Physiological Parameters Measurement Based on Wheelchair Embedded Sensors and Advanced Signal Processing

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***Abstract*—This paper presents a multisensing system with wireless communication capabilities embedded on a smart wheelchair that can measure physiological parameters such as heart rate and respiratory rate in an unobtrusive way. Ballistocardiography (BCG) sensors and a three-axis inertial microelectromechanical system accelerometer are embedded on the seat or in the backrest of the wheelchair and the acquired data are transmitted by Wi-Fi to a laptop computer for advanced data processing and logging. In addition, a 3-D accelerometer with ZigBee communication capability is used to extract information about the user's posture. Considering the static and dynamic use of the wheelchair, an extended set of measurements for different utilization scenarios was analyzed. An important part of this paper is focused on BCG noise and artifacts removal and heart rate and respiratory rate accurate estimation from BCG signal using wavelet-based filtering and independent component analysis algorithms. A study on wavelet-based filtering considering different types of mother wavelets and different levels of decomposition was also carried out. In the future, other signals will also be acquired to improve the system capabilities and flexibility.**

***Index Terms*—Ballistocardiography (BCG), independent component analysis (ICA), unobtrusive sensors, wavelet decomposition, wheelchairs.**

I. Introduction

HEALTH costs reduction leads to challenging problems in telemedicine, electronic health data logging, and remote monitoring of in-home patients [1]–[3]. With regard to physiological parameters and motion status of the assessed persons in a continuous healthcare context, different solutions, including portable instruments and wearable sensing systems, are reported in the literature [4], [5].

Monitoring physiological signs in an unobtrusive way can significantly reduce the stress impact of apparatus utilization on patients, particularly to those with a certain degree of physical limitation. However, up to now, only few devices have been proposed in the literature. Recent research has been focused on techniques for using a common flush toilet to monitor health, including measurements of weight, body fat, pulse, or even blood pressure [6]. Embedding sensors in office chairs for heart rate, respiration, and blood pressure monitoring has already been realized [7]–[9]. Devices for patient movement detection [10], [11] and vital signs monitoring in bed [12] or installed in household furniture are reported in the literature [13]. As far as we know, only one research group works on embedded physiological sensors on wheelchairs [14], [15]. In the referred prototype, one seat-type noncontact electromechanical film (EMFi) sensor was used to obtain the ballistocardiography (BCG) signal and 3-D accelerometers to help BCG noise removal. Their studies clearly showed that the BCG signal is seriously affected by the movement of the patients in the wheelchair, but the work that they report was focused on the signal acquisition module implementation using a personal digital assistant (PDA) and a ZigBee connection.

In this paper, we applied different kinds of algorithms to extract the information from BCG and acceleration. The noise removal is based on stationary wavelets transform [16], [17] multiresolution wavelet decomposition for signal feature extraction [18], [19] and independent component analysis (ICA) [20]–[22] are nowadays important techniques in biomedical signal processing, particularly for electrocardiography (ECG) and electroencephalography (EEG) [23]. The aforementioned methods were object of the research activity of our group with regard to BCG signal processing for cardiac and respiratory activity estimation.

The goal of this paper is to present a measurement system embedded on a wheelchair for accurate monitoring of the cardiac and respiration activity for different scenarios such as a stopped wheelchair, a self-driven hand-operated wheelchair, and a hand-operated wheelchair pushed by a helper. An important part of this paper is the experimental study of the artifacts generated by different mechanical impacts applied to the wheelchair.

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Fig. 1. Physiological parameters measurement system based on unobtrusive sensing units embedded on a wheelchair (W-DAQ module, CC&PS conditioning circuit, and power supply module, BCG-SP—ballistocardiography primary sensor, BCG-SS—ballistocardiography secondary sensor).

The analysis of BCG noise and artifacts removal for accurate measurement of the heart rate and respiratory rate for different wheelchair movement scenarios was done using a set of EMFi sensors and a 3-D accelerometer mounted on the wheelchair seat and backrest. The signals from the sensors are acquired using a remote data acquisition unit with Wi-Fi capability that communicates with a laptop PC. Wavelets algorithms and ICA software modules developed in LabVIEW were implemented at the PC level. Elements with regard to the measurement system power consumption are also included in this paper.

This paper is organized as follows. Section II mainly presents the unobtrusive multisensing system hardware, highlighting the sensors' characteristics and the general design of the smart wheelchair. Section III is dedicated to BCG signal processing, including a brief description of wavelets and ICA processing algorithms. Results obtained for different wheelchair usage scenarios, and for different data processing, applied algorithms are presented and discussed in Section IV, followed by a conclusion and a reference list.

II. Unobtrusive Multisensing System

The unobtrusive sensing system includes BCG sensing (BCG-S) and inertial sensing (INS) units embedded on the wheelchair's seat and backrest. The redundancy of BCG-S units was imposed to extract correlations between the BCG signals from different parts of the user's body, which reflects mechanical activity of the heart and the wave propagation through the blood vessels. As shown in Fig. 1, the primary and secondary BCG sensors BCG-SP and BCG-SS are embedded on the wheelchair seat and backrest, respectively. Because both sensors are closely placed, the main BCG waves may be considered synchronous for analysis.

The BCG and acceleration sensors are connected to a signal conditioning circuit and a power supply module (CC&PS), as depicted in Fig. 1. The outputs of the conditioning circuit are connected to a multichannel wireless data acquisition (W-DAQ) module. In addition, a ZigBee 3-D accelerometer was attached to the wheelchair user's chest to record information related to the user's posture (tilt angle) and acceleration values that are correlated with the values measured by the other sensors (wired accelerometers, BCG-SS, and BCG-SP; see Fig. 2).

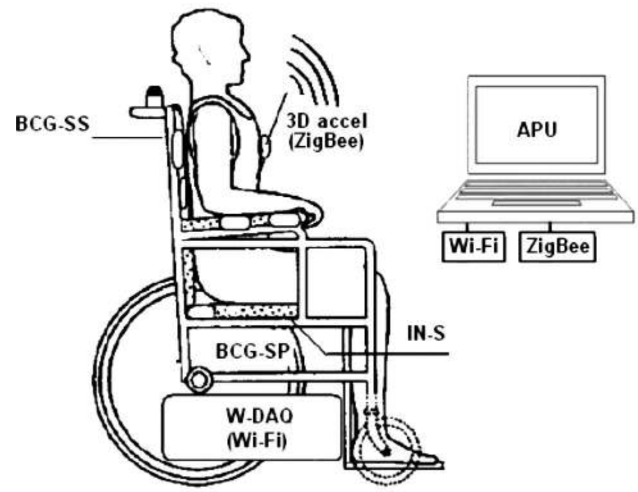

Fig. 2. Posture measurement unit based on an inertial-sensor (3-D accelerometer) ZigBee-compatible advanced processing unit (APU).

