Development of a Bio-Impedance Signal Simulator on the Basis of the Regression Based Model of the Cardiac and Respiratory Impedance Signals

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Abstract—**A software implemented bio-impedance signal simulator (BISS) is proposed, which can imitate real bio-impedance phenomena for analyzing the performance of various signal processing methods and algorithms. The underlying mathematical models are built by means of a curve-fitting regression method. Three mathematical models were compared polynomial, Fourier series and sum of sine waves with four different measured impedance cardiography (ICG) datasets and two clean ICG and impedance respirography (IRG) datasets were taken as the basis of the signals. Statistical analysis (sum of squares error, correlation and execution time) implies that Fourier series is best suited. The models of the ICG and IRG signals are integrated into the proposed simulator.**

In the simulator the correlation between heart rate and respiration rate are taken into account by means of ratio between them (5:1 respectively).

Keywords— **Regression based model, Signal Simulation and Modeling, Electrical Bio-Impedance, Impedance Cardiography, Respiratory Signal.**

I. .INTRODUCTION

Impedance cardiography (ICG) measurement has been offered as a cost effective and noninvasive method for monitoring haemodynemical parameters. The time variant part of the bioimpedance (BI) phasor reflects processes in patient physiological state since some changes in BI can be caused by normal activity or pathological reasons [1, 2].

Extracting information from impedance signals for diagnosing diseases and assessing heart function is essential for exploiting this method.

Working on real signals can be difficult; it is desirable to provide a simulation tool to enable simulation and control of such signals for analyzing the performance of various signal processing methods such as cardiac and respiratory separation algorithms, e.g. independent component analysis (ICA), adaptive filtering, ensemble averaging, and spectral methods [3, 4].

Modeling of the ICG signal has captured the interest of several researchers in the past few years, using different approaches such as described in [4, 5, 6].

In [4], Krivoshei proposed a simple bio-impedance signal synthesizer 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 e.g. separation algorithms.

Kersulyte et al. [5] proposed a cardio model based on the sum of exponential functions. The purpose of their work was to find out a model for cardio signals as precise as possible and compare complexity parameters of the real signals and that of the model for both healthy and sick persons. They compared two function types 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.

In [6] Matušek et al. proposed a cardiac signal model based on a series of real signals. By filtering and averaging the series of real signals, they estimated one average 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 change the parameters of the model.

Given the limitations of the above works, it was decided to compare the suitability of three mathematical models (polynomial, Fourier series, sum of sine waves) by means of Matlab's Curve Fitting Toolbox.

II. MODELING THE ICG AND IRG SIGNALS

The impedance cardiography and impedance respirography (IRG) signals are nearly periodic signals that can be approximated through various mathematical models. In this study, first were evaluated ten models, which are available in the toolbox and found out that three of these gave the better results, namely polynomial, Fourier series, and sum of sine waves. Then these three models were applied on four measured ICG datasets and two clean ICG and IRG datasets for evaluation and comparison purposes. What follows briefly describes the electrical bio-impedance (EBI) measurement procedure and then discusses each model separately.

A. EBI Measurement Procedure

The datasets were obtained using multiple pairs of electrodes with different electrode configurations. The EBI measurement electrode setup is shown in Figure 1.

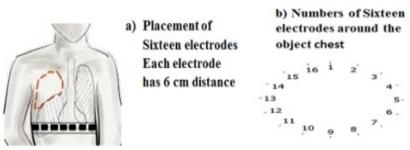

Fig 1. Sixteen electrodes configured belt, which is used for the EBI measurement procedure [2].

Such type of electrodes' setup is presumed to allow raising strong enough variations of the EBI in order to record the cardiac and respiration signals, which are caused by the heart and lungs. Further details about the EBI measurement setup can be found in [2].

The measured datasets are obtained from a healthy male subject aged between 40 and 50 years, in a seated position.

