

Article

Individual Wave Component Signal Modeling, Parameters Extraction, and Analysis

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Abstract: The accurate estimation of Individual Wave Components (IWC) is crucial for automated diagnosis of the human digestive system in a clinical setting. However, this process can be challenging due to signal contamination by other signal sources in the body, such as the lungs and heart, as well as environmental noise. To address this issue, various denoising techniques are commonly employed in bowel sound signal processing. While denoising is important, it can increase computational complexity, making it challenging for portable devices. Therefore, signal processing algorithms often require a trade-off between fidelity and computational complexity. This study aims to evaluate an IWC parameter extraction algorithm that was previously developed and reconstruct the IWC without denoising using synthetic and clinical data. To that end, the role of a reliable model in creating synthetic data is paramount. The rigorous testing of the algorithm is limited by the availability of quality and quantity recorded data. To overcome this challenge, a mathematical model has been proposed to generate synthetic bowel sound data that can be used to test new algorithms. The proposed algorithm's robust performance is evaluated using both synthetic and clinically recorded data. We perform time-frequency analysis of original and reconstructed bowel sound signals in various digestive system states and characterize the performance using Monte Carlo simulation when denoising is not applied. Overall, our study presents a promising algorithm for accurate IWC estimation that can be useful for predicting anomalies in the digestive system.

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1. Introduction

As advanced signal analysis techniques become more accessible and sophisticated, the need for larger amounts of data is becoming increasingly important to develop more innovative algorithms. In particular, automated diagnosis plays a critical role in human health, and processing more biomedical signals is necessary to develop more accurate algorithms. While there has been limited investigation into gastrointestinal tract sounds due to the irregularity of natural bowel sounds compared to cardiovascular sounds, researchers have made significant efforts to study the acoustic features of bowel sounds [1-4].

The recent development of a mathematical model for bowel sound generation may be considered a significant advancement in medical research. This model has successfully simulated various types of bowel sounds using an Individual Wave Component (IWC) as the building block [5]. With the evaluation of its effectiveness and the development of an algorithm for comparison to bowel sound recordings, the model has shown promise in accurately replicating the complexity and variation of bowel sounds.

The digestive system is a crucial component of overall health, and bowel movements are essential to fully functioning human health [6, 7]. The movement of the intestines produces the sounds and can provide insight into digestive system disorders. However, obtaining sufficient bowel sound recordings can be challenging due to the intermittent and variable nature of the sounds. Thus, a reliable and trusted model is necessary for generating synthetic data to improve abnormality detection and diagnosis. The new model's potential to improve the accuracy of diagnoses and may reduce the need for unnecessary invasive procedures in some cases is significant. Its synthetic data generation capabilities could be invaluable in facilitating research and testing of new treatments for digestive system disorders. With further research and development, this model could become a valuable tool in the hands of healthcare professionals worldwide.

This paper comprehensively analyzes the algorithm's performance by utilizing a mathematical model to generate IWCs and accurately estimate their parameters [5]. The paper presents the results of the algorithm's performance in different noise levels and develops a robust parameter extraction framework in Section II. To further enhance the model's capabilities, the model is expanded to account for time shifts within a burst, and the algorithm's effectiveness using synthetically generated IWCs are demonstrated in Section III.

In Section IV, a time-frequency analysis is conducted to verify the preservation of frequency content within a burst. Section V evaluates the performance of the parameter estimation and reconstruction algorithm using two different states of the digestive system. A comparison is made between the reconstructed IWCs using parameters extracted from clinical recordings and the original recording.

Section VI presents the steps involved in the IWC parameter extraction process. In Section VII, a Monte-Carlo simulation is performed to verify the accuracy of both the algorithm and the mathematical model under various signal-to-noise ratios.

Finally, we conclude in section VIII. The research presented in this paper provides a promising solution for overcoming the scarcity of recorded data. It demonstrates the potential for generating valuable synthetic data with high confidence, which is essential for developing statistical and machine learning algorithms for abnormality detection.

2. Parameter Extraction Approach

The mathematical model of the IWC is deduced by assuming the sound is generated from the vibration of the guts wall while the pressure onto it contains fluid changes. Thus, the motion can be viewed as a spring-mass-damping system. We then have a damped motion of a vibration frequency which we write as

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

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

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

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 the IWC is, which is related to the damping.

