Proceedings of the Estonian Academy of Sciences,
2016, **65**, 4, 345–357
doi: 10.3176/proc.2016.4.03
Available online at www.eap.ee/proceedings

BIOMEDICAL
ENGINEERING

A parametric framework for the development of bioelectrical applications: application to a bio-impedance signal simulator

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Received 31 August 2015, revised 5 January 2016, accepted 3 February 2016, available online 25 October 2016

Abstract. Extracting useful information from cardiac signals for the diagnosis of diseases and judgement of heart functioning is of special interest to medical personnel. However, exploiting such signals is subject to the availability of the signals themselves and to possible measurement errors. We thus argue that modelling such signals offers several advantages as compared to relying on measured data only. By using a formalized representation, the parameters of the signal model can be manipulated and/or modified, thus providing mechanisms that allow researchers to reproduce and control such signals by means of e.g. simulators. To guide both the signal modelling and simulator development phases, we propose a new generic framework. We then illustrate how it can be used to guide the modelling of the impedance cardiography and impedance respirography signals. We also show how the proposed framework has been used to guide the development of the corresponding Bio-Impedance Signal Simulator (BISS). As a result, the implemented BISS generates simulated Electrical Bio-Impedance (EBI) signals and gives freedom to the end-user to control the essential properties of the generated EBI signals depending on their needs. Predefined states of human conditions/ activities are also included for ease of use.

Key words: electrical bio-impedance (EBI), biological system modelling, biomedical signal processing, cardiography signals, respirography signals, signal analysis, signal processing algorithms, signal modelling, signal simulation.

1. INTRODUCTION

Extracting useful information from cardiac signals for the diagnosis of diseases and judgement of heart functioning is of special interest to medical personnel. Thus, the development of effective, robust, and efficient diagnostic tools for heart disease symptoms such as cardiac rhythm disorder and arrhythmia is highly desirable as they allow investigating and analysing the cardiac signals in detail (Gargasas et al., 2004; Kersulyte et al., 2009).

Generally speaking, the aim when developing new techniques and tools is to minimize the required cost and hospitalization times, as well as to increase patients' ease and safety (Solà et al., 2011). Thus, non-invasive electrical-based methods are now commonly used in a clinical context. The main advantage of this type of procedures is that they do not need to break the skin and are used not only for making a diagnosis but also for treating patients (e.g. electrotherapy, radiotherapy).

However, using non-invasive data acquisition techniques raises several issues, including:

- it is difficult to obtain accurate and valuable information from the body as it is inhomogeneous;
- typical body evaluation models are fairly complex since they are a combination of three different sub-level models, i.e. electrical, mechanical (hydraulic and pneumatic), and geometrical models of the body (Malmivuo and Plonsey, 1995);
- it is important to place the sensors according to the body model. The optimal positioning of the measuring sensors increases the measurement accuracy and

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influences the reliability of data, repeatability of the measurements, and accuracy of the evaluated haemodynamic parameters;
- the measured data is a combination of various signals (e.g. cardiac, respiratory, motion artefacts, etc.). For example, the measured data are useful only if one can separate cardiac and respiratory signals and simultaneously suppress the unwanted artefacts such as motion artefacts, noise, and stochastic disturbance.

Because of the above issues, there exist uncertainties regarding (a) the properties of the signal such as its amplitude, waveform, and components (e.g. cardiac vs respiration) and (b) the origin of the signal waveform (e.g. configuration/positioning of electrodes/sensors vs the condition of the patient). In turn, this limits the quality of the diagnostics of diseases and conditions. In this paper, we thus argue that modelling the measured signals offers several advantages as compared to relying on measured data only:
- By using a formalized (e.g. mathematical) representation, the parameters of the signal model can be easily manipulated and/or modified, thus providing mechanisms that allow researchers to reproduce and control such signals.
- In turn, having such a formalized signal model makes it possible to develop tools (e.g. simulators) that can be used for manipulating and understanding how the signal changes depending on various conditions, as well as for generating input signals for experimenting with and evaluating the performance of useful signal extraction methods such as separation algorithms.

Once the (bioelectrical) data have been measured, it is needed to model the corresponding signals for analysis. In this case, the so-called advanced user (i.e. a person who makes the decisions in each step and analyses the results in order to develop an application) must follow a structured approach to move from real measured data to the signals' model.

Our previous studies (Mughal et al., 2013; Mughal, 2014) provide the motivation for developing a signal model that imitates the real phenomena of cardiac and respiratory signals. In addition, the end-user (i.e. a user of the simulator) has the freedom to generate the required simulated signal(s) based on their needs as well as mix artefacts and noise artificially.

1.1. Overview of the existing methods of modelling Electrical Bio-Impedance (EBI) signals

Extensive research on modelling and simulation in the area of biomedical engineering has been carried out over the years. Simulator and software tools generally focus on cardiovascular simulation (this provides a general basis for how to structure and implement such a simulator) and on thoracic electrical bio-impedance (these provide valuable insights related to the effects of artefacts and estimation errors in EBI measurement and simulation) (Heldt et al., 2010; Abtahi et al., 2012; Ulbrich et al., 2012).

Several approaches related to cardiovascular simulation can be used to model the signals (Mughal et al., 2015a). The following three methods are deemed to be most relevant with respect to cardiac signal modelling.

1. A simple bio-impedance signal synthesizer was proposed by Krivoshei (2006) to generate cardiac and respiratory signals. The author used a piece-wise linear triangular function to model the cardiac signal and a trapezium to model the respiratory signal. The model, however, is too simple to fully imitate the cardiac and respiratory signals, and thus does not allow testing of e.g. separation algorithms (Mughal et al., 2015a).
2. A cardio model based on the sum of exponential functions was proposed by Kersulyte et al. (2009). Their purpose was to find an as precise as possible model for cardio signals and compare complexity parameters of the real signals and those of the model for both healthy and sick persons. They compared two function types, i.e. polynomial and sum of exponentials. Their results indicate that both methods lead to similar results in terms of fidelity; however, the authors also indicate that the polynomial equation depends on the signal length and number of intervals, which could lead to too many coefficients and increased computational requirements for complex signals (Mughal et al., 2015a).
3. A cardiac signal model based on a series of real signals was proposed by Matušek et al. (2012). By filtering and averaging the series of real signals, they estimated one average impedance cardiography (ICG) signal cycle and simply replicated this cycle over time to get the final signal model. One limitation of this approach is that it lacks a mathematical model and thus the user cannot easily reproduce the model and change its parameters (Mughal et al., 2015a).

1.2. Proposal for a modelling framework and its implementation

This work proposes a generic modelling framework and its implementation, exemplified with an EBI case.
- First, we devise a generic framework that can be used to guide both the modelling of the signals of interest and the development of an application for bio-electrical information for further processing.
- Second, we implement the framework as a specific example for an EBI case.