The total EBI dataset was divided into three different segments. Each segment contains 10 seconds of the total EBI raw data, about 10,000 samples. Accordingly, the structure of the three segments is as follows:

a) cardiac only (breathing was held),
b) cardiac + respiration (deep breathing),
c) cardiac + respiration + motion artefacts (normal breathing with added motion artefacts).

In what follows, the four ICG datasets correspond to b) and the clean ICG and IRG datasets correspond to filtered versions of a) and b), respectively.

B. Models and Evaluation Method

a) Polynomial Model

Polynomials are well suited for cases where a fairly simple empirical model is needed; they can be used for interpolation or extrapolation to characterize data by means of a global fit. The general polynomial model formula is given in Equation 1:

$$y = \sum_{i=1}^{n+1} p_i t^{n+1-i} \quad (1)$$

where n is the degree of the polynomial (highest power of the predictor variable), $n+1$ is the order of the polynomial (number of coefficients), p_i are the coefficients and t is time.

In this work, the polynomial model was evaluated for degrees 1 to 9 for the different datasets; degree 9, which is the highest order available in the toolbox, gave the best suitable results. The comparative results are shown in Table 1 and Figures 2 & 3.

b) Fourier Series Model

The Fourier series is a sum of sine and cosine functions that describes a periodic signal. The model formula is given in Equation 2:

$$y = a_0 + \sum_{i=1}^{n} a_i \cos(i\omega t) + b_i \sin(i\omega t) \quad (2)$$

where a_0 is the intercept, which is constant term in the data, ω is the fundamental frequency and n is the number of terms in the series. The model was evaluated with 1 to 8 terms for the different ICG datasets; the best suitable results were obtained for the degree of 8, the highest available in the toolbox. The comparative results are shown in Table 1 and Figures 2 and 3.

c) Sum of Sine Waves Model

This model consists of a sum of sine terms only. The model formula is given in Equation 3:

$$y = \sum_{i=1}^{n} a_i \sin(i\omega t + c_i) \quad (3)$$

where a is the amplitude, ω is the frequency, c the phase, which is constant for each term and n is the total terms in series.

The model was evaluated with 1 to 8 terms for the different datasets; 8 terms (the highest available in the toolbox) gave the most suitable results. The comparative results are shown in Table 1 and Figures 2 and 3.

d) IRG Signal with Polynomial, Fourier Series and Sum of Sine Waves Models

Following the same approach as for the ICG signal, the IRG clean dataset is also modeled with the polynomial,

Fourier series and sum of sine waves methods. The comparative results are shown in Table 1 (Clean IRG) and Figure 3(c).

C. Statistical Parameters

The performance of the three modeling methods is evaluated by means of the following fit measures.

a) Sum of Squares Error (SSE)

The SSE statistic assesses the total deviation of the data values from the fitted model, as expressed in Equation 4:

$$SSE = \sum_{i=1}^{n} w_i \, (y_i - \overline{y}_i)^2 \quad (4)$$

where n is the number of data points, y_i is the response data, and $\overline{y}_i$ is predictor data. SSE values close to 0 indicate that the model is fitted well and has a very small random error [7].

b) R-Square

R-Square measure is the square of the correlation between the data and the fitted model values. A value close to 1 shows a greater correlation between the data and the model whereas a value close to 0 shows a poor correlation. It is determined as the ratio of the sum of squares of the regression (SSR) and the total sum of squares (SST), where $SST = SSR + SSE$. The R-square measure is given in Equation 5 [7]:

$$R\text{-}square = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} \quad (5)$$

c) Execution time

The execution time is measured through Matlab stopwatch functions (tic, toc) and reported in Table 1.

III. EXPERIMENTAL RESULTS

Table 1 and Figures 2 and 3 show the fit of the three models with the various datasets. Generally speaking, the three models provide a reasonable fit across the four datasets: the average SSE value is 0.879e-07, the min and max values are 0.161e-07 and 1.9417e-07, respectively

Similarly, the average R-square value across the four datasets is 0.9762, the min and max values are 0.9512 and 0.9936, respectively.