The model separates the IWC into two fundamental elements, a sinusoidal oscillation, $\sin(2\pi f_{iwc} t)$. The main parameter is the frequency f_{iwc} , which can be easily obtained

from a spectrogram; and a more complicated envelope function A_{iwc} , where our parameter extraction algorithm is mainly concentrated. Taking the natural log of equation (2), we have

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

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

$$\frac{\partial}{\partial p} \log(A_{iwc}) = \frac{1}{p} \quad (4)$$

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

$$\frac{\partial}{\partial b} \log(A_{iwc}) = \log(t) \quad (6)$$

The partial derivatives of the envelope functions are reasonably simple. Thus, a non-linear 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 [8].

At this point, the problem is to select enough data points from one IWC to achieve convergence of the algorithm. According to the mathematical model, the IWC's points that are on the envelope function is when the oscillation $\sin(2\pi f_{iwc}t)$ equals to ± 1 . These are naturally the peaks of the IWC. Due to the relatively low frequency of bowel sounds, it is easy to obtain accurate peak values and their corresponding time t with oversampling. But it also poses a problem of too few peaks for one IWC if the resonant frequency is low or when the envelope decay into 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. But to maintain the characteristics of the IWC itself without too much deviation, only points that are close to the peaks are selected for non-linear regression.

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

3. Parameter Extraction Using Simulated Data

The parameter extraction process has been demonstrated to hold significant importance in developing and refining models in numerous fields. It serves as a critical step in capturing the essential characteristics and properties of a system or phenomenon under study. Parameters act as key variables that define the model's behavior, performance, and characteristics, allowing for accurate representation and prediction of real-world phenomena.

In fields such as physics, engineering, computer science, biology, and many others, parameter extraction plays a vital role in calibrating mathematical or computational models to real-world data or observations. The accurate estimation of parameters ensures that the model is representative of the actual system being studied and allows for meaningful analysis and interpretation of results.

Furthermore, parameter extraction enables model validation and verification, as it allows for the comparison of model predictions with experimental or empirical data. By extracting parameters from experimental data, researchers can assess the performance

and accuracy of the model, identify potential discrepancies, and refine the model accordingly.

In chip design, parameter extraction is used successfully to develop small-signal equivalent circuits for a very wide range of frequencies and bias values [9, 10]. In [11], a parameter extraction technique is used to develop an equivalent circuit model of a photovoltaic cell. The authors in [12] seek to extract micro-doppler properties of moving targets which are important parameters for target recognition.

With this mathematical model of the IWC described in equation (1), an example of a generated IWC is shown in Figure 1 for a chosen set of parameters. We note that all the estimated parameters will play an important role in the reconstruction process, and the interactions among the parameters are described in this section. Given that the measurements will be made in a noisy environment, some parameters are more sensitive to noise than others and will be estimated at lower or higher fidelity accordingly. The IWC is defined by the resonant frequency f_{iwc} , and is strictly bounded by the envelope function A_{iwc} . The shape of the envelope is mainly defined by the inhibitory relationship between parameters E , b and p , the envelope index, the shape index, and the pressure index. Since the pressure index p is a scaling factor, a normalized value can be used. By setting it to 1 while changing the other parameter, we can obtain different forms of the IWC. An example is shown in Figure 2.

The first step in the parameter extraction process is to find the envelope of the IWC. We start by finding the local minimums and maximums of the generated bowel sound signal. Setting a threshold for the peaks, then group the nearby ones so that we could obtain the points that belong to one single A_{iwc} .

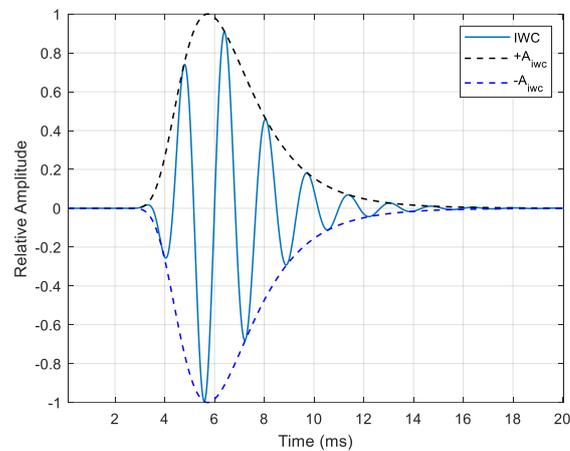


Figure 1. Generated IWC using the mathematical model. The bounding envelope of the IWC is also shown.