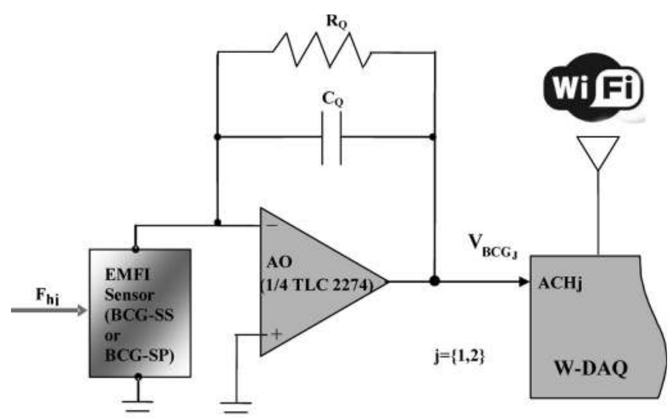

Fig. 3. BCG-SP and BCG-SS charge amplifier scheme and Wi-Fi—DAQ connection.

A. BCG-S Unit

The BCG-S is performed by an EMFi sensor (EMFIT L-3030) that is made of a thin porous polypropylene film structure, with several layers separated by air voids that are 10–100 μm wide and only a few micrometers high [24]. When an external pressure is applied on the surface, it will change the thickness of the air voids, which leads to electrical charges movement that will originate a voltage at the output of a two-channel charge amplifier (BCG-QA) [25]. The circuit uses a 1/2 TLC2274 quad low-noise rail-to-rail operational amplifier (OP), one for each sensor, BCG-SS and BCG-SP, and a parallel combination of $\mathrm{R_Q} = 10\ \mathrm{M\Omega}$, $\mathrm{C_Q} = 20$ pF (see Fig. 3). This operational amplifier is characterized by a high-impedance ($10^{12}\ \Omega$) and low-noise (9 nV/$\sqrt{}$Hz typical at f = 1 kHz).

The BCG-CC output voltage depends on the EMFi sensitivity [$\mathrm{S_q}$ (in picocoulombs per newton)] and the amplitude of the force applied $\mathrm{F_{hj}}$ (in newtons). It is expected that this force can somehow express the heart and respiration activity. $\mathrm{V_{BCGj}}$ is given by

$$V_{BCGj} = \frac{1}{C} \cdot S_q \cdot F_{hj} \tag{1}$$

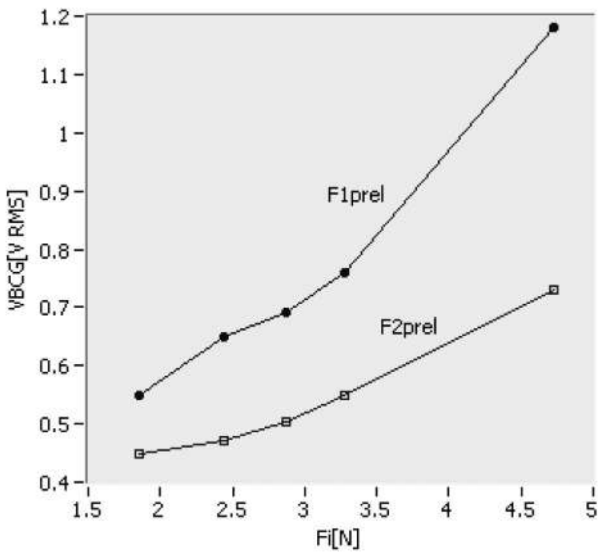

Fig. 4. EMFi response for different impact forces (Fi) when mechanically preloaded with F1 (39.2 N) and F2 (76.3 N).

where C represents the capacitance value associated with the charge amplifier scheme, j represents the BCG sensor index, and $\mathrm{j} = \{1, 2\}$. According to (1), for the same type of EMFi sensor that materializes BCG-SP and BCG-SS, better responses are obtained from the BCG-SP for passive interaction between the wheelchair user and the sensing system, whereas in the BCG-SS case, the BCG signal is more representative when the wheelchair user actively interacts with the sensing component. EMFi sensors present high sensitivity to perpendicular forces, because they lead to a variation of the sensor's thickness while showing very low sensitivity to tangential forces [26].

According to [27], the dynamic response characteristic of EMFi sensors is dependent on preload conditions. Thus an experimental procedure was set up to evaluate their behavior by preloading them first with a static force ($\mathrm{F1_{prel}} = 39.2$ N, and $\mathrm{F2_{prel}} = 76.3$ N) and then additionally applying an impact force in the form of an object in free fall. The impact forces were calculated as $\mathrm{F_i} = \{1.85, 2.44, 2.87, 3.27, 4.72\}$ [N], assuming that $\mathrm{F_i} = \mathrm{m_i g}$ for objects with a uniform mass distribution $\mathrm{m_j}$ that fall from a height of 30 cm to the preloaded sensor. The obtained results are presented in Fig. 4.

The voltage signals delivered by the BCG-CC (VBCG-SP and VBCG-SS) are acquired using the W-DAQ (NI WLS-9215) acquisition module, which presents the following characteristics: four simultaneously sampled analog inputs, up to 100 kS/s acquisition rate, and 16-bit resolution (see Fig. 5). The acquired data are wireless transmitted to the laptop PC, where they are digitally filtered to estimate the respiration and heart rates (based on the I or J peaks detection of the BCG-wave).

Fig. 5 presents an example of the signals obtained from BCG-SP and BCG-SS after being digitally filtered. The signals show a maximum variation of about ± 30 mV and correspond to the direct output of charge amplifier without amplification. An additional amplification stage can be included as part of the conditioning circuit. The gain must, however, be moderate to avoid amplifier saturation due to the high sensitivity of the sensor to the user's higher amplitude movements and to impacts between the wheelchair and different objects during motion.

B. INS Unit

The INS unit is expressed by a three-axis accelerometer LIS3LV02DQ (STMicroelectronics) that delivers a set of analog voltages, $\mathrm{V_x}$, $\mathrm{V_y}$, and $\mathrm{V_z}$, that reflect the wheelchair motion state, impacts, and quick motions of the user, respectively.

The accelerometer is embedded in the wheelchair seat, and $\mathrm{V_x}$, $\mathrm{V_y}$, and $\mathrm{V_z}$ are connected to the available input channels of W-DAQ. The W-DAQ four input channels are thus used to acquire the voltage from one BCG-S channel and the voltages from one of the 3-D accelerometer at a time. The acquired signals are wireless transmitted to the processing unit and used as inputs for BCG artifacts removal processing blocks.

C. Tilt Sensing Unit

To extract the correspondence between the user's postures resting on the wheelchair and BCG acquired signals, a set of accelerometers was included. The obtained information can be used to increase the accuracy of the algorithms associated with respiration rate and heart rate measurement based on BCG signal processing. The tilt angle associated with the user's posture while resting on the wheelchair is measured using ZSTAR3 3-D digital accelerometer sensor MMA7456L (Freecom) that communicates through the ZigBee protocol, with the receiving node connected by a Universal Serial Bus (USB) to the laptop PC. Based on the information delivered from the transmission node attached to the chest of the user, the tilt values are calculated by the ZSTAR3 software installed in the PC. One example of the variation of the tilt angle in the scenario of the user who is resting on the wheelchair is presented in Fig. 6.

