Bowel Movement Signal Modeling and Parameters Extraction

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Abstract— The characterization of each Individual Wave Component (IWC) is essential in determining the different types of Bowel movements. Equally important is the effective use of the IWCs to predict anomalies in the digestive system. As it is often the case, the rigorous testing of an algorithm is always limited by the quality and quantity of available data. Recently, a mathematical model was presented as an alternative to generating synthetic bowel sound data that can be used as a stimulus to test new algorithms. In this paper, we present an analysis of this model and a new algorithm to estimate the parameters of the individual wave components. The performance of the algorithm is evaluated in both synthetic and clinically recorded data.

***Index Terms*—Bowel Sound, Bowel Sound Modeling, Bowel Movement, Individual Wave Component, Parameter Estimation.**

I. Introduction

As the means to perform advanced signal analysis become more powerful and sophisticated, the necessity to acquire more data is gaining more attention. In this particular case where effective diagnosis plays a significant role in human life, there is the need to process more biomedical signals to develop better algorithms for a more accurate diagnosis. Unlike the sound signal of lung and heart, the investigation of gastrointestinal tract sounds has been very limited. This may be the result of the irregularity of natural bowel sounds as compared to cardiovascular sounds, which makes systematic analyses more difficult. Nonetheless, researchers have made a great endeavor to study the acoustic features of the bowel sound [1-3]. Different types of bowel sounds were then documented, along with the differentiation and classification methods utilizing a neural network or Bayes model [4-10]. However, the modeling of the bowel sound itself remains as the frontier of bowel sound study.

Very recently, a mathematical model of bowel sound generation was proposed [11]. In this model, the mathematical formulation and generation of Individual Wave Component (IWC) were proposed which is the building block for all types of bowel sounds. In the paper, the authors successfully simulated various types of bowel sound with the important tuning parameters of individual IWC and interdependent relationship between IWCs: Pressure Index (PI), Component Quantity (CQ), and Component Interval Time (CIT).

Due to the nature of the digestive system research, a large number of recordings are difficult to obtain. Therefore, if the model is accurate and thorough, it would give researchers the capabilities to generate valuable synthetic data with high confidence crucial to develop and evaluate the performance of algorithms such as machine learning for abnormality detection.

In this paper, we first validate and analyze the usefulness of the model. We simulate several types of bowel sounds. Then, we develop an algorithm that can extract the parameters of an IWC. We demonstrate the algorithm with synthetically generated IWC from the model to verify the effectiveness of the algorithm. We also verify, given a clinically recorded IWC, the feasibility to recreate the IWC using the model. Then, by comparing the reconstructed IWC using parameters extracted from clinical recordings with the original recording, we verify the accuracy of both our algorithm as well as the mathematical model.

II. Parameter Extraction Approach

The mathematical model of the IWC is deducted by assuming the sound is generated from the vibration of the walls of the guts while fluid changes because of the pressure onto the wall. Thus, the motion can be regarded as a spring-mass-damping system. As a result, we have a damped motion of a vibration frequency given by

$$p_{iwc} = A_{iwc}\,sin(2\pi f_{iwc} t) \quad (1)$$

where t is time, f_{iwc} is the resonant frequency, and A_{iwc} is the envelope of the IWC given by

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$$A_{iwc} = \frac{pe^{-E/t}}{t^b} \tag{2}$$

where p is the Pressure Index (PI) to scale the envelope of the signal, E is the envelope index that is influenced by the pressure, and b controls how narrow is the IWC which is related to the damping.

The model separates the IWC into two fundamental components, a sinusoidal oscillation $sin(2\pi f_{iwc}t)$ where the main parameter is the frequency f_{iwc} which can be easily obtained from a spectrogram; and a more complicated envelop function A_{iwc} where our parameter extraction algorithm is mainly concentrated. Taking the natural log of equation (2), we have

$$\ln(A_{iwc}) = \ln(p) + \frac{-E}{t} - b\ln(t) \tag{3}$$

The envelop function then becomes a linear combination of the parameters. Then take the partial derivatives with respect to each parameter p, E, and b, we have

$$\frac{\partial}{\partial p}\ln(A_{iwc}) = \frac{1}{p} \tag{4}$$

$$\frac{\partial}{\partial E}\ln(A_{iwc}) = -\frac{1}{t} \tag{5}$$

$$\frac{\partial}{\partial b}\ln(A_{iwc}) = \ln(t) \tag{6}$$

The partial derivatives of the envelope functions are reasonably simple. Thus, a nonlinear regression method is used in the algorithm to determine the value of the parameters. We then use the Levenberg-Marquardt algorithm for our parameter extraction method [12].