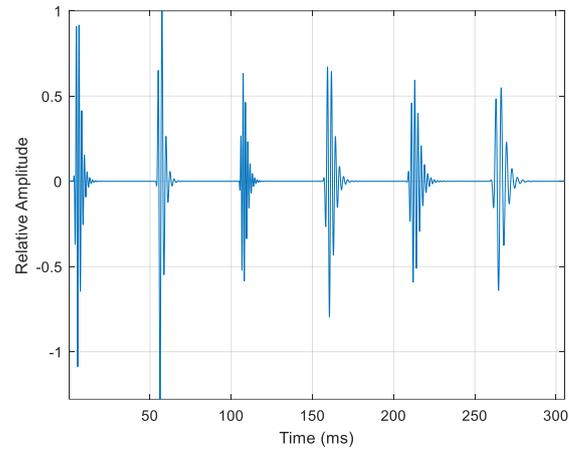


Figure 2. Multiple generated IWCs by the mathematical model. Changing the parameters can generate various forms of IWC at different frequencies and intensities. The periodicity of the IWCs can also be controlled.

As shown above, depending on the resonant frequency and the envelope decaying speed of the IWC, the number of minimums and maximums varies [Figure 3](#). In the case of low frequency and fast decaying IWC like in the figure above, the number of points for parameter extraction is insufficient to guarantee convergence which may be the case in actual recordings. 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 that are close to the peaks and within a difference threshold are considered. Shown in [Figure 5](#), are the points that are considered for the IWCs.

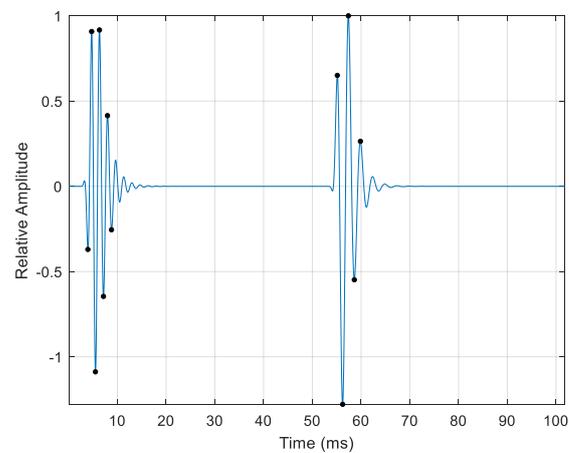


Figure 3. IWCs with local minimums and maximums identified.

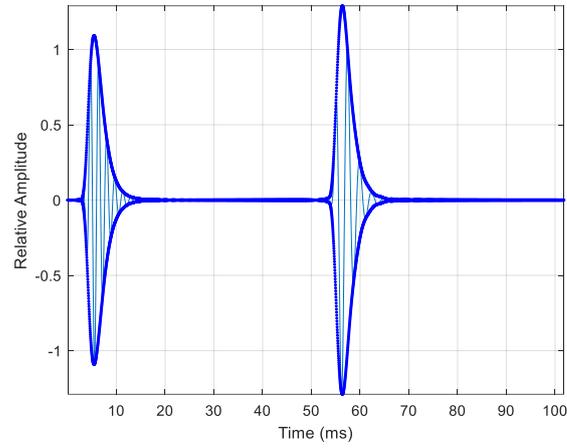


Figure 4. Envelop Estimation using the Hilbert Transform.

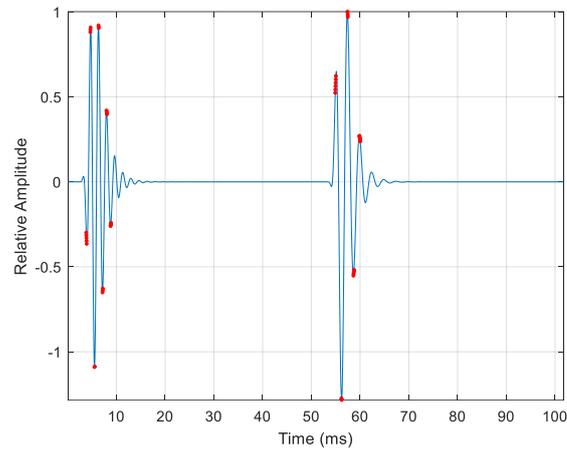


Figure 5. Two IWCs with the selected points for parameter extraction identified. The turning points are identified to facilitate the reconstruction procedure. The minimum and maximum turning points help determine the shape of the curve at these locations.