The modelling of the heart and lungs signals allows the advancement of knowledge regarding the interplay of anatomical structures and physical phenomena that contribute to cardiac and respiratory physiological and pathophysiological behaviours.

The main contributions of this paper are the following:

- A novel and unique generic framework for modelling the bio-electrical information is proposed. The framework provides a pathway between biological systems and bioelectrical applications.
- A bio-impedance signal model is derived, and the corresponding novel Bio-Impedance Signal Simulator (BISS) is developed.

To the best of our knowledge, the BISS is the first EBI signal simulator that both imitates the real phenomena related to ICG and Impedance Respirography (IRG) signals and gives the freedom to the end-users to simulate EBI signals as they need.

2. METHODS

This section discusses the measurement of the EBI signals, the specific measurement setup used in our work, the proposed novel generic framework for modelling the bioelectrical information, and finally, as an example, the implementation of the proposed novel generic framework for the EBI signals.

2.1. Measurement of the EBI signals

This study focuses on the modelling of the ICG and IRG signals as an example. In practice, the measured EBI data are used to model those two signals.

The ICG process does not separate signals from different objects during the measurement. Electrode positioning can help (somewhat at least) if the electrodes are placed properly relative to what is required to be both measured and calculated such as heart rate (HR), stroke volume (SV), cardiac output (CO), respiration rate (RR), muscular movement, etc. In this case ICG is one of the very promising methods among non-invasive methods (the details are discussed in Section 2.4) (Muhammad, 2015; Mughal, 2016).

The measurement set-up and the 16-electrode configuration method used to acquire the EBI data from a healthy male subject is described in (Mughal, 2014; Mughal et al., 2015a).

2.2. Measurement set-up

The measurement set-up shown in Fig. 1 is used to acquire the EBI data (corresponding to the measured

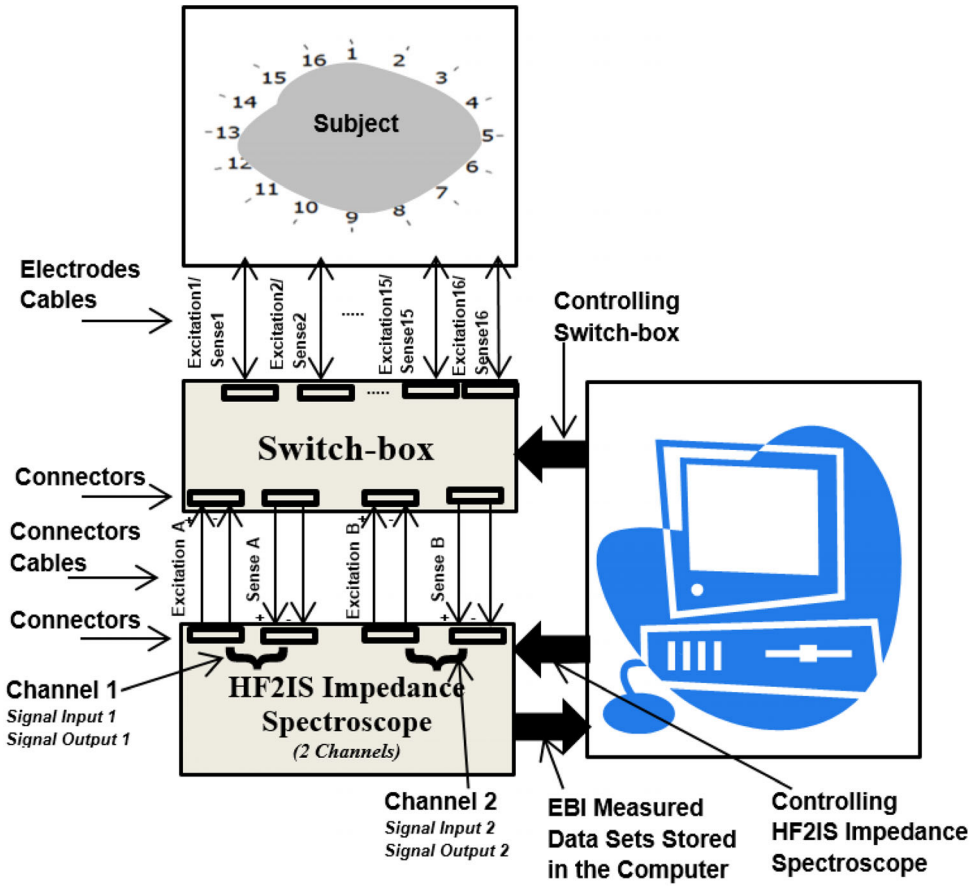

Fig. 1. Set-up for measuring the electrical bio-impedance (EBI) of a subject.

EBI signal). The 16-electrode belt is worn around the thorax of the subject.

A Zurich HF2IS Impedance Spectroscope (Zurich Instruments, 2015) is the measurement equipment that was used in this work. The HF2IS is used to excite the subject and to measure the EBI data sets from the subject through sense electrodes. The HF2IS is connected to a switch-box with connectors' cables.

The HF2IS was limited to two channels (channels 1 and 2, Fig. 1); because of this, at a given time four electrodes (two electrodes from each channel (Excitation A and B)) were used to excite the subject, and four electrodes (two electrodes from each channel (Sense A and B)) were used to sense the EBI data. Thus, eight electrodes are active at a time.

The sensed (measured) EBI data sets were stored in a computer for further analysis. The attached computer is also used to control the switch-box and HF2IS impedance spectroscopy equipment.

A program developed at Thomas Johann Seebeck Department of Electronics, Tallinn University of Technology, Estonia, was used to control the switch-box that automatically switches/selects the configuration of the electrodes at each time step. Nevertheless, the configuration of the electrodes can also be set up by the advanced user.

2.3. Proposed novel generic framework for modelling the bioelectrical information

A generic framework is proposed to guide the modelling of signals and to develop a corresponding simulator for the bioelectrical information. First, the bioelectrical information must be modelled based on template signals (a template signal is an ideal signal that has been measured and cleaned) and then a corresponding signal simulator must be developed (Mughal et al., 2015b). Before describing the proposed framework, a block diagram illustrating the relation between the modelling of the template signals and the development of the corresponding simulator for the bioelectrical information from which the need for the framework arises is proposed (Fig. 2).

The template signals could be modelled with the help of methods such as curve fitting (e.g. polynomial), sum of sines, Fourier series, etc. (with the help of tools such as Matlab Curve Fitting toolbox, EzyFit, TableCurve 2D, PeakFit), or waveform generation (e.g. Matlab Waveform Generator), etc. (Fig. 2).

