Towards numerical temporal-frequency system modelling of correlations between ECG and Ballistocardiogram

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***Abstract* — Ballistocardiogram (BCG) is a bio signal which is measured and recorded by the mechanical activity of the heart (ballistic forces). Due to technological advancements in the recent years BCG has regained its interest and has become an active field of research. Morphological study of the BCG is one of the approach which is prominent in establishing correlations between ECG and BCG, however in our work we try to establish a statistical approach by building BCG-ECG models. By establishing such models we improve the clinical significance of the BCG and improve our understanding about BCG with respect to ECG in a clinical perspective. BCG trial data were acquired from 6 different subjects for analysis and a suitable protocol was followed during the process. The data were synchronized with the ECG for building transfer function models and a novel algorithm was adapted for increasing the efficiency of the model. We demonstrate the accuracy of the model by comparing the RMSE values of simulated ECG model using BCG as input with the original ECG signal.**

I. Introduction

Ballistocardiogram (BCG) is the term used for the signal presented by the mechanical, or ballistic effects of the pulsatile flow of blood out of the heart and into the arterial tree [1]. Since it covers the cardiac cycle, the BCG signal is periodic like its counterpart, the Electrocardiogram (ECG) signal with the same periodicity. However, since the BCG arises out of mechanical forces exerted by the blood ejected from the heart and its vibrations in the musculoskeletal system, the waveform of the BCG differs quite significantly from that of the ECG which arises from electrical polarization and depolarization of the cardiac muscles.

Despite this difference between the BCG and the ECG, there is a lack of numerical models that attempt to address the relationship or mapping from one waveform to the other. If such models could be constructed they would be useful from a number of perspectives. First, these models would improve the clinical significance of the BCG since ECG is the norm or standard in measuring and monitoring cardiac functioning. Second, these models would help improve the quality of BCG and aid in the removal of artefacts. Third, these models would aid in our understanding of subtle details of hemodynamic system and their electrical and mechanical inter-relationships. Last, but not the least, such models would pave the way for a long awaited acceptance of BCG as a medical grade vital sign.
In this paper we contribute, as far as we know, the first attempt at establishing an ECG model using the BCG as our input which validates the correlation between ECG and BCG.

A. Challenges in building a ECG-BCG model

Most researchers are in agreement that the peaks and troughs may be labelled as H-I-J-K-L and so on, the peaks and valleys may go on further depending on the sensor's sensitivity and the mechanical properties of the medium. The problem is compounded by noise and inter-relations with external mechanical stimuli. Furthermore, the environmental noise (temperature, humidity, static electricity, other movements in the vicinity) may affect the BCG signal. Since BCG is measured mechanically with mere skin contact, minor movements and even speech introduce motion artifacts in the signal. The extent to which the body is in contact with the sensor is also important. If there is no contact for some period of time, then data is lost. For these reasons, until today BCG has not emerged significantly in the domain of physiological monitoring and measurement, despite the fact that it has been around for almost a hundred years.

In this paper we attempt at a novel approach for building an ECG signal model from a BCG waveform. Since BCG does not possess a coherent structure, generating an ECG model is difficult. Hence we decompose the ECG signal and use the output in the system identification (Implemented in Matlab) where BCG signal is fed as its input.

The remainder of this paper is organized as follows. Section II presents the data collection method used, Section III presents the novel algorithm used for estimating the ECG-BCG model and the Section IV briefly presents the acquired model results. Conclusions are presented in Section V.

II. OPTIC SENSOR DATA COLLECTION

Traditionally, BCG data is obtained by placing the sensor in bed [2], [3] and seat [4]. We use a fiber optic sensor (FOS) pressure mat which was redeveloped for our current application from [5] for recording the BCG signal from the subject. Fiber sensor was chosen due to its lightweight, chemically inactive and its resistance towards Magnetic interferences. It consisted of a graded multimode fiber clamped between micro bends. When small amount of pressure is applied to the mat the displacement between two micro bends changes. Here, the beating of the heart introduces pressure change and thereby the displacement between the micro bends also changes. This introduces variation in the light intensity and a modulated signal is generated, which is the BCG [6]. The fiber optic sensor used was less than 2mm in thickness thereby minimizing the transmission loss. The BCG data was digitized by the transceiver and was transmitted using Bluetooth to the computer.