After collecting suitable points for envelope function fitting, the Levenberg-Marquardt algorithm is applied for parameter extraction. The Levenberg-Marquardt algorithm is widely used for nonlinear curve-fitting least-squares problems [8]. These problems typically arise when we need to fit a parameterized mathematical model to a set of data points to minimize the errors between the model and the data set [13-16]. First, to account for a time shift, we add another parameter τ to the model. The next step is to define the function to be fitted. As described in section II, we take the natural log of the equation (2). 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

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

Then according to equation (9), the logarithmic values of the points in [Figure 5](#) form pairs of (x_i, y_i) , and with an initial guess of the parameter vector β , we compute

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

where J_i is the i^{th} row of the Jacobian matrix. Then, we solve the following 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, and y is the vector signal of interest. Upon solving for δ , the parameter vector is updated by $\beta + \delta$. To verify the extracted parameters, we reconstructed the IWCs and evaluated the error signal between the original and the reconstructed IWC. We can observe that our algorithm could accurately reconstruct the generated IWC [Figure 6](#).

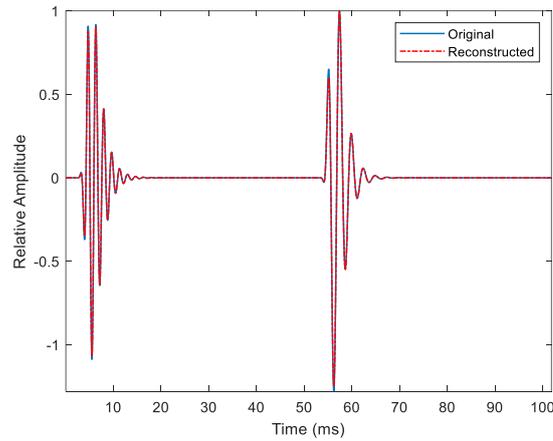


Figure 6. Generated and reconstructed Individual Wave Components. The algorithm reproduces the IWCs correctly up to a small amplitude difference.

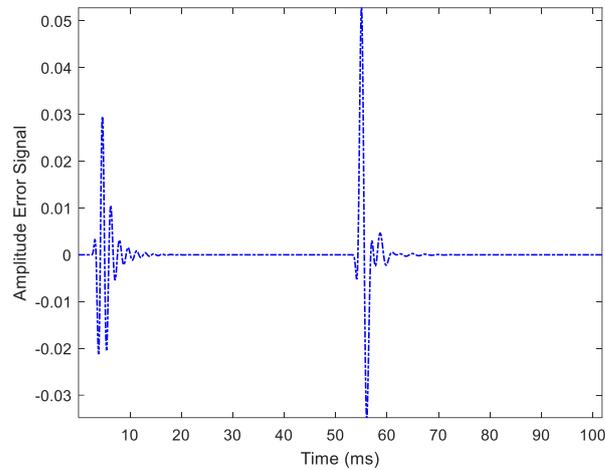


Figure 7. Amplitude error signal between the original and reconstructed IWC. The error follows the shape of the Individual Wave Component. The amplitude level shows a small error in the reconstruction process.

4. Frequency Analysis of Recorded and Reconstructed Bowel Sounds

The time-frequency analysis is used to display different frequency content of a signal in time. The goal here is to evaluate the difference between the original and reconstructed plots to the extent that the frequency is maintained. Visually, we see the bursts in [Figure 8](#) where the IWCs intensities are strong but further analysis of the two plots is necessary. An agreement in the plots shows the frequency content is maintained using the algorithm in approximating the IWCs. A typical bowel sound lies between 50 and 5000 kHz [17, 18]. Similar to previously reported works that revealed the limits where the largest component of the power spectrum of bowel sound is concentrated in the frequency range 100 Hz to 500 Hz [17, 19-21]. In our bowel sound recorded signal, we also see the signal’s high-intensity component is between 50 and 500 Hz.

