Regression based Model of the Impedance Cardiac and Respiratory Signals for the Development of a Bio-Impedance Signal Simulator

Yar M. Mughal
Th. J. Seebeck Dept. of Electronics, Tallinn University of Technology, Estonia. (yar@elin.ttu.ee)

***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 (i.e. polynomial, sum of sine waves, and Fourier series) with four different measured impedance cardiography (ICG) datasets and two clean ICG and impedance respirography (IRG) datasets. 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 the mean of ratio (5:1 respectively).

I. Introduction

Impedance cardiography (ICG) measurement has been offered as a cost effective and noninvasive method for monitoring haemodynemical parameters. 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.

Modeling of the ICG signal has captured the interest of several researchers in the past few years.

II. 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.

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 Matlab's Curve Fitting Toolbox, gave the best suitable results. The comparative results are shown in Table 1 and Figures 1 and 2.

B. Fourier Series Model

The Fourier series is a sum of sine and cosine functions that describes a periodic signal. The model was evaluated with 1 to 8 terms for the different ICG datasets; the best suitable results were obtained for degree 8, the highest available in Matlab's Curve Fitting Toolbox. The comparative results are shown in Table 1 and Figures 1 and 2.

C. Sum of Sine Waves Model

This model consists of a sum of sine terms only. 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 1 and 2.

D. IRG Signal with Polynomial, Sum of Sine Waves and Fourier Models

Following the same approach as for the ICG signal, the impedance respirography (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 2(c).

III. Statistical Parameters

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

The Sum of Squares Error (SSE) statistic assesses the total deviation of the data values from the fitted model.

The R-Square measure is the square of the correlation between the data and the fitted model values.

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

IV. Experimental Results

Table 1 and Figures 1 and 2 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.

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TABLE 1. EVALUATION CRITERIONS RESULTS FOR THE MODELED SIGNALS

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-Sq Avg**
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	9.70e-01	0.335e-07	0.9758	1.13e-07	0.969	0.879e-07			0.9762
SSE Min, R-Sq Min	8.05e-08	0.161e-07	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.

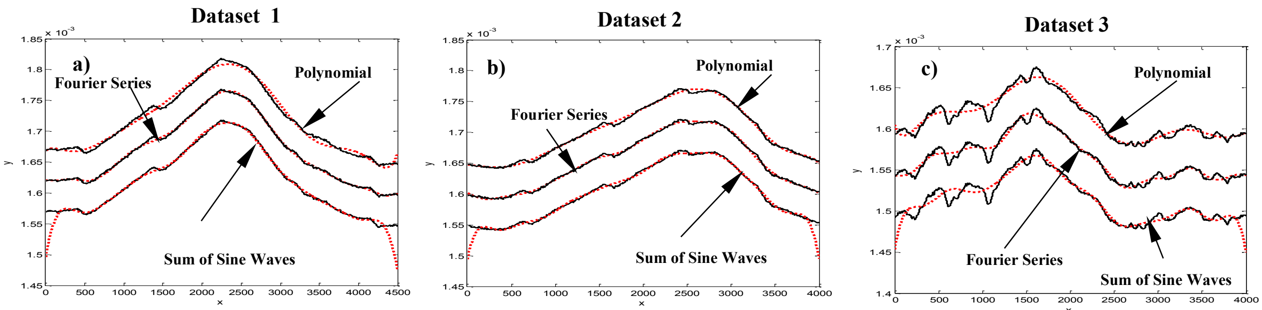

Figure 1. Measured datasets (solid-lines) and fitted models (dotted-lines) for three EBI datasets:
a) results of fitting of the EBI dataset 1, b) results of fitting of the EBI dataset 2, c) results of fitting of the EBI dataset 3.
Results for the Sum of sine waves model are presented without offset,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

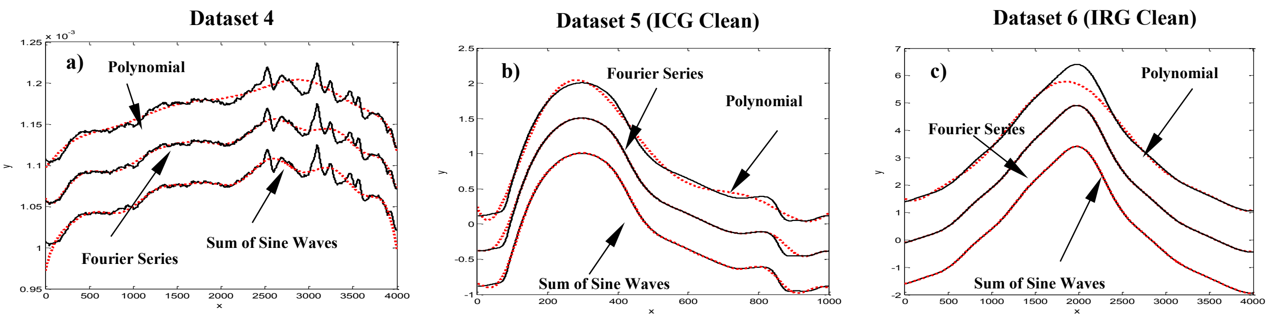

Figure 2. Measured (a) and cleaned (b, c) datasets (solid-lines) and fitted models (dotted-lines) for other three EBI datasets:
a) results of fitting of the EBI dataset 4, b) results of fitting of the cleaned ICG dataset 5, c) results of fitting of the cleaned IRG dataset 6.
Results for the Sum of sine 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].