At this point, the problem is to extract enough data points from the IWC to achieve the curve-fitting convergence of the algorithm. According to the mathematical model, the IWC's points that coincide with its envelope is when the oscillation $sin(2\pi f_{iwc}t)$ equals to a minimum or a maximum. Due to the relatively low frequency of bowel sound, it is easy to obtain accurate peak values and its corresponding time t with oversampling. But, it also poses a problem of too few peaks from the IWC if the resonant frequency is low or when the envelope decay into the noise level very fast. To address this problem, we utilize the Hilbert Transform on the IWC to generate additional points close enough to the IWC within a tolerance. To maintain the characteristics of the IWC itself without too much deviation, only points that are close to the peaks are selected for nonlinear regression.

In the following section, simulation is carried out to demonstrate the algorithm in detail with generated IWCs according to the mathematical model.

III. Parameter Extraction with Simulated Data

With this mathematical model described by equation (1), a generated IWC is shown in Figure **1**. The IWC is defined by the resonant frequency f_{iwc}, and is strictly bounded by the envelop function A_{iwc} which shape is mainly defined by the inhibitory relationship between parameter E and b. Since p is just a scaling factor, by fixing it to a constant value, for instance $p = 1$, while changing the other parameters, we can obtain different forms of IWC Figure **2**.

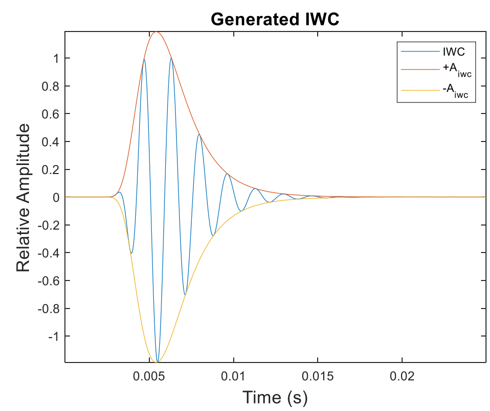


Figure 1: An IWC with its bounding envelope

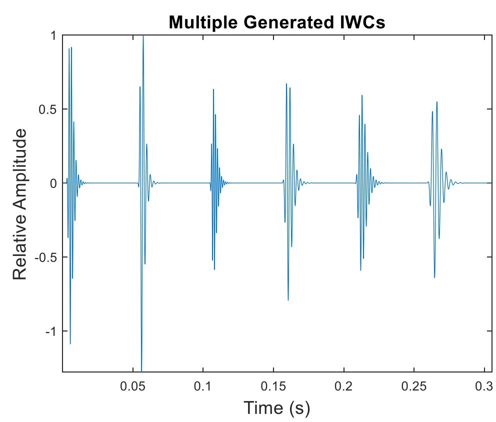


Figure 2: Multiple IWCs with changing parameters.

Figure 1 shows the result of generating one IWC using the model while Figure 2 shows the flexibility to generate multiple IWCs at varying values of the parameters. The first step in the parameter extraction from the envelope function is to find the peaks of the generated bowel sound signal. Then, we set a minimum threshold for the peaks and group the nearby peaks so that we could obtain the points that belong to one single A_{iwc}, as shown in Figure **3**.

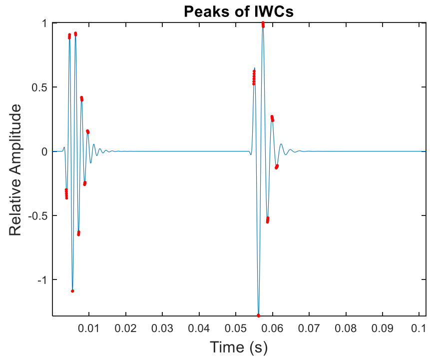


Figure 3: Peaks of IWC obtained from its envelop function

As shown above, depending on the resonant frequency and the decaying speed of the IWC envelope, the number of peaks varies. In the case of lower frequency and fast decaying IWC like the one on the right in Figure 3, the number of points for parameter extraction is insufficient to guarantee convergence. Thus, we introduce the Hilbert transform that provides an estimated envelope of the IWC, shown in Figure **4**.