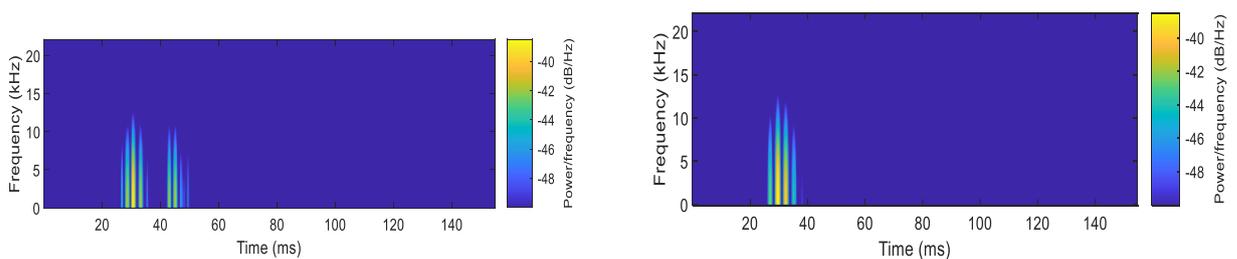


Figure 8. Spectrograms showing bowel sound recordings. In both plots, the individual wave components are identified. The top figure shows the spectrogram of the original recording. The bottom figure shows the spectrogram of the reconstructed signal of the first

A small deviation in the plots indicates that the parameters of the time-frequency analysis algorithm can be further tuned to achieve a more accurate result for this class of signals.

5. Simulation Results Using Recorded Bowel Sound

The state of the digestive system plays a major role in the type of bowel sounds it generates. In [22], the authors look at the impact of small bowel obstruction in the diagnosis of a particular disease and highlight the importance of the need for additional procedures to develop a successful treatment plan. Therefore, for any automated bowel

sound analysis to be successful, all types of obstructions must be fully understood. [Figure 9](#) represents the human digestive system with the four quadrants identified. [Figure 10](#) is the domain signal for two different states of the digestive system. The top plot in [Figure 10](#) is from a patient with water entering the digestive system. We notice a normal rhythm in the recorded bowel sound signal, and the signal level is stable throughout the recording with only one peak. [Figure 10](#), the bottom plot, shows the bowel sound recording from a patient with an empty digestive system. In the bowel sound recording, we can see that the signal is less stable or rapidly varying. This is because, with an empty digestive tract, the individual wave components bounce against the digestive system wall creating more echo signals. As a result of these interactions between the IWCs and the digestive system wall, we end up with destructive and constructive interaction of the signals, which also generates overlapping IWCs. The expectation is that such interaction should gradually manifest as we move from one extreme case, overfilled, to the other, an empty digestive system.

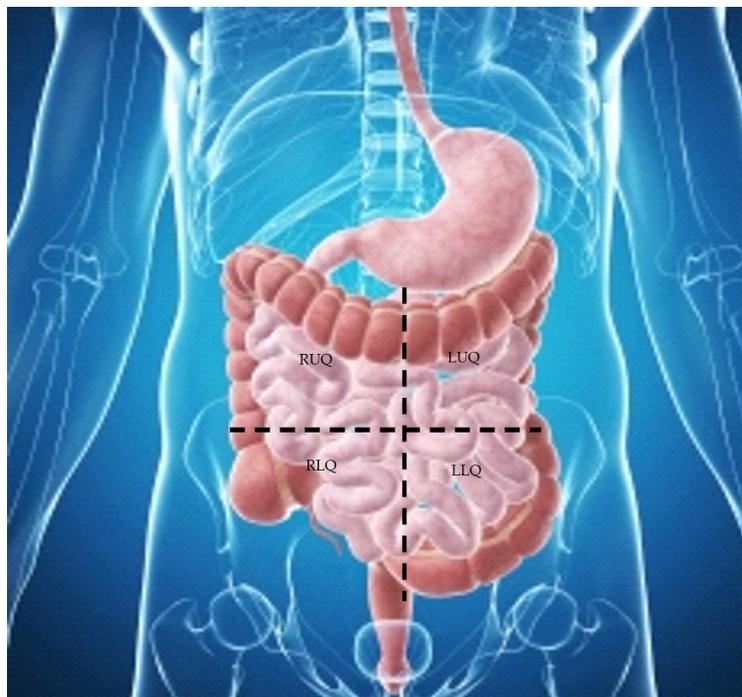


Figure 9. Human digestive system with all four quadrants identified.