The Fourier series model minimizes the error (average SSE=0.335e-07) and has also a high correlation across the four datasets as compared to the other models. However, it took 1.275 more seconds to execute as compared to the polynomial model; it is nevertheless much faster (by 44.476 seconds or nearly 10 times) than the sum of sine waves model.

In this study, the most suitable results were obtained with eight terms for the Fourier series model, which gives 18 coefficients. For the polynomial model, we set the degree to 9, leading to ten coefficients. It is preferable to limit the number of coefficients for relating them to the patients' condition. However, this has to be traded-off for a lower fit, as shown in Table 1.

Table 1. Evaluation Criterions Results for the Modeled Signal

Datasets	Sum of sine Waves (24 coeff)		Fourier (18 coeff)		Polynomial (10 coeff)					
	SSE	*R-Sq*	*SSE*	*R-Sq*	*SSE*	*R-Sq*	*SSE Avg*	*SSE Min*	*SSE Max*	*R-SqAvg*
Dataset 1	1.0424e-07	0.9917	0.1612e07	0.9987	1.2270e-07	0.9903	0.810e-07	0.161e-07	1.23e-07	0.9935
Dataset 2	0.9044e-07	0.9875	0.1786e-07	0.9976	0.3050e-07	0.9959	0.463e-07	0.179e-07	0.904e-07	0.9936
Dataset 3	1.9417e-07	0.9274	0.6476e-07	0.9758	1.3185e-07	0.9506	1.326e-07	0.6476e-07	1.9417e-07	0.9512
Dataset 4	0.8054e-07	0.9714	0.3506e-07	0.9876	1.6683e-07	0.9409	0.941e-07	0.3506e-07	1.6683e-07	0.9666
SSE Avg, R-Sq Avg	1.17e-07	0.970	0.335e-07	0.9758	1.13e-07	0.969	0.879e-07			0.9762
SSE Min, R-Sq Min	8.05e-08	0.161	0.161e-07	0.9758	0.305e-07	0.941		0.161e-07		0.9512
SSE Max, R-Sq Max	1.94e-07	0.9917	0.648e-07	0.9987	1.67e-07	0.996			1.9417e-07	0.9936
Clean ICG Signal with different scale										
Clean ICG	0.1996	0.9994	0.0611	0.9999	2.8229	0.9937	1.0279	0.0611	2.8229	0.9959
Ex. Time (s)	~49.170		~4.694		~3.419					
Clean IRG Signal with different scale										
Clean IRG	7896.1e-07	1	2890.6e-07	1	19.5782	0.9983	6.5264	2890.6e-07	19.5782	0.9994

Regarding the difference between the polynomial and the sum of sine waves models, it can be seen that for Datasets 2 and 3, the polynomial model minimizes the error (0.3050e-07 and 1.3185e-07, respectively) and is highly correlated with the datasets (0.9959 and 0.9506, respectively). On Datasets 1 and 4, the sum of sine waves model minimizes the error (1.0424e-07 and 0.8054e-07, respectively) and is highly correlated (0.9917 and 0.9714 respectively) with the datasets. However, 8 terms were used for the sum of sine waves model, which gives 24 coefficients (versus 10 for the polynomial model) and a much longer execution time.

For the clean ICG and IRG datasets, the Fourier series model performed very well among all to minimize the error (0.0611 and 2890.6e-07, respectively) and is highly correlated (0.9999 and 1, respectively) with the datasets. It is followed by the sum of sine waves model, which has the second minimum error (0.1996 and 7896.1e-07, respectively) and high correlation (0.9994 and 1, respectively) but also has a larger number of coefficients (24) and larger execution time (49.170 seconds) as compared to the polynomial model.