The developed signal model should ideally be validated against the template signals. This validation could be done based on e.g. statistical parameters such as sum of squared error (SSE), correlation between the modelled signal and template signal, execution time, and so on. The best-fit modelling method can then be chosen. Alternatively, a visual inspection could be performed to evaluate the fit of the model against the template signal. However, if a very accurate model is required, both approaches should be used.

Once the developed signal model has been validated against template signals, and thus can imitate the real phenomena, the original values of the signal model parameters ($P1_O$, $P2_O$, $P3_O$, …, Pn_O, where the subscript O denotes the original signal's parameters and n the number of parameters) are set. These values will only be modified in the simulator by the end-user.

Next, it is necessary to build a corresponding signal simulator where the predefined signal model parameters ($P1_O$, $P2_O$, $P3_O$, …, Pn_O) are also possibly controlled (i.e. overwritten) by the end-user. Moreover, other parameters (internal to the adaptation process) could also be introduced in the simulator by the end-user and controlled by them. These are used inside the adaptation process to tune the signal model in order to reflect the actual phenomena that take place in the biological system/object of interest.

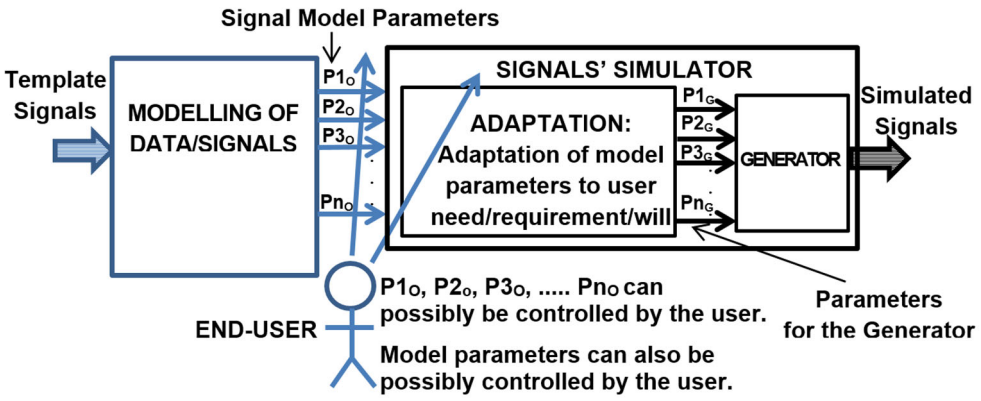

Fig. 2. Block diagram of the generic system for modelling the template signals and for developing the corresponding simulator. $P1_O$ … Pn_O are signal model parameters and $P1_G$ … Pn_G designate end-user prescribed parameters.

The core mechanisms of the simulator include adaptation. The generator generates the simulated signals as per the end-user prescribed parameters ($P1_G$, $P2_G$, $P3_G$, …, Pn_G, where G denotes the generated signal's parameters and n is the number of parameters), so that the end-user is able to control the signal model parameters and generate the simulated signals as desired.

The flow diagram proceeds according to the proposed framework as depicted in Fig. 3. This flow chart guides the advanced user (technical user who makes the decisions on each step) step-by-step with the help of the predefined blocks. Each diagram has specific criteria that are required to be kept in mind and follow the guidelines.

Figure 3 shows the flow diagram of data acquisition and processing as well as modelling and simulation of the bioelectrical information. This flow diagram is the pathway to application in order to model the signals. It is implemented for the specific case of EBI based on the IRG and ICG signals.

In this work the generic framework is implemented, as an example, for the EBI case. The generic framework provides guidelines on how to measure the EBI data from the subject, how to clean the measured EBI signals in order to achieve the ideal (template) of ICG and IRG signals, and how to build signal models for ICG and IRG signals. The signal model approach is discussed in (Mughal et al., 2015a). Then, the simulator is actually built, as discussed in Section 3.

2.4. Implementation of the proposed novel generic framework for the development of the EBI signal simulator

In this section, each step of the framework for developing the EBI signal simulator is described in detail.

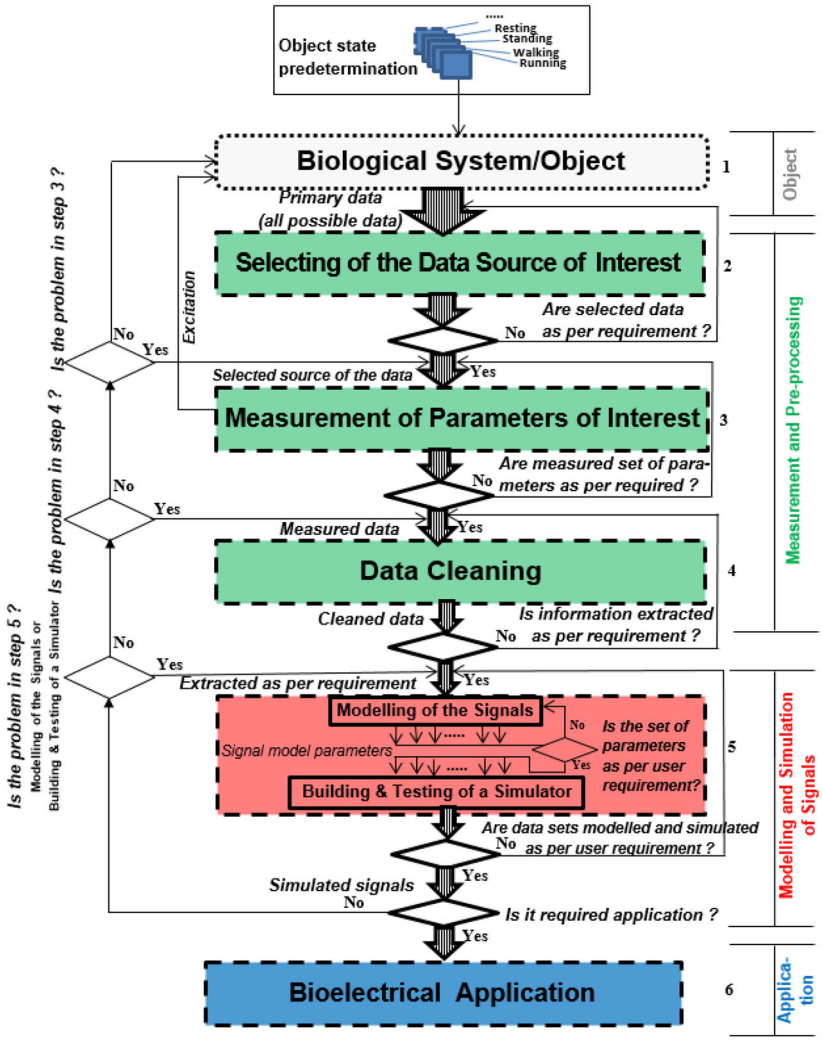

Fig. 3. Flow diagram of the proposed novel generic framework for modelling and simulating the bioelectrical information.