However, due to noise during the recording of the actual bowel sound, treating the Hilbert envelope as the IWC envelope function would introduce distortion. To preserve the fidelity of the original A_{iwc}, only points with a distance less than a threshold ε to the peaks are considered. Shown in Figure **5** are examples of the points that we consider for the IWCs.

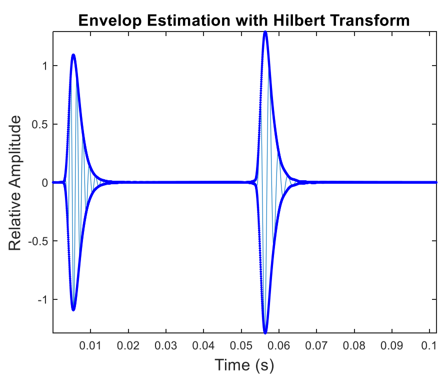
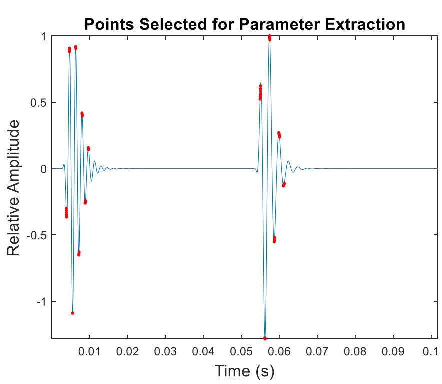


Figure 4: Envelop Estimation using the Hilbert Transform.



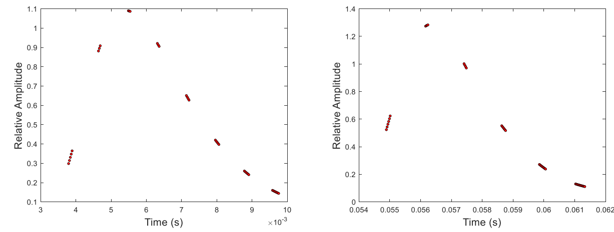


Figure 5: The upper graph shows points on the Hilbert Transform envelope that are close to the peaks are selected. The graph in the middle shows the points in red from the IWCs selected for curve fitting. Lower left is the absolute values of the points of the first IWC for curve fitting; while the lower right points are from the second IWC.

After collected suitable points for the envelope function fitting, the Levenberg-Marquardt algorithm is applied for parameter extraction. The Levenberg-Marquardt algorithm is widely used for nonlinear curve fitting problems [12]. First, we defined the function to be fitted. As described in section II, we take the natural log of the equation first, yet to compensate for a time shift, we add another parameter τ to the model defined in [11]. So, the envelope function becomes

$$A_{iwc} = \frac{pe^{-E/(t+\tau)}}{(t+\tau)^b} \quad (7)$$

with β is the vector of parameters

$$\beta = [p\ E\ b\ \tau] \quad (8)$$

Thus

$$f(\beta) = \ln(A_{iwc}) = \ln(p) + \frac{-E}{t+\tau} - b\ln(t+\tau) \quad (9)$$

Then according to Equation (9), the logarithmic values of the points in Fig.5 form pairs of (x_i, y_i), and with an initial guess of parameter vector β, we compute

$$J_i = \frac{\partial f(x_i, \beta)}{\partial \beta} \quad (10)$$

where J_i is i-th row of the Jacobian matrix, then solve the equation for δ

$$(J^T J + \lambda I)\delta = J^T[y - f(\beta)] \quad (11)$$

where λ is the damping factor that is modified according to the gradient reduction for faster convergence. Upon solving for δ, the parameter vector is updated by $\beta + \delta$. The results are shown in Figure 6 below.

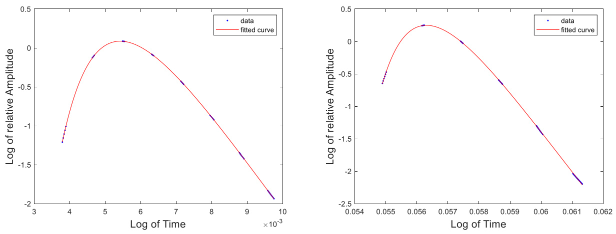


Figure 6: Levenberg–Marquardt curve fitting on the two IWCs

To verify the parameter extracted, we reconstructed the IWCs. We can observe that our algorithm could accurately reconstruct the generated IWCs as shown in Figure 7.

