it largely outperforms previous results, in which the highest r^2 (0.44) was obtained with the adjusted FFT method [6].

Also, the use of a different VR headset, with a more stable sampling frequency of the accelerometer and gyroscope signal, potentially contributed in improving signal quality, as the interpolation and digital filtering operations for non-uniform sampling rate could amplify the noise and introduce undesirable artifacts [19]. Adopting a different ECG gold standard (instead than 30-sec separate acquisitions obtained without electrodes by simple contact of the device with the chest or the thumbs) also improved the signal quality and the synchronization with the BCG signal.

Additional improvements in HR estimation can also be attributed to the computation of the kinetic energy, which allowed single-beat identification by thresholding. Future studies should consider further improvement in BCG beats identification by applying advanced techniques, considering for example also the cross correlation of the signal with a template [20], as well as machine learning methods [21]. Moreover, rejection artifacts algorithms should be implemented to allow accurate beat-to-beat HR measurements from which to extract additional physiological markers of cardiac activity, such as ultra-short HRV indices related to the sypatho-vagal modulation of the heart.

Such improvements would pave the way to the development of health-related VR applications, conveying bio-feedbacks aimed at modulating and personalizing the user experience according to the measured physiological reaction to the proposed scenario.

V. CONSLUSION

This preliminary study demonstrated the feasibility to automatically detect beat-by beat the cardiac activity from the head BCG signal obtained through the VR headset embedded inertial sensors, by computing and opportunely thresholding the derived kinetic energy signal. Best results were obtained using the rotational kinetic energy while maintaining the head still in both supine and sitting positions. The proposed approach provides important insights on the possibility to monitor physiological parameters in an accurate and non-invasive way, using MEMS already embedded in commonly used devices.

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