2.4.1. Biological system/object (Step 1)

The first part the biological system or object (subject) is presented in Fig. 4. It consists of three sub-systems: cardiovascular, respiratory, and muscular sub-systems. Each sub-system is described through its parameters. The relationships between the parameters are shown in the form of arrows connecting them with one another, mainly within the same system, but some are also connected with parameters that belong to one or both of the two other sub-systems.

The following description begins with the baro-receptor reflexes and follows the natural flow of the three sub-systems.

Parameters of the cardiovascular system:

- *Baroreceptor Reflexes* (BRR) control Blood Pressure (BP). Changes in the BP affect the frequency of action potentials sent to the cardiovascular control centre from the BRR (Timischl, 1998).
- *Cardiovascular Control Centre* (CCC). Heart Rate (HR) is controlled by both the sympathetic nervous system (SPP) and the parasympathetic nervous system (PSP); the SPP increases the HR while the PSP decreases it. The HR varies from 60 to 180 beats per minute (bpm).
- *Heart Rate* (HR) corresponds to the frequency of heart beating, i.e. the number of heart beats per minute or the reciprocal of the duration of heart cycle $Yc = 1/Tc$ bpm.

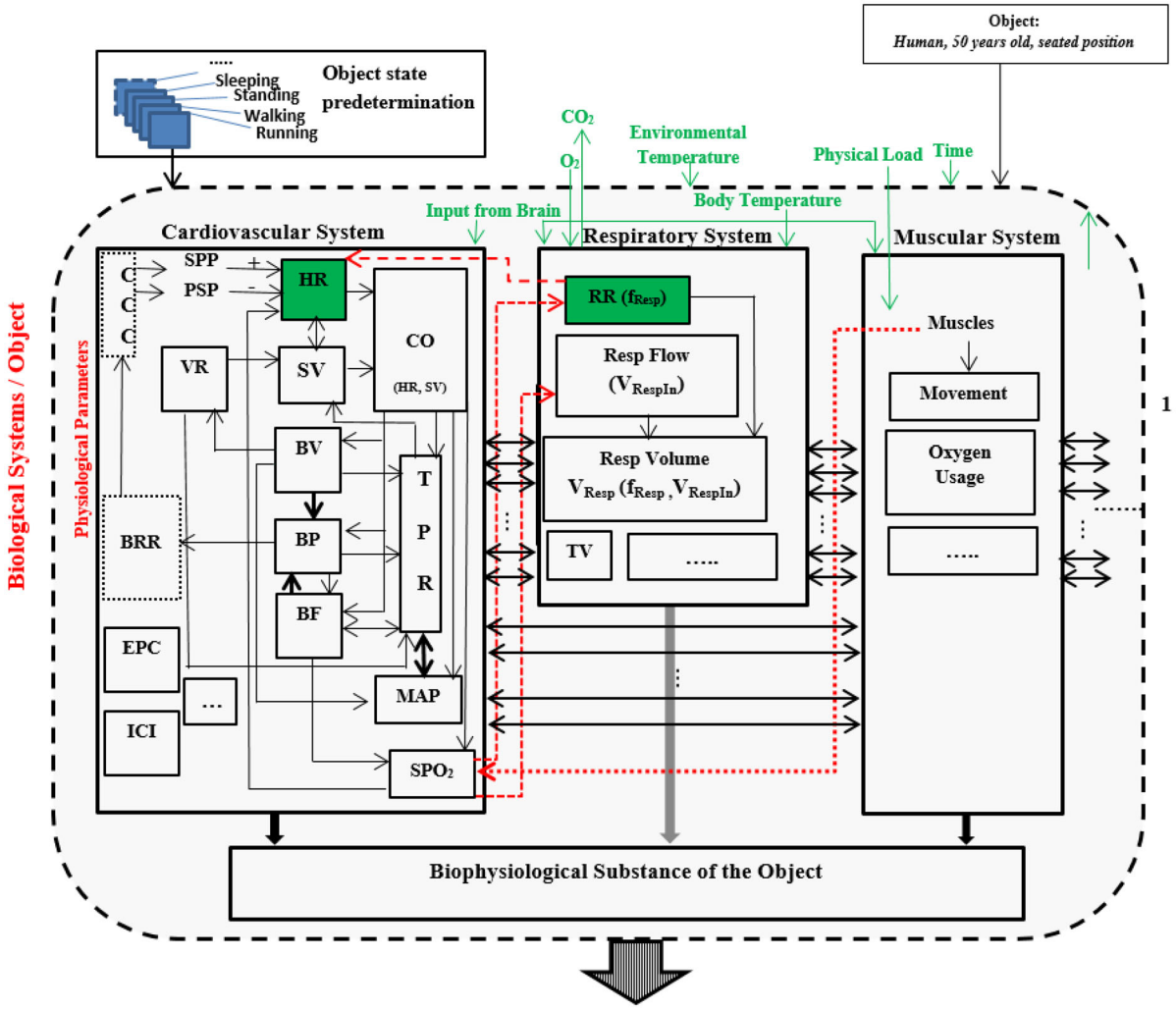

Fig. 4. Block diagram illustrating relationships between the parameters of the three main systems of the organism (cardiovascular, respiratory, and muscular). Parameters of the greatest interest are highlighted. Thin arrows (solid line) show dependence on other parameter(s) within the same system. Thick arrows (solid line) show a direct relation or strong dependence on the other parameter(s) inside the same system. Thin arrows (dotted line) show dependence on other parameter(s) within other systems. Thick arrows (dotted line) show a direct relation or strong dependence on parameter(s) within other systems. Thick arrows (in both directions) show direct proportional dependence on each other within the same system. See Section 2.4.1 for abbreviations.