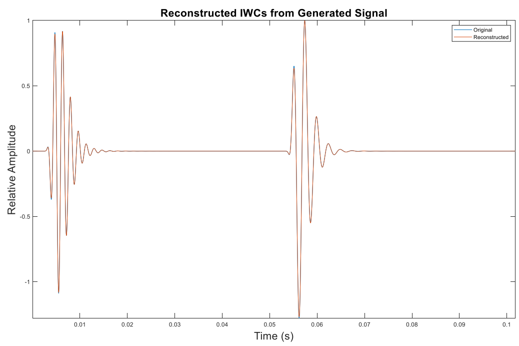


Figure 7: Comparison of reconstructed vs. original IWC

IV. Model Validation

To validate our parameter extraction algorithm as well as the mathematical formulation, we applied the algorithm to the clinically recorded bowel sound signals. Figure **8** shows an IWC of clinically recorded bowel sound.

We then applied the algorithm introduced in the previous section using tunning parameters and with a higher threshold of peak detection to eliminate the noise. Figure **9** shows the results for the Hilbert transform envelope of the parameter extraction.

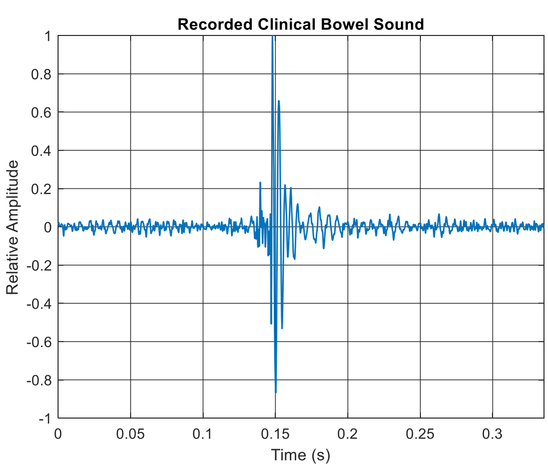


Figure 8: An IWC from a recoded bowel sound

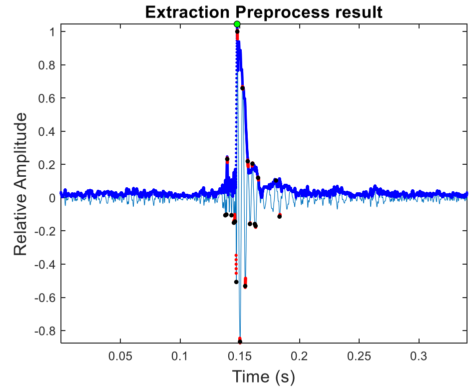


Figure 9: The graph is the Hilbert transform for the IWC, where red points are selected for curve fitting.

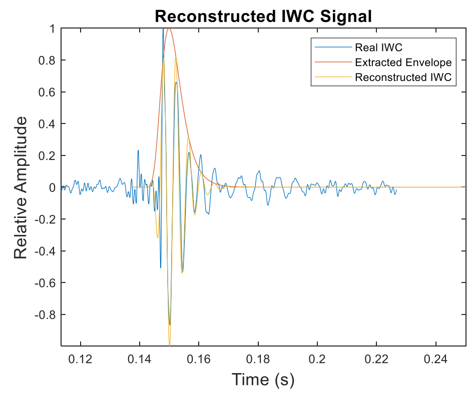


Figure 10: Comparison of reconstructed vs. real IWC

The extracted parameters allow reconstruction of this IWC as shown in Fig 10. The high accuracy of the reconstruction validates the capability of the proposed mathematical model in [11], and the effectiveness and robustness of our parameter extraction algorithm.

V. Conclusion

The accurate diagnosis of the digestive system remains a problem in the medical community. One of the issues is the lack of a computerized system that would capture bowel movement at all the identified locations accurately. While a computerized system will help alleviate the problem, a reliable model can help develop better algorithms to address this critical problem where recorded clinical data is not available. This paper expands on a previous model and presents a new algorithm to estimate the parameters of an IWC and also provides a reconstruction of the original Individual Wave Component from the estimated parameters.

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