The obtained results highlight that, when the wheelchair user is resting, the tilt angle variation is small, and thus, low-level artifacts will affect the BCG signals. In contrast, a motion wheelchair scenario can conduct to a high level of tilt variation that strongly affects the BCG signals, making signal processing tasks more difficult.

III. BCG Signal Processing

Using the aforementioned system, the BCG signal samples are received by the laptop PC, where several signal processing modules are implemented. The main tasks performed are given as follows: 1) noise and artifacts removal from the BCG signal; 2) physiological parameters estimation, including heart rate and respiration rate estimation; and 3) wheelchair motion status estimation and wheelchair obstacle detection.

Considering that, in the BCG signal case, the useful information is in a frequency band of 0–30 Hz, a set of IIR Butterworth digital low-pass filters (LPFs) characterized by $\mathrm{f_c} = 30$ Hz, $\mathrm{N} = 20$ (N-filter order) were implemented as part of the signal processing software. Thus, in the first processing stage, $\mathrm{V_{BCG1}}$, $\mathrm{V_{BCG2}}$, $\mathrm{V_x}$, $\mathrm{V_y}$, and $\mathrm{V_z}$ signals are acquired at a 1-kS/s sampling rate and are digital filtered. For the utilization of 1 kS/s as a sampling rate, we considered the possibility of performing offline, or even online, processing of the BCG to estimate the heart rate variability by using the time intervals between two successive peaks (I-I, J-J) of the BCG waves [7]. We also

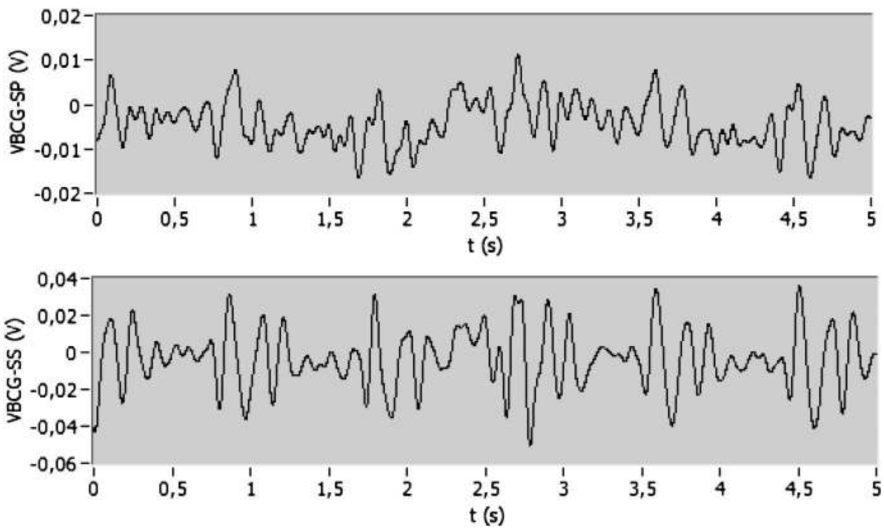

Fig. 5. BCG waves obtained from BCG-SP and BCG-SS after digital filtering.

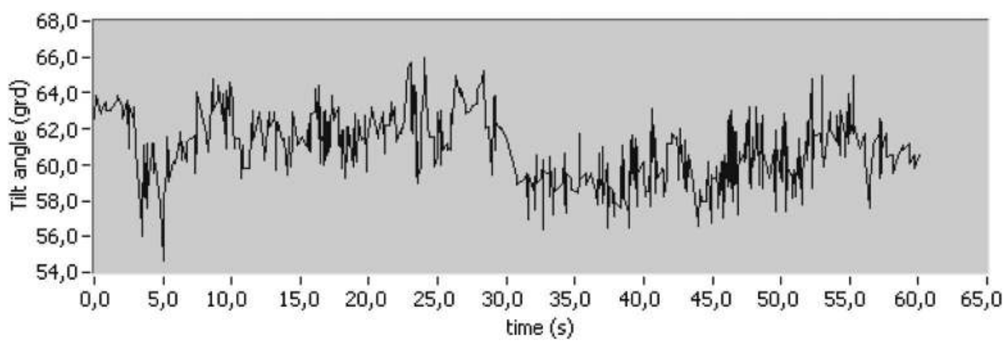

Fig. 6. Tilt angle variation with the user in the resting position seated on the wheelchair (60 samples/s).

took into account the Task Force Standard recommendations with regard to the used acquisition rate for accurate heart rate variability estimation from ECG signals [26]. However, the noise (that can be generated by muscle movements) and artifacts (that can be generated by wheelchair motion) are still present in the BCG signals. A set of advanced signal processing software modules for enhancing the quality of the BCG signals, i.e., stationary wavelet filtering (WF) with soft thresholding, were designed and implemented [16] and ICA.

A. Wavelet Filtering

Two digital filtering stages (WF1 and WF2) based on wavelet algorithms were implemented. WF1 is based on discrete stationary wavelet transform (SWT) combined with soft thresholding techniques, whereas the second stage (WF2), which receives the processed signal from WF1, is based on the discrete wavelet transform (DWT), and it is used for cardiac and respiratory activity signal estimation through heart rate and respiration rate calculation. WF2 is implemented as a digital filter bank that consists of pairs of digital high-pass filters (HPFs) and LPFs organized in a tree structure. Thus, the $\mathrm{V_{BCG-SS}}$ and $\mathrm{V_{BCG-SP}}$ signals are decomposed at each scale (e.g., the j scale) into details coefficients $(\mathrm{d_j})$ as a result of HPF and approximation coefficients $(\mathrm{a_j})$ as a result of LPF. Thus, the wavelet coefficients can be expressed by the following inner products:

$$d_j(k) = \langle x(l), \Psi_{j,k}(l) \rangle \tag{2}$$

$$a_j(k) = \langle x(l), \phi_{j,k}(l) \rangle \tag{3}$$

where $\Psi_{j,k}(l)$ and $\phi_{j,k}(k)$ are, respectively, the scaled and translated versions of the basis functions (e.g., Daubechies-type) associated with the HPF and LPF impulse response, i.e.,

$$\Psi_{j,k}(l) = 2^{-j/2}\Psi(2^{-j}l - k) \tag{4}$$

$$\phi_{j.k}(l) = 2^{-j/2}\phi(2^{-j}l - k). \tag{5}$$

Different decomposition levels (j = 4 to 10) were considered in this paper for accurate estimation of the considered respiration or heart activity by the processing of the BCG signals.

Daubechies db4, db5, ..., db8 mother wavelets were used for representation of the respiratory and heart signals (Resp(n) and Heart(n)) in digital form, i.e.,

$$\mathrm{Resp}(n) = a_J(n) = \sum_{k \in Z} a_J(k)\phi_{j,k}(n) \tag{6}$$

$$\mathrm{Heart}(n) = \sum_{k \in Z} d_m(k)\Psi_{m,k}(n) + \sum_{k \in Z} d_p(k)\Psi_{m,k}(n). \tag{7}$$

Applying the advanced peak detection functions from LabVIEW, the Resp(n) and Heart(n) acquired waves were processed to extract the values for respiration rate and heart rate values that were compared with those obtained using reference measurement equipment (a photoplethysmograph from Medlab and a spirometer from ADInstruments).