- *Venous Return* (VR) is the amount of blood that returns to the heart. VR depends on the blood volume.
- *Stroke Volume* (SV) is the volume of blood that is pumped out by the heart with a single beat. SV depends on the VR and total peripheral resistance. The typical SV value for a healthy person is approximately 50 mL in a single stroke. The HR and SV are proportional to each other.
- *Cardiac Output* (CO) is the volume of blood that is pumped out by the heart per minute. It is a function of the HR and SV and can be calculated based on the HR and SV: CO = HR · SV.
- *Blood Pressure* (BP) usually refers to the arterial pressure of the systemic circulation. It is partly dependent on the CO and the vessels, and directly (strongly) depends on the blood volume and the blood flow (Timischl, 1998). For a healthy person, the typical upper level is 120 mmHg.
- *Blood Volume* (BV) is the volume of blood in the circulatory system of any individual. For a healthy person it typically ranges from 3 to 5 L.
- *Total Peripheral Resistance* (TPR). The blood vessels provide resistance to the flow of blood. The resistance and pressure are directly proportional to each other. If the resistance increases, the pressure will increase (TPR depends on CO, BV, BP, BF, and MAP).
- *Blood Flow* (BF). The flow of blood through the vessels of the circulatory system is a function of the BP and TPR (BF depends on BP, TPR, and CO (Timischl, 1998)). It is approximately equal to the CO.
- *Mean Arterial Pressure* (MAP) represents the average driving force for the blood flow through the arterial system (MAP depends on the CO and BV and is directly proportional to the TPR). It is approximately 20% lower than the upper BP.
- *Saturation Pressure of Oxygen* (SPO_2). The muscles highly depend on the SPO_2 because if the muscle starts to work, it requires more oxygen (SPO_2 depends on muscles, CO, and BF). For a healthy person, the typical percentage is about 100%.
- *Intra-Cardiac Impedance* (ICI) reflects the variations of the cardiac output internally.
- *Epicardial Potential* (EPC) is the internal ECG potential.

Parameters of the respiratory system:

- *Respiration Rate* (RR) is the number of cycles per minute. It is not directly dependent on the HR but, under certain conditions, it depends on the HR and SPO_2.
- *Respiration Flow* (RF) is the inspiration or expiration volume of airflow in a minute. It depends on the SPO_2.
- *Respiration Volume* (RV) is the volume of air that is inhaled and exhaled per minute. It is a function of the RR and RF. For a healthy person, the typical RV ranges from about 2 to 5 L/min.
- *Tidal Volume* (TV) is the volume of gas inhaled or exhaled during one respiratory cycle; details are discussed in (Krivošei, 2009).

Parameters of the muscular system:

- *Muscles:* The ability of muscles to work is highly dependent on the oxygen supply (SPO_2).
- *Movement:* Body movement from Biological Systems/ Object as prescribed.
- *Oxygen Usage:* It depends on the real physical load.

2.4.2. Selection of the data source of interest (Step 2)

The diagram of selecting the data source (2 in Fig. 3) is divided into three sub-diagrams as shown in Fig. 5. In this diagram, the objective is to select the desired physiological parameters of interest; here these are HR and RR, which are both directly measurable. Based on the selected area of thorax, it is assumed that strong variations of the ICG and IRG signals can be obtained and that it is possible to measure the physiological parameters HR and RR.

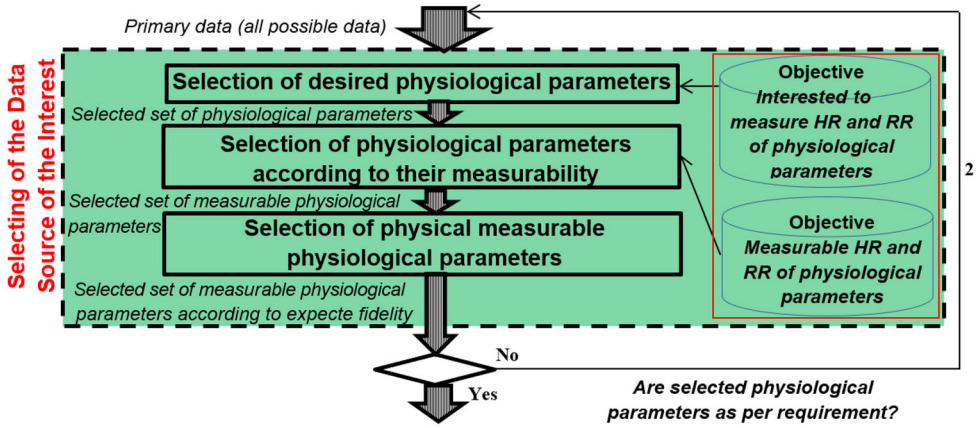

Fig. 5. Flow diagram of the selection process of the data source of interest. The box on the right shows the specific parameters of interest selected by the advanced user for this example. HR – heart rate, RR – respiration rate.

After selecting the source of data and acquiring the EBI data set and physiological parameters, it is necessary to ensure that these are as per the user's needs.

2.4.3. Measurement of parameters (Step 3)

The diagram of measuring the parameters of interest (3 in Fig. 3) is divided into four sub-diagrams as shown in Fig. 6. In this step, the objective is to select the type and configuration of the electrodes. For acquiring the EBI data set, a 16-electrode configuration belt was worn on the human thorax area and 3M disposable surface EMG/ECG/silver/silver chloride electrodes were chosen to measure the physiological parameters, namely HR and RR, and the ICG and IRG signals.

After deciding the parameters for all these sub-diagrams, the EBI data, which are location and time dependent, can finally be measured.

2.4.4. Data cleaning (Step 4)

The fourth diagram of data cleaning (4 in Fig. 3) is divided into two sub-diagrams as shown in Fig. 7. In this diagram, preprocessing is performed to clean the ICG and IRG signals, including EBI signal normalization (scaling), conditioning, and filtering to attenuate the undesired parts of the signal.

After preprocessing the EBI signal, further processing is performed to extract the features (e.g. waveform and trend) from the clean ICG and IRG signals. At this point, careful visualization of the representation of the ICG and IRG signals waveform with templates of the ideal ICG and IRG signals waveform is required.

2.4.5. Modelling and building a simulator (Step 5)

The diagram of building and testing a simulator (5 in Fig. 3) is divided into two sub-diagrams: modelling of

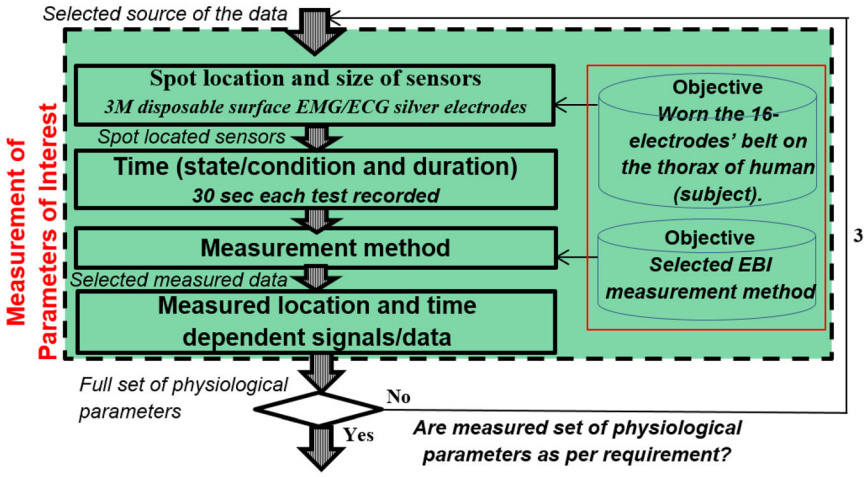

Fig. 6. Flow diagram for the measurement of the parameters of interest. The box on the right shows the specific configuration of electrodes and the measurement method selected by the advanced user for this example. EBI – electrical bio-impedance.