V. 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 3, the simulated bio-impedance signal is generated by summing the ICG signal ($S_{\Delta Z\ ICG}$), the artefacts ($S_{Artefacts}$), a white Gaussian noise (S_{Noise}) and the Respiration signal ($S_{\Delta Z\ IRG}$) such as:

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

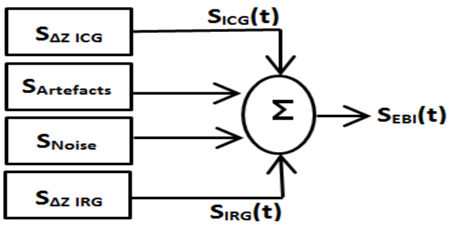

Figure 3. Block diagram of the Bioimpedance Signal Simulator

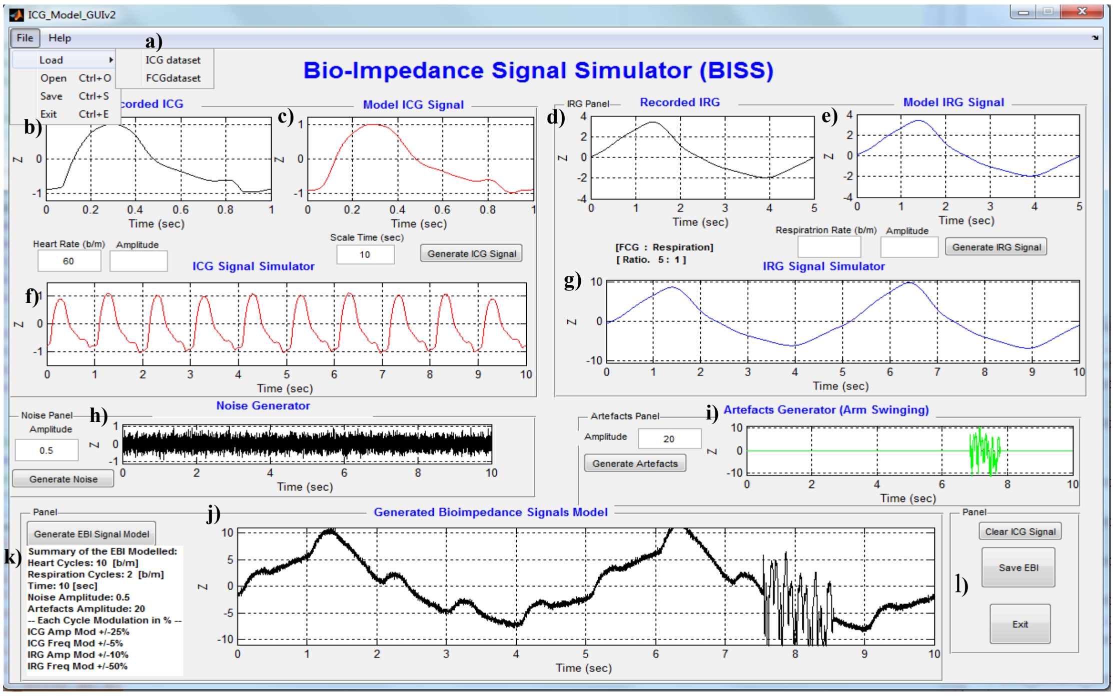

Figure 4. Bioimpedance Signal Simulator (BISS).
The time scale, heart rate, respiration rate, amplitudes and noise amplitude parameters are user-controlled

The BISS' GUI is shown in Figure 4, where a) is the menu to perform different operations such as load different datasets (ICG/FCG) to simulate the signal, save the final generated EBI signal model for further processing and exit 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 respiration signal model, f) the continuously simulated ICG signal. In order to take the real phenomena of BI signals into account, a random modulation is introduced with each cycle (amplitude ±25 and 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 ±10 and frequency ±50).

The respiration rate is correlated by the mean of the cardiac heart rate ratio. The ratio is 5:1 (5 cardiac cycles and 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 4 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.

VI. Conclusion

Although the polynomial model is relatively simple, 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 is implemented between the heart rate and the respiration rate. 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 law will be taken into account to introduce amplitude and frequency modulation in each cycle (cardiac and respiratory).