B. Independent Component Analysis

According to their morphology in the time domain, the components that result from the ICA of the BCG signals received and stored in the laptop PC level can roughly be divided into three categories: 1) normal BCG (normal BCG from the seat and normal BCG from the backrest); 2) continuous noise (associated with muscle activity and body movements); and 3) abrupt changes (wheelchair—obstacle impact). The ICA model is defined by

$$X = A \cdot S \tag{8}$$

where the vector S represents m independent sources, the matrix A represents the linear mixing of the sources (mixing matrix), and the vector X is composed on m observed signals. The aim of ICA application is to recover the original sources (e.g., the heart's mechanical activity expressed on the BCG signal) by assuming that they are statistically independent. The implemented ICA algorithm is related to the matrix U, $\mathrm{U} = \mathrm{A}^{-1}$, to undo the mixing effect; thus

$$S_e = U \cdot X \tag{9}$$

where S_e represents an estimate of sources. To solve this problem, different algorithms are known. One of them is FastICA [27], which minimizes mutual information between sources, and estimates individual independent components as projection pursuit directions. To ensure easy integration of the ICA processing module on the system software, the LabVIEW Advanced Signal Processing Toolkit (Time-Series Analysis Tool) was used [28]. Thus, the signals acquired from one of the BCG-S channel and from the 3-D accelerometer were processed using a set of statistical analysis functions, including ICA. To ensure optimal noise removal, the kurtosis (Kurt) values (10) are calculated for time segments (e.g., 10-s time segments) associated with independent source signals obtained by applying a fast ICA algorithm. For a Kurt module value less than an imposed threshold (e.g., 0.5), the independent source signal associated the ICA component is considered a continuous noise and will be multiplied by 0 before the reconstruction of the BCG and accelerometer signals using the calculated mixing matrix

$$Kurt(x) = \frac{\sum_{i=1}^{N} (x_i - \overline{x})^4}{(N-1) \cdot \sigma^4} \tag{10}$$

$$\sigma = \sqrt{\frac{1}{N} \cdot \sum_{i=1}^{N} (x_i - \overline{x})^2} \tag{11}$$

where $\overline{x}$ represents the arithmetic mean, σ the standard deviation, and N represents the number of samples.

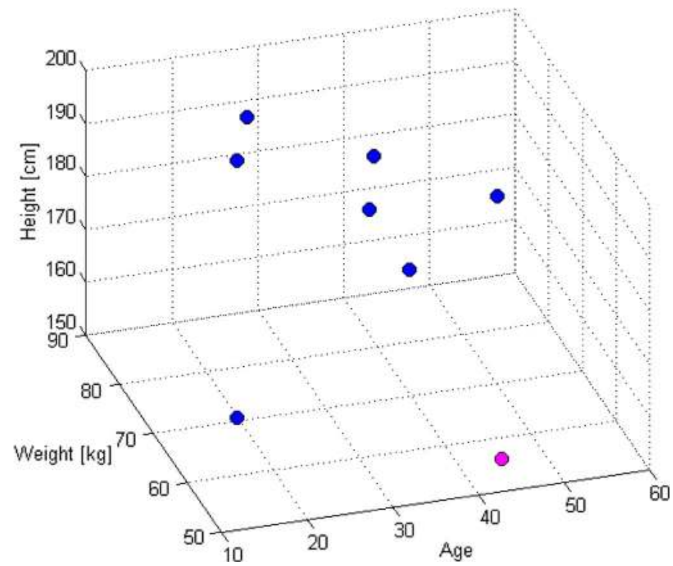

Fig. 7. Volunteer age, weight, and height distribution.

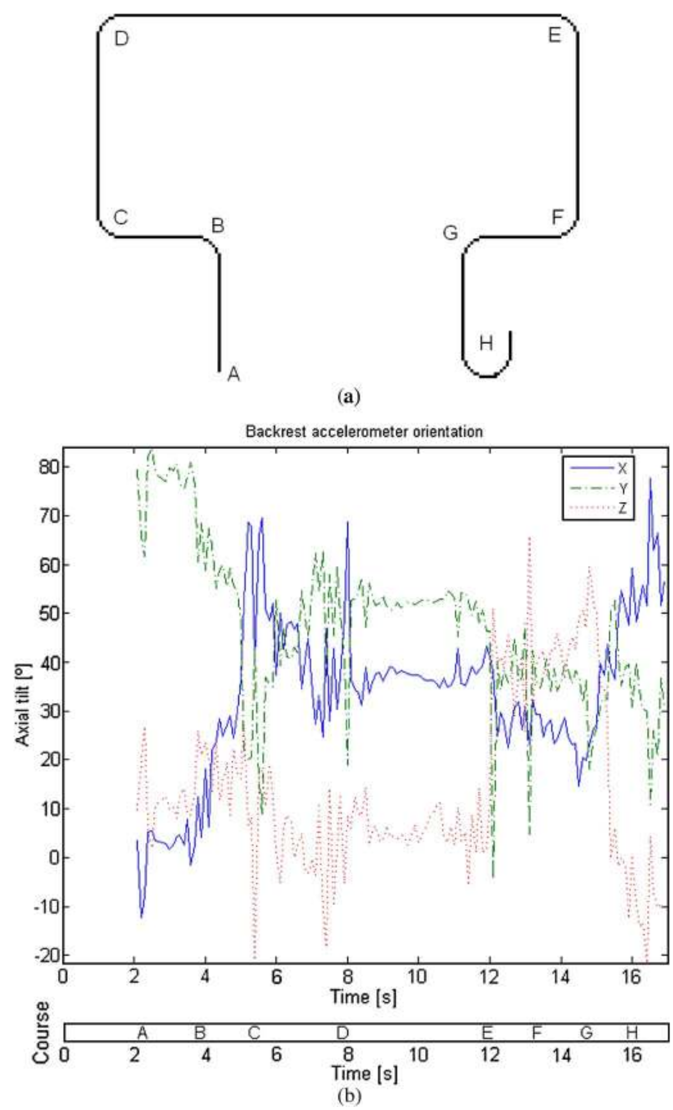

Fig. 8. Wheelchair-driving path (a) and the corresponding tilt angle variation during one course registered with a free scale accelerometer mounted on the user's chest (b).