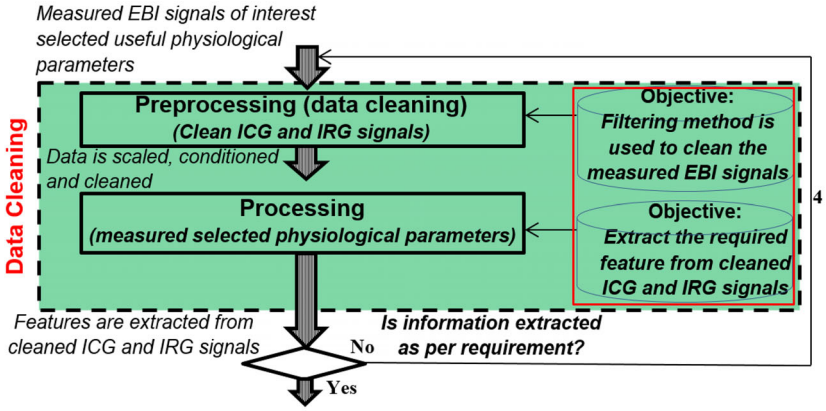

Fig. 7. Flow diagram of the data cleaning process. The box on the right shows the cleaning of the impedance cardiography (ICG) and impedance respirography (IRG) signals and extraction of the feature from the cleaned signals. EBI – electrical bio-impedance.

the signals and building a corresponding simulator, as shown in Fig. 8. In the diagram, the signals are modelled based on the clean features of the extracted ICG and IRG signals. The Fourier series method was chosen from among other curve-fitting methods to model the ICG and IRG signal parameters, as discussed in our previous study (Mughal et al., 2015a).

The corresponding simulator, BISS, was built based on the modelled parameters of the ICG and IRG signals.

2.4.6. Selection Bio-electrical applications (Step 6)

The sixth diagram in Fig. 3 is that of the bio-electrical application. The application BISS, which simulates the EBI signal, was developed (Fig. 9). The BISS can be a useful tool to simulate the EBI signals in order to e.g. evaluate the performance of signal processing algorithms as well as for teaching and training in physiological courses to engineering and health science students as

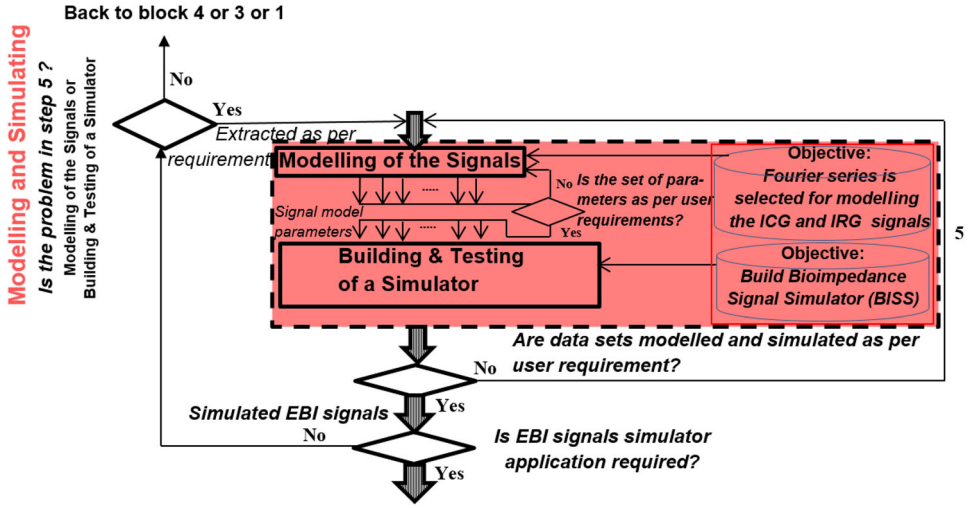

Fig. 8. Flow diagram for modelling the impedance cardiography (ICG) and impedance respirography (IRG) signal parameters based on Fourier series and for building a corresponding bio-impedance signal simulator (BISS). EBI – electrical bio-impedance.

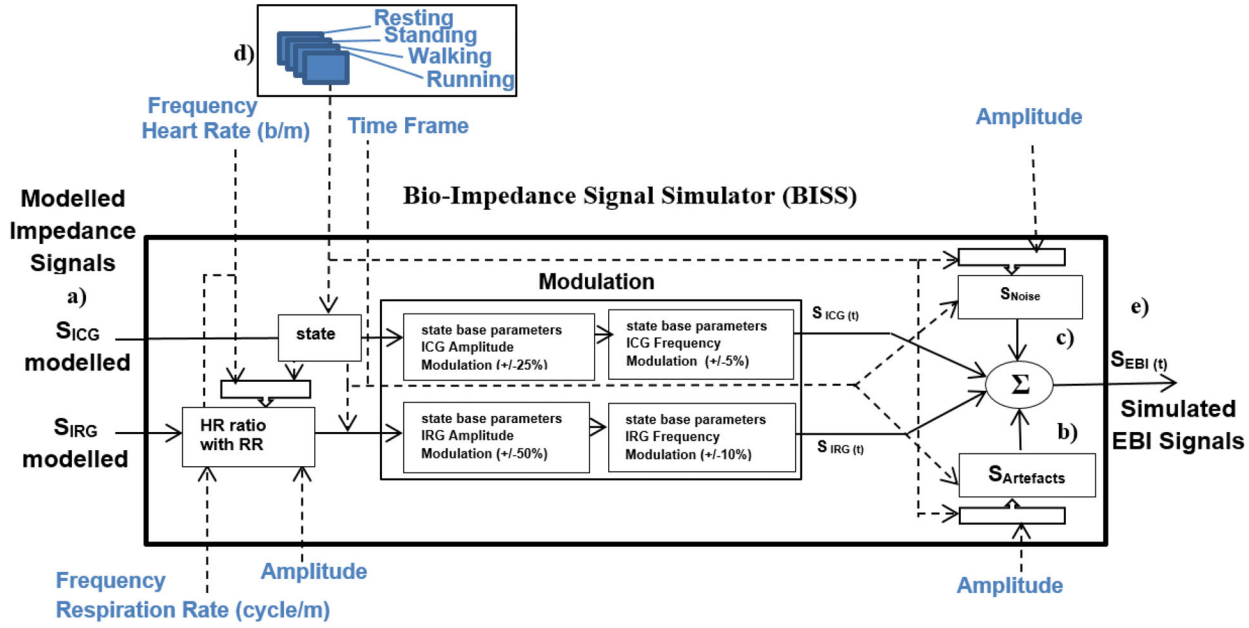

Fig. 9. Block diagram of the BISS for the modelling of the impedance cardiography and (ICG) and impedance respirography (IRG) signals and for the development of a corresponding simulator for electrical bio-impedance (EBI) signals. HR – heat rate, RR – respiration rate, S_{ICG} – impedance cardiography signal, S_{IRG} – impedance respirography signal, S_{EBI} – impedance electrical bio-impedance signal.

it can give hands-on means to the students to understand the complicated physiological phenomena.