The sound caused by bowel movements in the digestive system produces different perceptible levels when the stomach is full compared to when it is empty. The empty stomach produces an amplified sound because of the empty spaces. As a result, one must pay particular attention when analyzing bowel sounds from the human body, as the state of the digestive system plays a major role. To that end, we analyze the performance of the parameter extraction algorithm in these cases, and the results are presented in sub-sections A and B. Although a fair comparison would be to consider both states, full and empty stomach, for the same patient, due to the rare occurrence of collecting recorded bowel sounds, we could not obtain this data. We are fairly confident that the result will not be impacted much as the goal in this paper is to show the performance of the algorithm in various cases, empty or partially empty digestive systems. In future correspondence, the case where the analysis is done for a single patient will be addressed. At the default of obtaining recorded data from the same patient with an empty and full stomach, we limit

our analysis to the ability to extract the parameters of the IWC and reconstruct it with high accuracy.

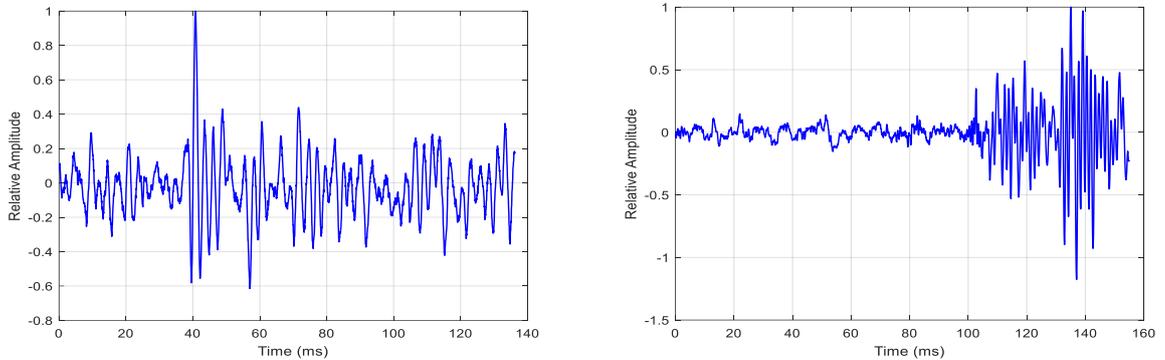


Figure 10. Time-domain bowel sound signals of two different states of the digestive system. The top figure represents a recorded bowel sound signal when water enters the stomach. The bottom figure represents a bowel sound generated by a patient with an empty stomach.

A. Bowel Sound Analysis with Empty Stomach Patient

An empty stomach produces high-intensity bowel movements. In the evaluation process of the IWCs and later burst for automated diagnosis, the characterization of the bowel signals in this state of the digestive system is paramount. Figure 11 below looks at a burst of bowel sound recordings, extracts the parameters for each initial wave component, and reconstructs the burst. We see that all the relevant IWCs are reconstructed that can be used to make inferences for a meaningful diagnosis.

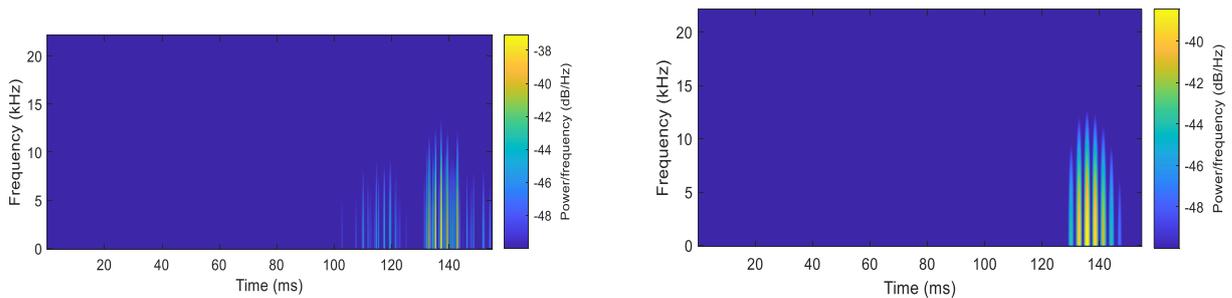


Figure 11. Spectrograms of recorded bowel sounds from a patient with an empty stomach. The top figure is the original recorded bowel signal. It shows a lot of activities once the bowel movement starts. The bottom figure shows the reconstruction of a series of individual wave components. The echo signals from the main individual wave components bounce against the digestive system’s empty wall, creating more individual wave components but at a lower intensity.