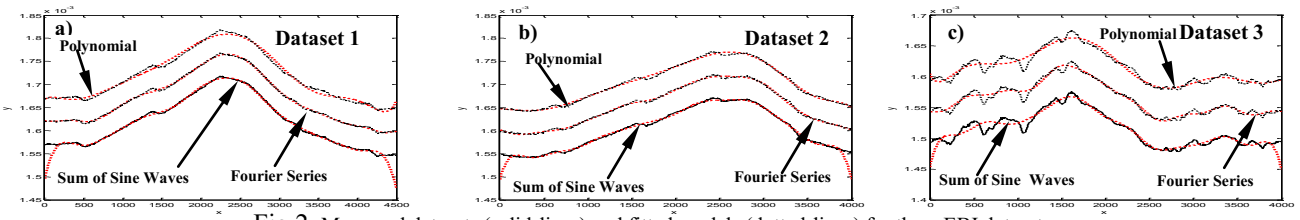

Fig 2. Measured datasets (solid-lines) and fitted models (dotted-lines) for three EBI datasets:
a) results of fitting of the EBI dataset 1, b) results of fitting of the EBI dataset 2, c) results of fitting of the EBI dataset 3.
Results for the sum of sine waves model are presented without offset, results for Fourier series model are offset by 0.05×10^{-3} and results for Polynomial model are offset by 0.1×10^{-3}.

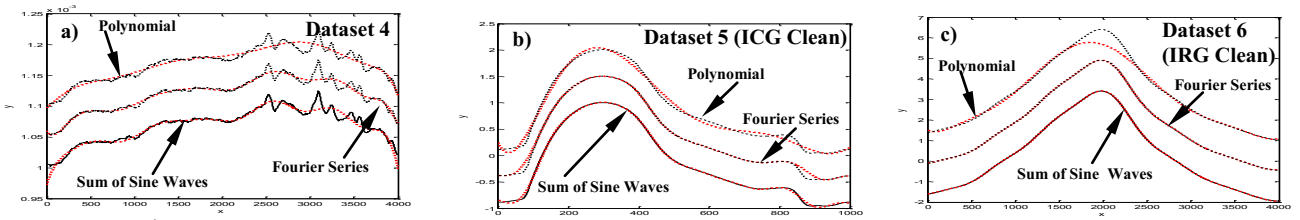

Fig 3. Measured (a) and cleaned (b, c) datasets (solid-lines) and fitted models (dotted-lines) for other three EBI datasets:
a) results of fitting of the EBI dataset 4, b) results of fitting of the cleaned ICG dataset 5, c) results of fitting of the cleaned IRG dataset 6.
Results for the sum of sine waves model are presented without offset, results for Fourier series model are offset by offset a) 0.05×10^{-3}, b) offset 0.5, c) offset 1.5) and results for Polynomial model are offset by (a) 0.1×10^{-3}, b) 1, c) 3].

IV. The Bioimpedance Signal Simulator (BISS)

This section describes how the Fourier series model was included in our Bioimpedance Signal Simulator (BISS).

As shown in Figure 4, the simulated bio-impedance signal is generated by summing the ICG signal ($S_{\Delta Z\ ICG}$), artefacts ($S_{Artefacts}$), a white Gaussian noise (S_{Noise}) and the IRG signal ($S_{\Delta Z\ IRG}$) such as:

$$S_{EBI(t)} = S_{\Delta Z\ ICG} + S_{Artefacts} + S_{Noise} + S_{\Delta Z\ IRG} \quad (6)$$

The BISS' GUI is shown in Figure 5, where a) is the menu used to perform different operations such as loading different datasets (ICG/FCG) to simulate the signal, saving the final generated EBI signal model for further processing and exiting from the BISS environment, b) a recorded clean ICG period, c) a period of the ICG signal model, d) a recorded respiration period e) a period of the IRG signal model f) the continuously simulated ICG signal.