3. RESULTS

The signal model used in the BISS was built based on the Fourier series, which is discussed in our earlier publication (Mughal et al., 2015a).

The simulated EBI signal is generated by summing the ICG signal (S_{ICG}), IRG signal (S_{IRG}), artefacts ($S_{Artefacts}$), and a white Gaussian noise (S_{Noise}). The bandwidth of the Gaussian noise is set to half of the sample rate (sampling frequency; here 500 Hz for 1000 samples per second).

Figure 9 depicts (a) the modelled S_{ICG} and S_{IRG} (modelled by means of the Fourier series method (Mughal et al., 2014, 2015a), (b) the recorded motion $S_{Artefacts}$ (e.g. swinging arm) added to the simulated EBI signal, and (c) a S_{Noise} also added to the simulated EBI signal.

The block diagram of the BISS shows that different pre-recorded states (d) corresponding to healthy persons resting, standing, walking, and running are included in the simulator. The parametric values and cardiac relationships with respiration vary between the states/conditions. Nevertheless, the end-user also has the possibility of changing the parameters as per their needs such as heart rate, respiration rate, time frame, amplitude of respiration, artefacts, and noise.

Finally, (e) shows that the simulated EBI signals are a mixture of ICG, IRG, artefacts, and noise. Such simulated EBI signals can then be used for further processing (e.g. to evaluate the performance of separation algorithms).

The outer parameters (blue in Fig. 9) such as heart rate (beats/min), time frame (s), respiration rate (cycles/min), amplitude for respiration, artefacts, and noise are controlled by the end-user (possibly overriding the values loaded from a pre-recorded state).

The graphical end-user interface (EUI) of the BISS is illustrated in Fig. 10 for a healthy running person. The interface includes (a) a menu where the end-user can load the different states of a person, open existing simulated EBI signals, save the current simulated EBI signals, and exit from the simulator; (b) the measured and cleaned ICG signal; (c) the ICG signal modelled by means of the Fourier series method; (d) the measured and cleaned IRG signal; and (e) the IRG signal modelled by means of the Fourier series method.

The cardiac amplitude in the BISS (Fig. 10 (f)) models the systolic and diastolic activities in order to imitate the

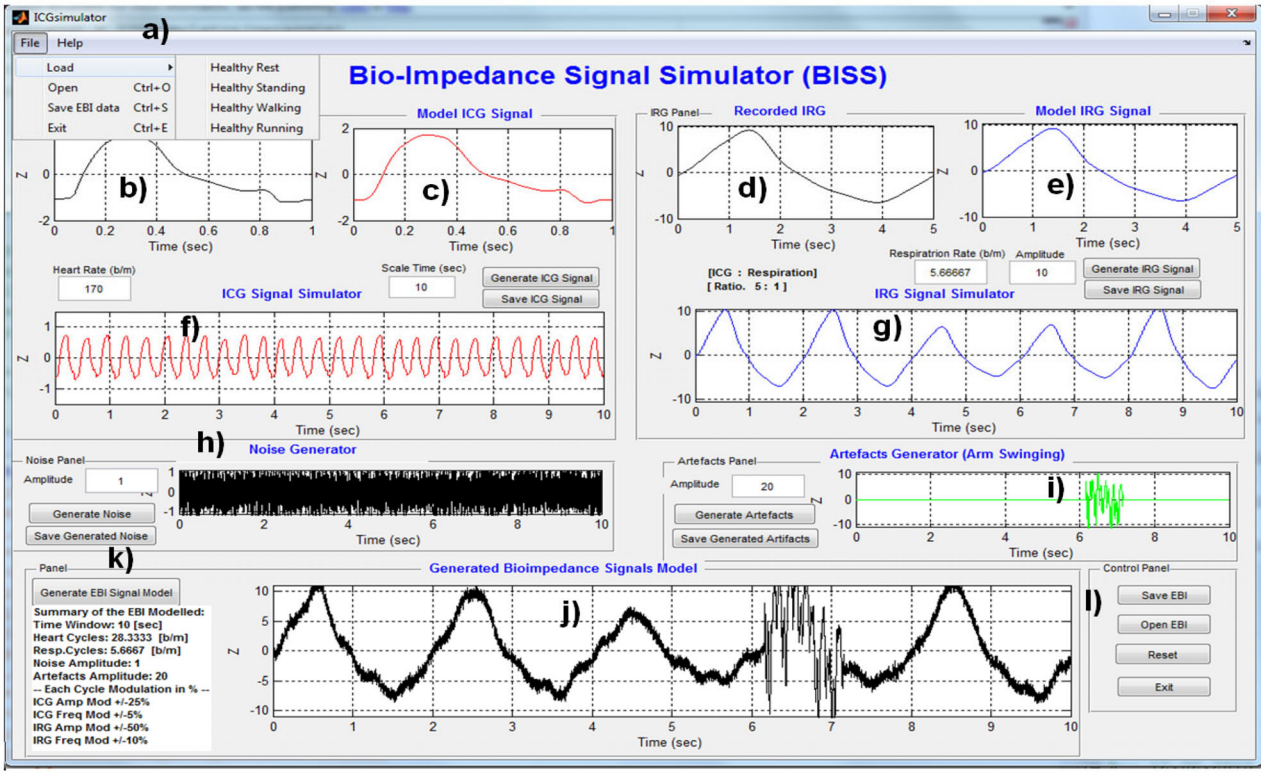

Fig. 10. End-user graphical interface of the bio-impedance signal simulator (BISS) with the signals simulated for the state 'healthy person during running'.

real phenomena of the heart. If the heart rate increases, the amplitude of the ICG will decrease and the diastole period will also decrease. If the heart rate decreases, the amplitude of ICG will increase and so will the diastole period. A variation is also introduced in the systolic and diastolic activities as per cardiovascular phenomena. The ICG signal is continuously moving in time and it is simulated where modulation is introduced with each cycle in amplitude and frequency.