The raw BCG signal obtained from the FOS is filtered for extracting the vital features. For measuring the heart rate 50 beats/minute was considered as the lower limit and 150 beats/minute was the higher limit. The BCG signal was filtered using a Lowpass filter of 250Hz to eliminate the high frequency output from the transceiver. The signal obtained from completing this process is compared with the ECG signal (Ground Truth) of the same subject from an ECG sensor used in health care centres. The filtered BCG data is used for analysis purpose. This data still may contain undesired beats which arises due the artifacts and several other noises present in the system. So, it is manually labelled and the beats which are considered random or which may ruin the quality of the signal are removed.

The ECG signal obtained from the medical grade ECG sensor is considered the Ground truth. So for the purpose of analysis it is important that the BCG signals are well synchronized with the ECG signal. Considering this, a virtual clock known as stimcode is used. The stimcode eliminates the time drift between the ECG and the BCG signals and allows beat by beat analysis of the ECG and BCG.

A. Data Collection Process

The data was collected from over 6 volunteering human subjects in a optimum laboratory environment. All the subjects were made to undergo relaxation activities before acquiring their BCG data. This data was collected from 3 different channels from every subject namely the abdomen region (using seat cushion), chest (using bed matress) and back of the neck (using pillow). The sensor mat and the transceiver were embedded in these positions. Data spanning a time of about 10 minutes were collected from each of the subjects. The fig. 1 shows the original ECG data (obtained from a medical grade ECG sensor), 3 Channel BCG data sychronized by a stimcode.

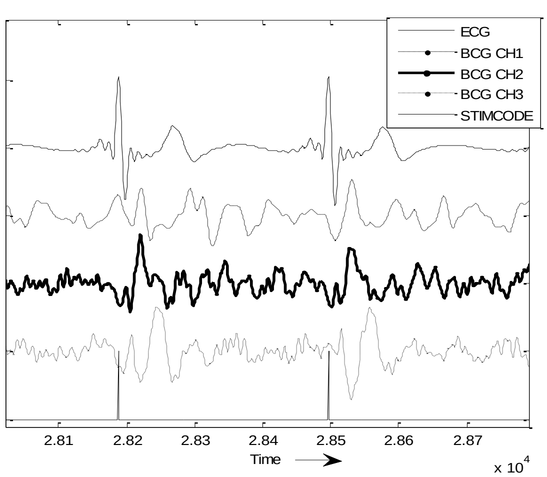


Figure 1. ECG and 3 Channel BCG synchronized with stimcode.

III. PROPOSED ECG ESTIMATION ALGORITHM

ECG has well defined properties and highly studied morphology, so BCG models with high level of accuracy can be developed from the ECG. Hence, we are interested in developing an ECG-BCG model using the BCG as standard. Here, we use the system identification tool in MATLAB for acquiring the results. Since the BCG data is vulnerable to noise and motion artifacts establishing an ECG-BCG model using BCG data is a cumbersome process. Preprocessing was required to estimate the ECG signal from the BCG signal. Here, the mechanism involved the use of wavelet decomposition. Wavelet is an orthogonal function which can be applied to a countable (fixed) number of dataset. The functionality of the wavelets resembles the discrete Fourier transform where the transforming function is orthogonal. Discrete time samples are the input for these wavelets. Wavelet equation is a modified Fourier series equation. To introduce the wavelet function we require two parameters. Function f(t) can be decomposed upon the orthonormal bases $\psi_{j,k}(t)$ which is shown in equation 1 [7] as:

$$f(t) = \sum_k \sum_j a_{j,k} \psi_{j,k}(t) \quad (1)$$

Where,

$\psi_{j,k}(t)$ is the wavelet function which is orthogonal.
J, k are integer values.
$a_{j,k}(t)$ is the discrete wavelet transform coefficient.