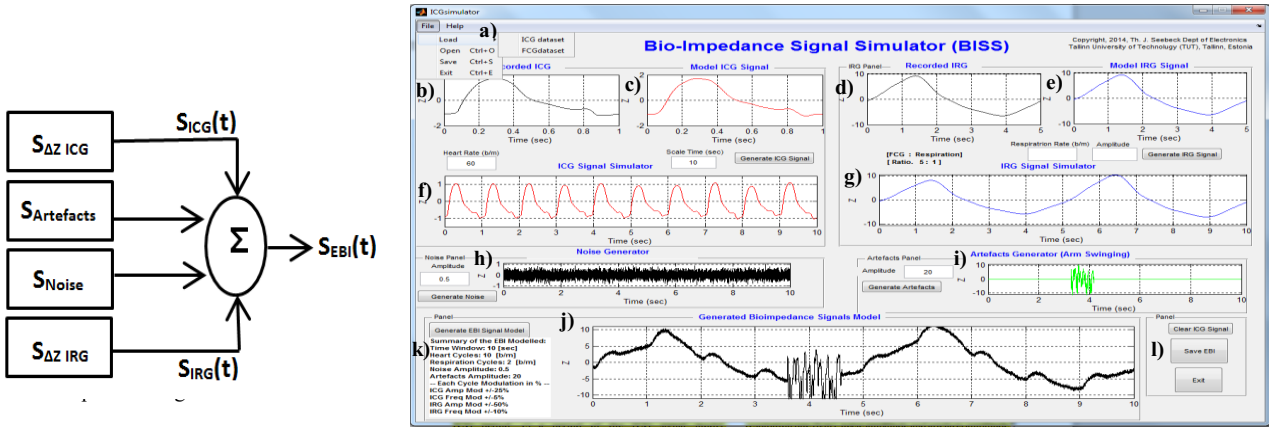

Fig 5. User Interface of the Bioimpedance Signal Simulator (BISS).
The heart rate, time scale, respiration rate, noise and atefacts amplitude parameters are user-Controlled

In order to take the real phenomena of BI signals into account, a random modulation is introduced with each cycle (amplitude ±25, frequency ±5). Moreover, the user should specify the heart rate in beats/min and time window. g) is the continuously simulated respiration signal where a random modulation is introduced with each cycle (amplitude ±50, frequency ±10).

The respiration rate is correlated to the cardiac heart rate by means of the ratio. The default ratio is 5:1 (5 cardiac cycles for 1 respiration cycle). Nevertheless, the user can control the respiration rate as well. h) is the noise generator, i) the recorded artefacts caused by swinging the arm during the measurement (randomly moving in the defined time window, j) the generated bio-impedance signal model based on the user entered parameters, k) the detailed summary of the generated bio-impedance signal model and l) buttons that let the user clear all simulated model signals and start again, save the EBI signal model and exit from BISS' GUI environment.

Figures 5 f), g), h) and i) illustrate the effect of the user-controlled parameters such as time scale window, heart rate (b/m), respiration rate (b/m), noise amplitude and artefacts amplitude.

V. Conclusions

The polynomial model is relatively simple, but it does not provide the best results for our application. The sum of sine waves model produces better results than the polynomial one, but is less suitable than the Fourier series one because it has a higher number of coefficients, higher SSE values, lower R-Square values, and higher execution times.

Overall, the Fourier series model fits with the measured datasets very well, minimizes the error and has high correlation values as compared to the two other models; only its execution time is slightly higher than that of the polynomial model.

Furthermore, the correlation between the heart rate and the respiration rate is implemented by means of a ratio (default 5 ICG cycles for 1 IRG cycle).

Finally, the user can enable the insertion of the recorded artifact in the final EBI model.

Nevertheless, the resulting simulated signal does not model all aspects of the real bioimpedance data yet. Thus, future work will refine the model by means of piece-wise segmentation of the datasets for finer grain curve-fitting while maintaining the number of coefficients to the required minimum for reflecting the pathological conditions (i.e. not necessarily 24, 18, and 10 as shown in Table 1).

The Starling's and Poiseuille laws will be taken into account in the model to reflect the systolic and diastolic phenomena respectively.

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