In order to imitate the real phenomena, signal modulations are included in the BISS. The ICG amplitude modulation range is ±25% and the frequency modulation range is ±5%, depending on the heart rate. This makes cycles different from each other. Similarly, modulation is also introduced for the respiration (IRG) amplitude (±50%) and frequency (±10%). Medical doctors confirmed these modulation ranges as realistic ones.

The IRG signal is continuously moving in time. It is a simulated signal where modulation is introduced with each cycle.

The respiration rate is correlated to the cardiac heart rate by means of a ratio. The default ratio is set to 5 : 1 (5 cardiac cycles for 1 respiration cycle). Nevertheless, the end-user can control the respiration rate as well.

Furthermore, in Fig. 10, (h) is the noise generator, (i) the recorded artefacts caused by motion (in this example, by swinging the arm during the measurement) randomly moving in the defined time window, (j) the simulated EBI signals model based on the end-user loaded state (healthy running), (k) the detailed summary of the simulated EBI signals model, and (l) are buttons that let the end-user save the simulated EBI signals, open existing simulated EBI signals, clear all simulated model signals, and start again and exit from the BISS GUI environment. Note that the time scales of (d) and (e) are not the same as those of (g) and (j) due to the 5 : 1 ratio discussed earlier.

4. DISCUSSION

The review performed regarding the ways in which other researchers approach the problem to build a signal model for cardiac and respiratory signals shows why these methods are not suitable. This is mostly because other researchers used either a simple method, i.e. one which does not model the signal realistically; a method lacking a mathematical signal model; or a method which is computationally expensive.

We thus argue that it is preferable to model the ICG and IRG signals based on measured EBI data rather than relying on measured data only. For this, a novel generic framework for modelling the bioelectrical information is proposed. The framework provides a pathway between biological systems and bioelectrical applications.

The generic framework was used to implement a practical EBI application. Building on the Fourier series model, the BISS was developed to simulate the EBI signals. The BISS gives the end-user the freedom to simulate the EBI signal as per their needs for further analysis. Nevertheless, predefined states are included in the BISS. The simulator imitates the real phenomena of ICG and IRG signals, and thus the EBI simulated signals could be used to evaluate and assess the performance of separation algorithms, for example. Moreover, the developed BISS could also be used for teaching and training purposes.

This being said, there are several limitations that should be addressed in the future work. Currently, the implementation of the BISS is focused on the simulation of the EBI signals and thus only EBI signals are modelled (namely ICG and IRG signals); however, the BISS could be extended to other methods of bioelectrical information, such as Foucault Cardiography (FCG), Opto-Electronic Plethysmography (OEP), Electrical Impedance Tomography (EIT), and so on. This would require modelling the signals used in that method (e.g. cardiac and respirogram in the Foucault method) and integrating them in the BISS. For this purpose, the proposed generic framework would provide valuable guidelines about the different steps that need to be undertaken to measure and model the signals, as well as for building the corresponding simulators.

Another desirable work would be to relate the variations observed in the generated EBI signal to the actual physiological phenomena, e.g. the relation between the model coefficients and parameters and the states/ activities of the subject. This would require extensive study of the dynamics of the physiological phenomena, which is a very complex task requiring deep knowledge of the human physiology.

Furthermore, the BISS could be advanced by adding extra functionalities to calculate physiological features such as stroke volume and cardiac output from the simulated EBI signals.

Finally, in the current implementation, the states are focused on a healthy person's resting, standing, walking, and running states. However, by repeating the steps described in the framework, it would be relatively easy to add other states (e.g. for someone with a heart condition) to the simulator. This would require acquiring a data set (sets) from either new measurements or existing databases.

5. CONCLUSIONS

Based on measured and cleaned extracted signals, the impedance cardiography (ICG) and impedance respirogram (IRG) signals have been modelled, and a corresponding bio-impedance signal simulator (BISS) has been developed to simulate electrical bio-impedance (EBI) signals for evaluating the performance of various signal processing algorithms on such signals.

In order to guide the development of the above signal models and simulator, a significant part of this work is focused on developing a physiological parametric framework for modelling measurable bioelectrical information and implementing this parametric framework with a pragmatic approach on the bioimpedance example.

Thus, a novel generic framework was proposed for modelling the bioelectrical information, which was then implemented for the case of EBI as an example. Based on the results, it is concluded that the proposed bioimpedance signal model imitates the real ICG and IRG phenomena and is realistic to imitate the ICG and IRG phenomena.

Moreover, it is also concluded that the proposed framework provides a pathway between biological systems and bioelectrical applications by means of various steps, including the measurement of the bioelectrical data from the subject, the cleaning process for the measured bioelectrical data, and the development of the corresponding simulator.

Finally, it is also concluded that the novel BISS EBI signal simulator implements the developed signal models and imitates the real ICG and IRG signal phenomena. The BISS also gives the end-user the freedom to simulate EBI signals as per their needs.

ACKNOWLEDGEMENTS

The authors thank Dr Toomas Parve, Prof. Mart Min, and Dr Andrei Krivošei for providing valuable advice. This research was supported by the European Union through the European Regional Development Funding in the frames of the research centre CEBE, by the Estonian Ministry of Education and Research (Institutional Research Project IUT19-11) and ETF8592, the Archimedes Foundation ESF DoRa, Estonian Science Foundation Grant (9394) and IT Doctoral School.

The publication costs of this article were covered by the Estonian Academy of Sciences.

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Parameetriline raamistik bioelektriliste signaalide käsitlemiseks: rakendamine bioimpedantssignaalide simulaatori väljatöötamisel

Yar Muhammad, Paul Annus, Yannick Le Moullec ja Toomas Rang

Inimese tervise hindamisel kasutatakse üha enam erinevaid sensoreid ja nendelt saadavaid signaale. Kasuliku, näiteks südametegevust iseloomustava komponendi eraldamine sensorsignaalist või signaalide kogumist on aga tihti komplitseeritud. Selliste signaalide tekkemehhanismidest ja levimisest arusaamine ning modelleerimine annab erinevates rakendustes olulisi eeliseid, võrreldes näiteks ainult mõõteandmete töötlemisega. Üheks simuleeritud signaalide oluliseks rakendusvaldkonnaks on uute signaalitöötlusmeetodite ja algoritmide arendamine ning valideerimine.

Antud artiklis on välja pakutud üldistatud parameetriline raamistik bioelektriliste signaalide käsitlemiseks. Saadud tulemusi on konkreetselt rakendatud bioimpedantssignaalide modelleerimiseks, mis lisaks südametegevuse ja hingamisega seonduvatele komponentidele sisaldab ka häireid ning müra. Uuringute tulemusena loodud bioimpedantssignaalide simulaator (BISS) võimaldab genereerida erinevaid, kasutaja poolt soovitud parameetritega kunstlike mõõteandmete kogumeid.