B. Bowel Sound Analysis when Water Enters a Hungry Belly

In this section, we analyze a partially empty digestive system as the patient drinks water and record the effect of the bowel sound as the liquid goes through the digestive tract. This state of the digestive also produces well-defined IWCs necessary to evaluate the reconstruction algorithm.

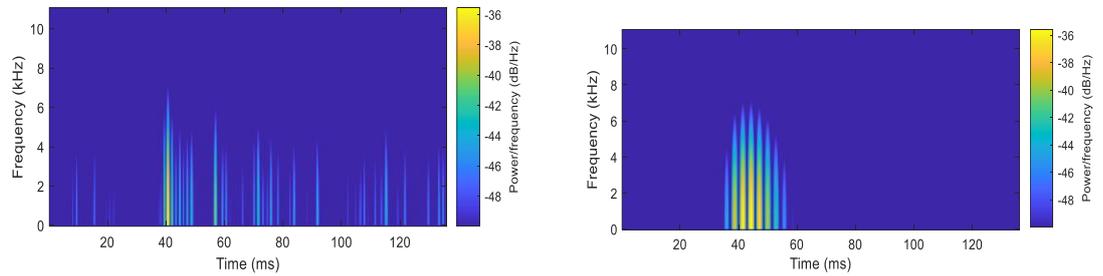


Figure 12. Spectrograms of recorded bowel sounds from a patient with an empty stomach. The top figure is the original recorded bowel signal. It shows a lot of activities once the bowel movement starts. The echo signals from the main individual wave components bounce against the digestive wall.

6. Model and Algorithm Validation

In this section, we demonstrate the complete parameter extraction and individual wave component reconstruction procedure. To validate our parameter extraction algorithm as well as the mathematical formulation, the algorithm is applied to the actual recorded bowel sound signal. We first note the difference between the generated IWC signal from the mathematical model and the recorded signal from a person. [Figure 133](#) is an IWC of a recorded bowel sound. As seen and expected, the signal is not as well defined as shown in [Figure 1](#). This is due to noisy environments, measurement, and quantization errors.

The algorithm introduced in section III is then applied with a higher peak detection threshold to minimize the noise contribution. [Figure 144](#) shows the results for the Hilbert transform envelope parameter extraction.

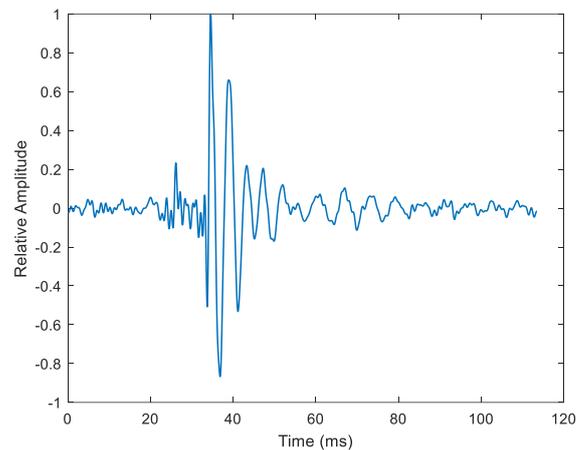


Figure 13. Recorded clinical bowel sound signal in a noisy environment.

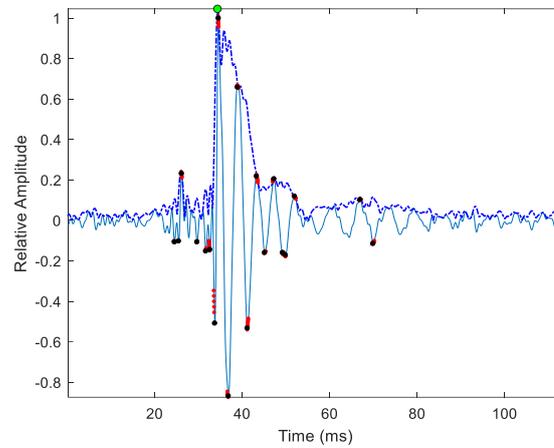


Figure 14. The complete extraction process. The envelope is obtained using the Hilbert transform of the IWC, and the red and black points are selected for curve-fitting.