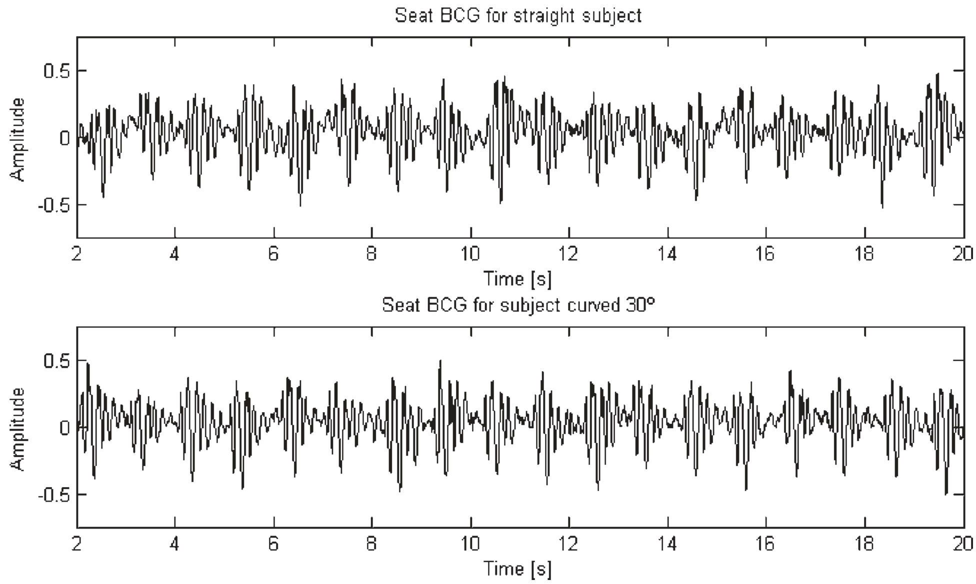

Fig. 9. BCG wave evolution for straight and 30° tilt angle for a volunteer with a height of 188 cm and a weight of 81 kg seated on the wheelchair.

Referring to the ICA-based artifact removal, the variance index $(var = \sigma^2)$ is used. After noise removal (associated with Kurt calculation), the remaining ICA components are divided into N nonoverlapping time segments. The variances of the N segments are calculated, and for an imposed threshold, it can be identified as the time segments that correspond to the artifacts. The component whose variance is above a predetermined threshold is marked as an abrupt change component and is multiplied by 0. The signal reconstruction is done using mix matrix A, as in the noise removal case, and the resulting signals are used to obtain the physiological parameters using wavelets algorithms as described on Section III-A.

IV. Results and Discussions

The designed and implemented system was tested using eight volunteers whose age, weight, and height are represented in Fig. 7.

With regard to the imposed conditions during the wheelchair tests, the subjects were kept seated for 15 min and were told to relax. Considering that the user's position and movements when seated on the wheelchair during motion can induct important changes on the BCG waves, different tests were carried out. A volunteer's tilt angle was measured when the wheelchair was driven along a predefined path. The used path and the values of tilt angle for a wheelchair user are presented in Fig. 8(a) and (b).

The influence of path profile on tilt angle and on BCG waves was analyzed in order to estimate the wheelchair user's posture. The BCG acquired signals are shown in Fig. 9 for two tilt angles of the user who is resting on the wheelchair. The comparison of the BCG waves profile acquired when the tilt angle was less than 30 degrees has shown no significant differences that underlines the robustness of BCG measurement.

Using BCG-SP and BCG-SS measurement channels connected to the W-DAQ module, different signals for the static and dynamic conditions were wirelessly received by the laptop PC. Figs. 10 and 11 present examples of the acquired signals for the aforementioned time interval from BCG-S units for two new scenarios: a) the user rests on the wheelchair and b) a self-driven manually operated wheelchair.

With regard to signal processing, different steps are carried out according to the various scenarios. Thus, when the user rests on the wheelchair (static test), the acquired signal is directly processed using digital filtering and wavelets, whereas in the self-driven operated wheelchair, the artifact removal based on the ICA algorithm is followed by digital filtering and wavelets decomposition to extract the information about heart rate and respiration rate.

To extract the respiration signal, the WF algorithm, expressed by multiresolution wavelet decomposition, is applied. A study with regard to the optimal WF (DWT decomposition) that permits to estimate the respiratory signal Resp(n) and respiration rate from the BCG signals was carried out. Different types of mother wavelets (Daubechies db2, db3, db4 to db8) and different decomposition levels (7, 8, 9, and 10) of the cardiac signal were considered for an accurate respiratory rate and heart rate estimation based on the peak detection procedure followed by detected peaks count for periods of 1 min. The respiration signals obtained for the particular case of db4 and level 9 of wavelet decomposition is presented in Fig. 12. As it can be observed, both sensing units BCG-SP and BCG-SS provide useful and coherent information for respiration rate estimation [RespR = 18 (BCG-SP case) and RespR = 17 (BCG-SS case)]. Based on wavelet decomposition details, the HR information was also obtained.

A study with regard to the heart rate estimation error was carried out for different mother wavelets and for different levels of decomposition. A graphical representation of the respiration signal obtained as a tenth-wavelet approximation and of the cardiac signal reconstructed from D8, D9, and D10 details is presented in Fig. 13. Based on an implemented peak/valley detector, the heart rate is estimated. The capabilities of the implemented heart rate estimation algorithm that combines wavelet

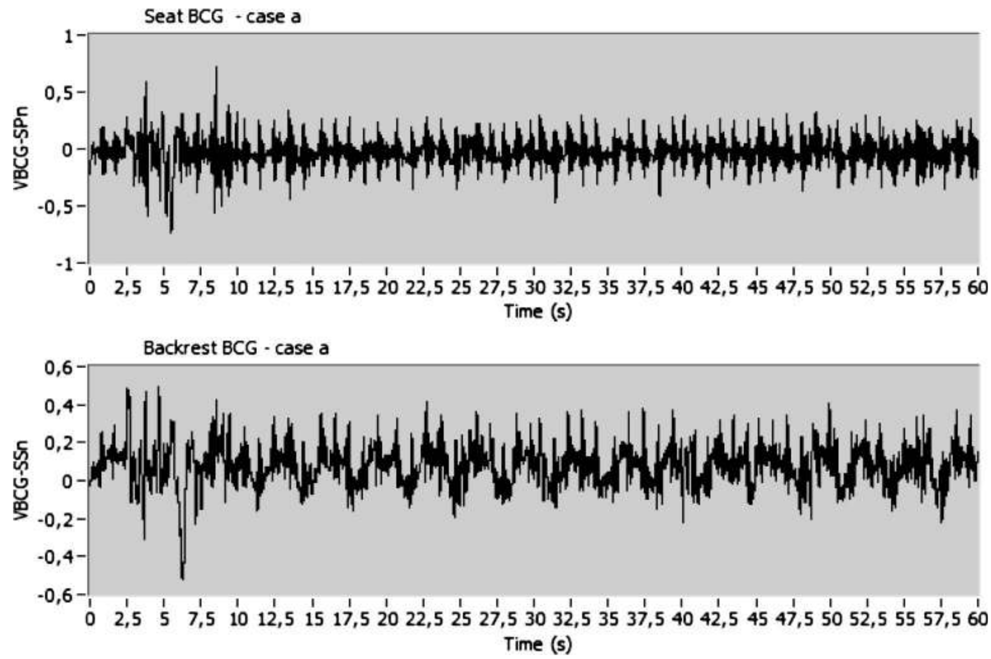

Fig. 10. Normalized values of BCG signals acquired from the BCG-SP and BCG-SS units when the user rests on the wheelchair (scenario a).