A. Algorithm for ECG-BCG Modelling.

The algorithm presented uses the level 5 daubechies (DB) wavelet transform. This wavelet transform filters the input ECG Signal into its corresponding low frequency and high frequency components. The advantage of using the daubechies wavelet transform is that it is easier to analyse than the haar wavelet transform. The low frequency components are called the approximations and the high frequency components are the details. Since it is level 5, we get a filtered output of five different approximations and details. The first level is obtained from the input ECG signal which we pass and the following levels of approximations and details are obtained from the previous approximation. D1, D2, D3 contribute little detail to the signal whereas D4 and D5 contribute the maximum. The scaling function of the DB wavelet transform is given by equation 2 [8].

$$V_m^1 = \alpha_1 V_{2m-1}^0 + \alpha_2 V_{2m}^0 + \alpha_3 V_{2m+1}^0 + \alpha_4 V_{2m+2}^0 \quad (2)$$

α is a constant coefficient.

Subsequent scaling functions can be obtained from translation of time units from previous scaling signal. For example second scaling signal can be obtained by translation of first signal by 2 time units. The function (f) i.e. the original

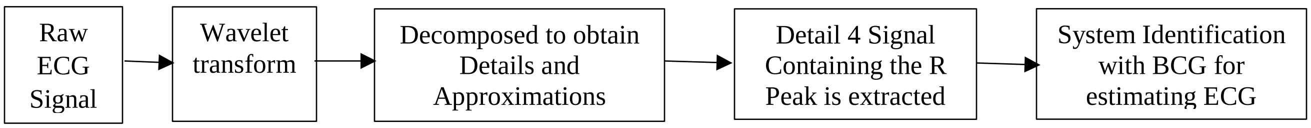


Figure 2. Procedure for the estimation of the ECG signal from the BCG signal.

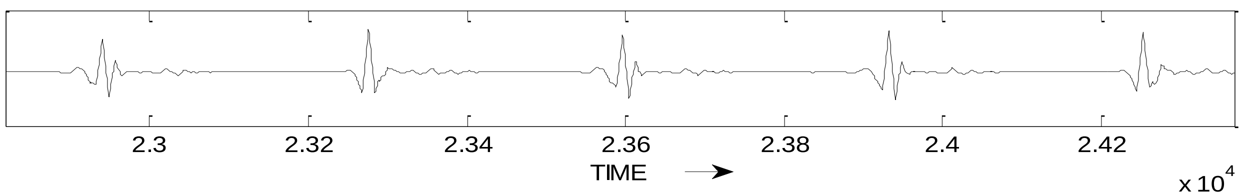


Figure 3. Extracted Details 4 signal containing ECG R wave

signal can be obtained by summing the approximation signal of the last level (A^m) with all the details signal. It is shown in equation 3 [8] as:

$$f = A^m + D^m + D^{m-1} + \ldots + D^2 + D^1 \tag{3}$$

A and D denotes approximations and details.

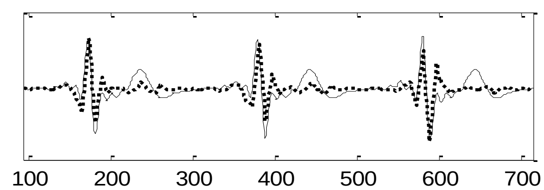
The fig. 2 shown explains the ECG estimation algorithm. After performing the 5 level decomposition we extract only the details 4 (D4) signal which contains the major information of the ECG R wave. Now, we use this signal for our analysis. The obtained Details 4 signal is shown in fig. 3. The system identification toolbox in MATLAB requires a measured input and a measured output for processing and getting a simulated output. The measured input is our BCG. It analyses the signal by predicting the output dataset using the predefined validation dataset which is the measured D4 in this case. The details 4 has the R wave information of the ECG to be recovered. We obtain the simulated output which is our estimated ECG. By using this algorithm we have formulated a numerical model between ECG and BCG.

IV. RESULTS

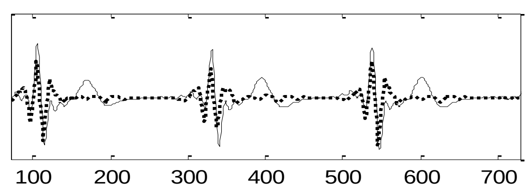
Well established models can be achieved by the process of system identification on the input signal. Trial data was collected from over 6 subjects, however we consider data obtained from 4 different subjects for the purpose of analysis and relative comparison. Here we import the BCG signal as input and the details 4 signal obtained by performing the algorithm as measured output for system identification which will be used to generate the corresponding simulated ECG output model. The toolbox assumes the input data as the working and the validation data. It generates a time plot of the input and the output before analysing it.