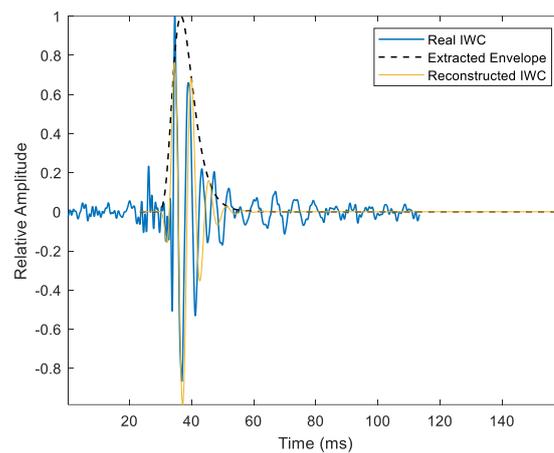


Figure 15. Original and reconstructed IWCs. The reconstructed bowel sound signal maintains the shape and features of the original.

7. Performance Analysis

Monte Carlo analysis is a commonly used method for evaluating the performance of algorithms by varying the Signal-to-Noise Ratio (SNR) and assessing performance using the Root Mean Squared Error (RMSE) as the performance measure. The baseline IWC is generated using equation (1) with arbitrary parameters, and random white Gaussian noise is added to the signal at the desired SNR level. The parameter extraction algorithm is applied directly to the noise-contaminated signal, and the IWC is reconstructed based on the extracted parameters. The squares error of the baseline signal and the reconstructed signal is computed at each iteration, and for each value of SNR, 500 runs are averaged to determine the RMSE value. Figure 166 shows that the algorithm performs well even when the SNR is set to -10 dB. It is noted that this analysis was done without signal denoising, a process that is often used in biomedical signal processing. It is also observed that as the SNR approaches 10 dB there is a significant drop in the RMSE value. With that, we can predict a significant gain in performance when denoising is applied to the contaminated signal before parameter extraction.

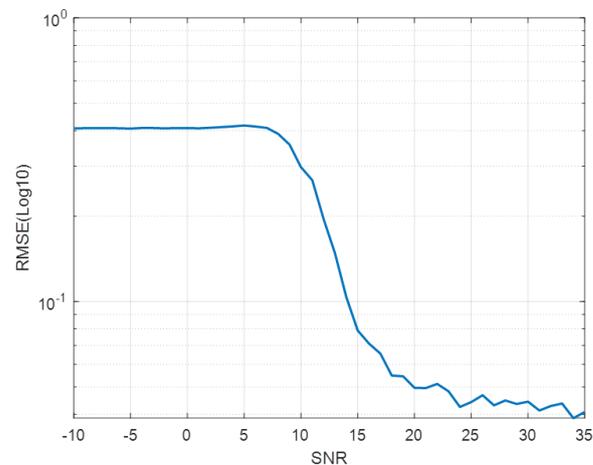


Figure 16. Root Mean Square Error (RMSE) of an IWC. We average over 500 iterations per SNR value.

8. Conclusion

The diagnosis of digestive system disorders continues to pose a significant challenge for the medical community. One of the major issues is the absence of a reliable computerized system capable of accurately capturing bowel movements at all identified locations approved by the medical community. In addition, data is scarce to enhance the performance of existing algorithms. Therefore, there is a need for a reliable model to generate synthetic data. It is also crucial to consider the state of the digestive system during recording, as it can significantly influence bowel sound recordings. Therefore, evaluating multiple scenarios, including an empty stomach, partially empty, partially full, and a full stomach, is essential to develop an adaptive system.

We consider the characterization and reconstruction of the individual wave component as the foundation for an automated diagnosis of the digestive system. While a computerized system can help address the diagnosis problem, a dependable model can facilitate the development of improved algorithms where clinical data is not available. This paper builds on a previous model and presents a novel algorithm and a procedure to extract essential parameters from individual wave components for successful reconstruction. Furthermore, we evaluate the algorithm's performance using Monte-Carlo simulation, specifically in cases where denoising is not applied.

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