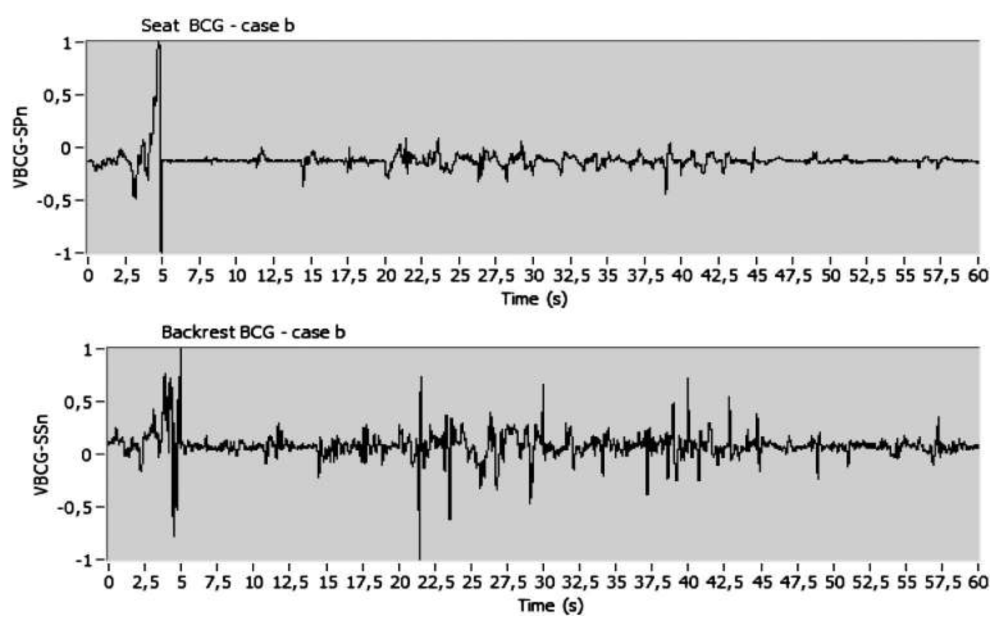

Fig. 11. Normalized values of BCG signals acquired from the BCG-SP and BCG-SS units in the scenario b)—self-driven hand-operated wheelchair.

decomposition, wavelet reconstruction, and peak/valley detection were estimated using a Medlab (P-100X) physiological parameter measurement system that calculates the heart rate from ECG and plethysmogram signals. For validation of the respiration rate estimation, a Spirometer system (ML311 and Power Lab from ADInstruments) was used.

The algorithm capabilities were evaluated using two parameters: 1) false positives (FPs) and 2) false negatives (FNs). The total number of FPs represents a detector error of BCG J-wave that is not presented in the analyzed signal, whereas the total number of FNs represents a detector error of missed BCGJ-waves detection in the analyzed signal. Thus, the error rate is defined by $e[\%] = ((\mathrm{FP} + \mathrm{FN})/\text{total number of beats})100[\%]$. The values calculated by a set of BCG processed signals were less than 1% for an acquisition time of less than 60 s.

Considering scenario b), when the user who is seated self drives the wheelchair, the BCG signals are characterized by an important quantity of artifacts that are sensed by the three-axis accelerometer (see Fig. 14).

Based on the correlations between the acceleration signals (Vx, Vy, and Vz) and the BCG signal acquired from the BCG-SP unit, a fast ICA algorithm is applied for noise and artifact removal. The signals from the measurement channels acquired for 120–150 s at 1 kS/s were used in the first step to calculate two statistic parameters, Kurt and variance index, whose values express the noise or artifacts in the acquired signal. Fig. 15

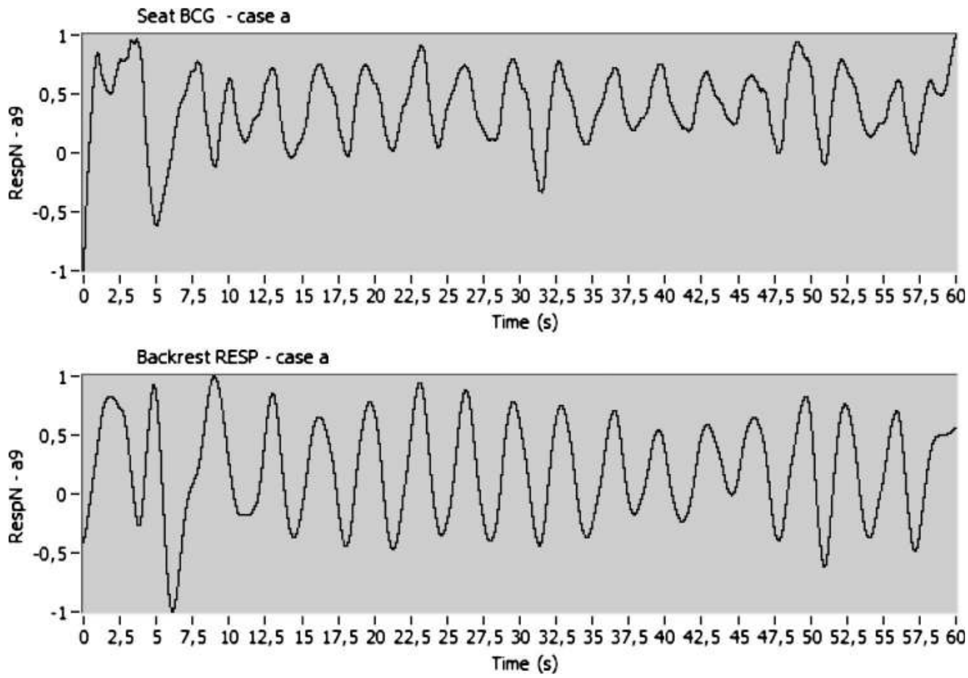

Fig. 12. Respiration signal estimation based on wavelet filtering of the BCG signals acquired from the BCG-SP and BCG-SS units in scenario a)—the user rests on the wheelchair.