There are many models available for system identification like, correlation models, transfer function models, polynomial models etc. We use the transfer function model for estimating the best fit with minimal error. The transfer function model thus obtained will be the simulated ECG model. Different transfer function models are generated by choosing different sets of poles and zeros.

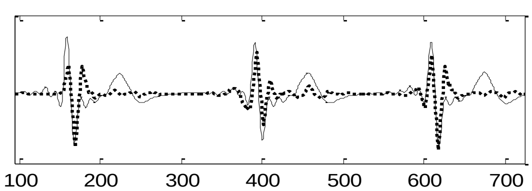
Fig. 4 (a, b, c, d) illustrates the obtained ECG-BCG model of 4 different subjects evaluated from the channel 2 BCG as the input.



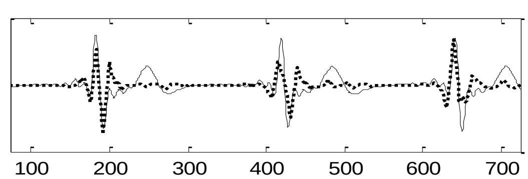
(a). ECG-BCG model of subject 1



(b). ECG-BCG model of subject 2



(c). ECG-BCG model of subject 3



(d). ECG-BCG model of subject 4

Figure 4. Model results obtained from different subjects (dotted line) and Original ECG (solid line)

We have tried to develop the ECG model without applying the algorithm using system identification, but we were not able to recover the R Peak of the ECG cleanly. The model developed without using the algorithm from channel 2 BCG data of subject 1 is shown in fig. 5. Hence, instead of using raw ECG signal as measured output we use the result obtained from the algorithm for generating the ECG model. By developing these models we validate that, vital features of ECG can be extracted from BCG. These models also improves the medical significance of BCG in a different perspective.

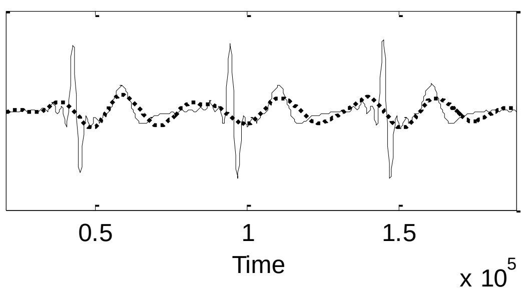


Figure 5. ECG model (dotted line) developed without using the algorithm and original ECG (Solid line).

For comparing our model results with the original ECG we use the Root Mean Square Error comparison. RMSE is computed for the simulated output ECG (Developed model) and the original ECG. The corresponding poles and zeros of the transfer function (During system identification) are selected whose RMSE value is the lowest. By experimenting with different poles and zeros, the ideal combination was found to be 5 poles and 2 zeros. This process is repeated for all the three channels of BCG data set.

The RMSE of the model shown in fig. 5 (model developed without using the algorithm) was found to be 22.068. Table 1 below shows the comparison of RMSE of the models of different subjects generated by using the algorithm.

	RMSE		
	CH 1	CH 2	CH 3
SUB 1	6.839	5.678	7.236
SUB 2	6.988	5.832	7.352
SUB 3	6.654	5.489	6.986
SUB 4	7.124	5.712	7.236

TABLE I. RMSE COMPARISON OF THE 3 CHANNELS OF BCG BETWEEN DIFFERENT SUBJECTS.

From the table 1, we find that the RMSE of channel 2 is less than the other channels. So, we can infer that the best channel input BCG data was obtained from channel 2 (chest region). Also, RMSE of the models generated by using the algorithm is comparatively less than the RMSE of the model without using the algorithm. As a part of our future work, we are planning to develop more statistical ECG-BCG models with high level of precision.

V. CONCLUSION

In this paper we have demonstrated a numerical model between ECG and BCG which ascertains the use of BCG hand in hand with the ECG. We recorded the raw ECG and BCG signals of different healthy human subjects using a fiber optic sensor mat. After some extensive analysis we have developed an algorithm which can be used for estimating the ECG model from the BCG wave. We have tested and validated the algorithm on different subjects and have shown its clinical importance in future.

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