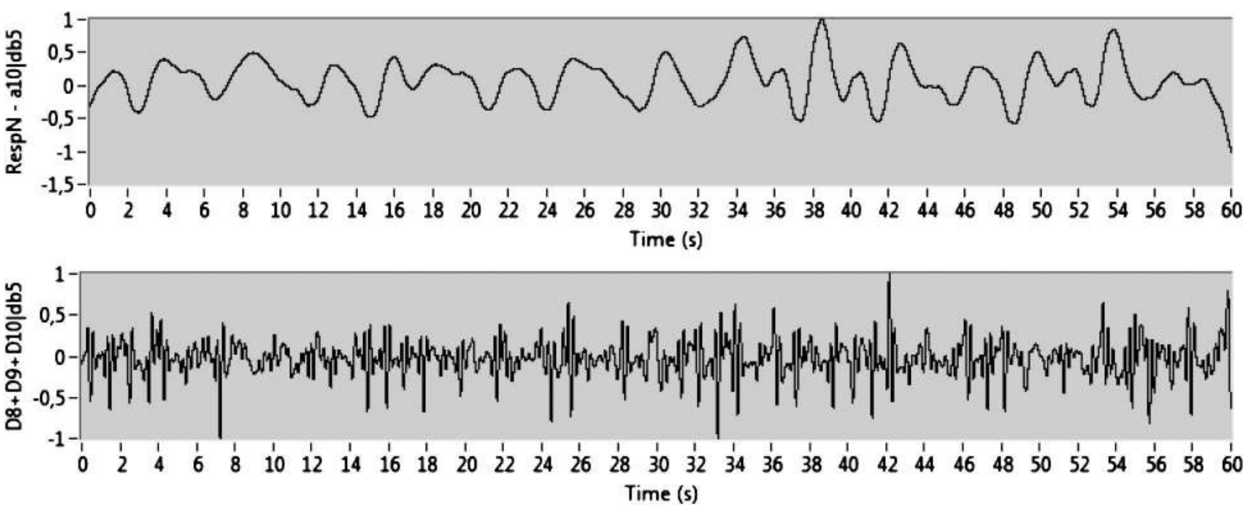

Fig. 13. Respiration signal and cardiac signal as a result of tenth-wavelet decomposition for db5 mother wavelets in scenario a)—the user rests on the wheelchair.

shows the evolution of Kurt for ICA1, ICA2, ICA3, and ICA4 resulting from the implemented fast ICA algorithm based on the TSA ICA LabVIEW Function [28].

Four ICA components were calculated for the signals presented in Fig. 5 and correspond to wheelchair motion. Low values of Kurt (Fig. 15) reveal a region characterized by noise. Imposing a Kurt threshold of 5, noise removal will be done by multiplying by 0 the ICA3 and ICA4 samples associated with 2–11 time segments $(2 \leq \text{Nts} \leq 11)$ and reconstructing the BCG and acceleration signals using the mixing matrix already calculated.

To identify the time segments characterized by artifacts, the variance index is calculated. Fig. 16 presents the variance values for the aforementioned Nts time segments.

High values of the variance index signify the presence of artifacts. In this case, ICA1 and ICA2 present relatively high values of variance for Nts ≥ 12. For these values of Nts, ICA1 and ICA2 are multiplied by 0. The signals reconstruction was done using ICA3 and ICA4 and the mixing matrix. For the particular case of Nts $= 13$, some results are presented in Fig. 17.

This figure shows that additional processing, which is based on wavelets, might be used to eliminate the large artifacts associated with the wheelchair motion. The utilization in the present application of a Wi-Fi-compatible (IEEE802.11g) W-DAQ makes the measurement possible when the wheelchair is in motion, which represents the main strength of the implemented solution. Considering the IEEE802.11g indoor wireless communication range (about 200 m) and the data communication rate (54 Mbps), the used solution represents a better choice compared with a Bluetooth-based solution. However, the Wi-Fi communication protocol is characterized by intensive power consumption, which limits the autonomy

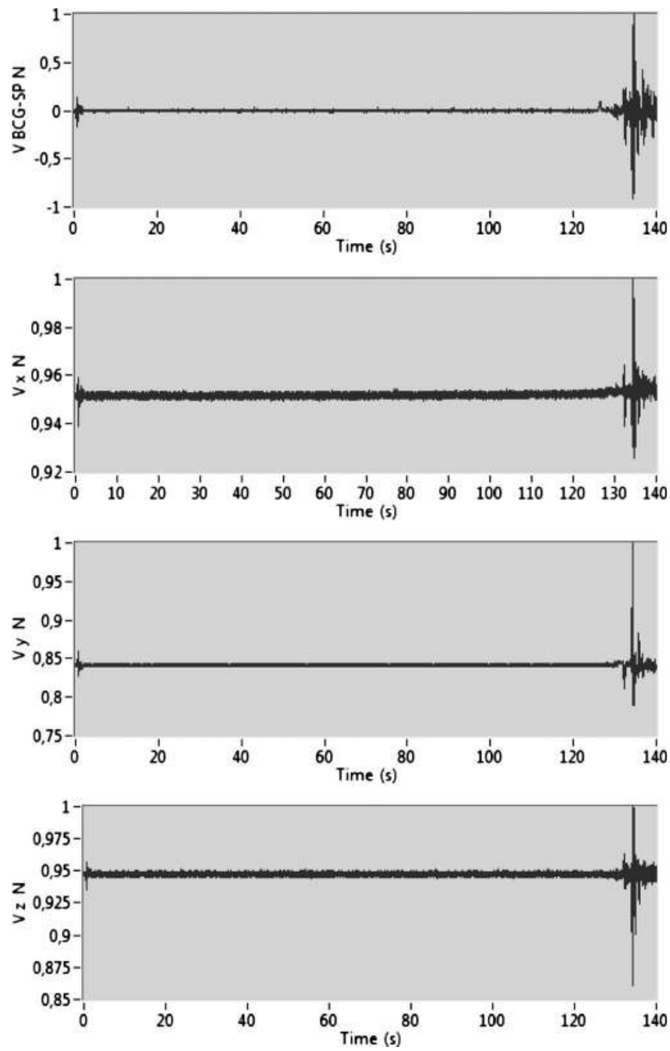

Fig. 14. BCG signal provided by the BCG-SP unit for 140 s when the wheelchair is in motion and subject to strong artifacts.

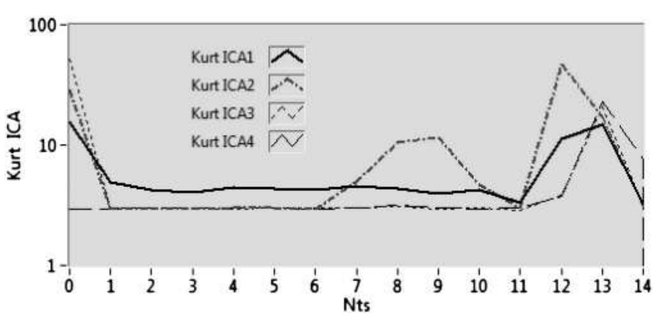

Fig. 15. Evolution of Kurt for a set of ICA components and for a number Nts of 10-s time segments.

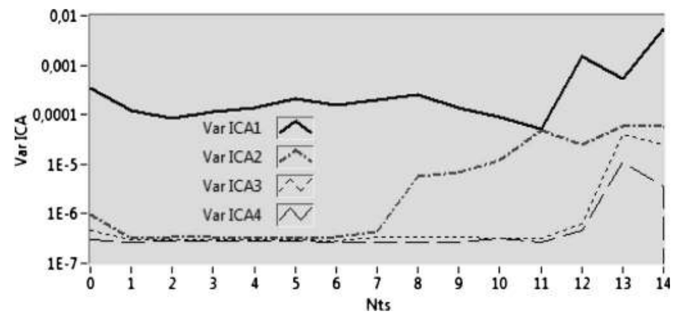

Fig. 16. Evolution of variance index for a set of ICA components and for a number Nts of 10-s time segments.

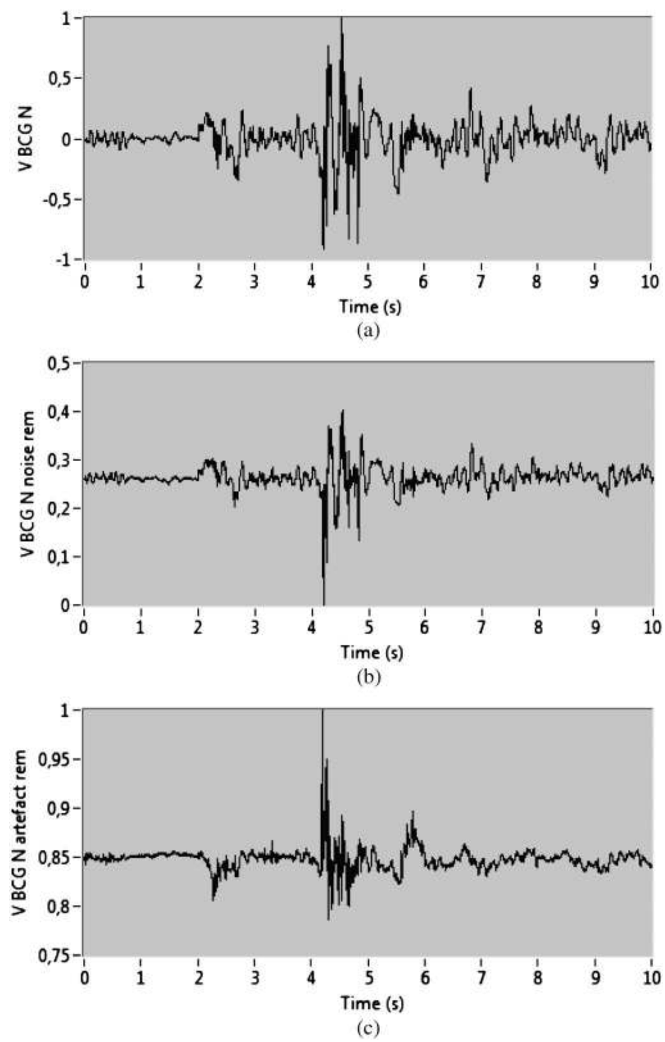

Fig. 17. BCG signal reconstruction from ICA components for 10-s segment. (a) All of ICA components were used. (b) Two ICA components were used according to the noise removal criteria. (c) Two ICA components were used according to the artifact removal criteria.

of the system. To evaluate the system's autonomy when a 12-V/7-Ah battery is used, different tests were carried out. Part of the results are presented in Fig. 18. The figure shows the current, voltage, and power variation during the operation for an *ad hoc* implemented architecture. Two kinds of operation status were considered: 1) Wi-Fi connection between PC and W-DAQ without data communication (no acquisition) and 2) Wi-Fi connection between PC and W-DAQ with data communication (the acquisition of the voltage from the BCG and acceleration measurement channel is carried out). With regard to the power consumption, it can be underlined that the Wi-Fi communication is the main contributor (3.1 W, in standby mode, and no data transmission), because data transmission and remote acquisition are responsible for only about 0.2 W (3.3 W, overall).

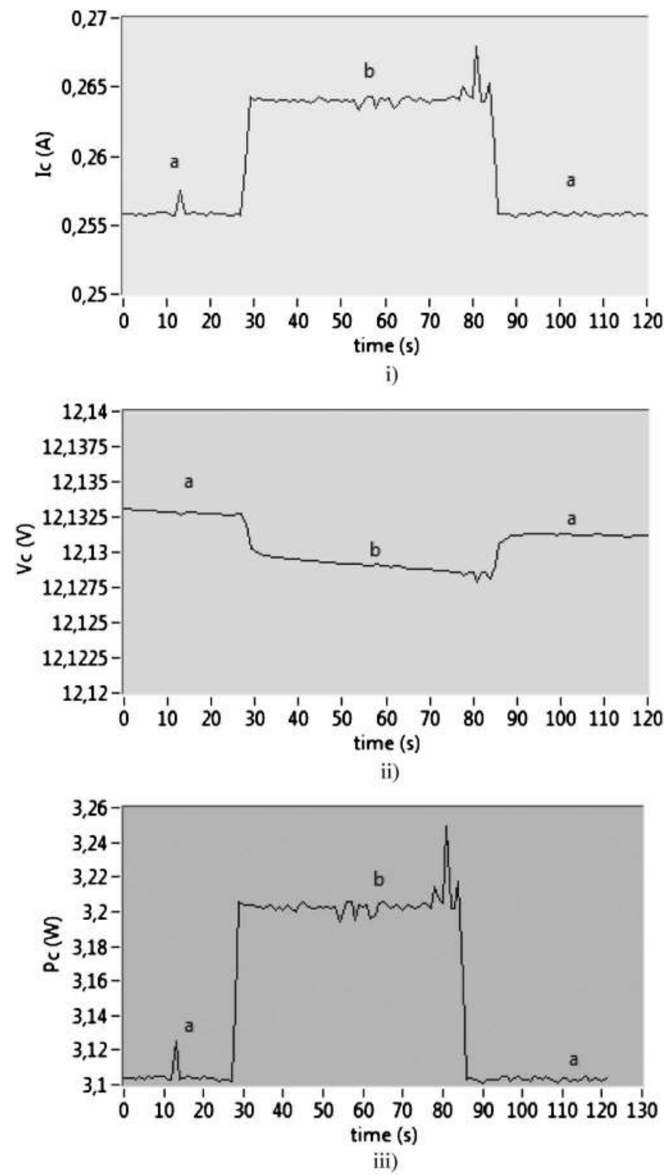

Fig. 18. W-DAQ voltage, current, and power consumption evolution with (b) and without (a) sensor data wireless acquisition.

V. Conclusion

This paper has presented an unobtrusive way of recording vital signs from a user seated on a wheelchair. The proposed system can significantly reduce the stress caused by the usual apparatus, therefore improving the quality of health care services and allowing continuous patient monitoring. The multichannel sensing units of BCG and acceleration provide signals that are acquired by a data acquisition module with wireless capabilities (Wi-Fi) and then transmitted to the advanced processing unit expressed by a laptop PC. The usage of two BCG channels materialized by EMFi sensors placed on the seat and on the backrest of the wheelchair ensures high reliability and sensitivity of the system and also permits fusion of the information to extract the physiological information in an unobtrusive way for different scenarios of usage of this smart wheelchair. With regard to BCG and acceleration signal processing, wavelets and ICA algorithms were implemented in software using LabVIEW and Advanced Signal Processing Toolkit (Time-Series Analysis Tool). Good results of heart rate and respiration rate were obtained by calculating the wavelet decomposition of the acquired BCG signals using Daubechies mother wavelets. To ensure artifacts removal, an ICA algorithm was implemented, and a set of the obtained results was presented.

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