# Bowel sounds Frequency analysis by use of Fast Fourier Transform, Spectrogram and Hilbert-Huang Transform

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Abstract—Bowel sounds occur by movement of the intestines as food are pushed through. Intestines are hollow such that bowel sounds echo through through the abdomen. They contain a wide range of frequencies contaminated with noise and artifacts, and the goal is therefore to use a variety of methods to analyze these sounds. A small section of the signal that had been identified by audio to include bowel sounds was chosen and analyzed. By using FFT and STFT low frequency components, below 100Hz was identified as noise in the signal. A high pass filter with cutoff frequency 100Hz was used to filter out low frequency components, then a new analysis was done with FFT and EMD. The signal showed three short bursts and these frequencies was identified to be around 1400Hz, 900Hz and 400Hz

#### I. INTRODUCTION

Bowel sounds, often also called abdominal sounds, is noises made within the small and large intestines, typically during digestion. The cause behind bowel sounds are most likely related to movement of digested food, liquids and air inside the abdomin [1].

Humans have as early as 1905 [2] experimented around the practical value of abdominal auscultation. The sounds were then reported resembling the sound of bursting bubbles. In later years, the research area has grown larger and it has been applied to a variety of areas within the medical field. In a study from 2011 it was concluded that patients with Parkinson's disease and multiple system atrophy have reduced bowel sounds [4]. Another study from 2010 found that analyzing bowel sounds is a useful modality in the assessment of the abdomen [3].

Recorded bowel sounds are often nonstationary, nonlinear and contaminated with noise and artifacts from which the bowel sounds must be differentiated. This paper investigates the various forms of bowel sounds with the purpose of finding the different frequency components. These components can from there on be useful in classification methods.

# II. BACKGROUND

### A. Source

The bowel sound data used in this report was recorded and provided to the making of this report by Konstanze Kölle, research scientist at SINTEF. Further research using this dataset can therefore be found in the paper "Feasibility of early meal detection based on abdominal sound" [6].

The acquired data consists of sound measurements from the abdomen of a self-de clared healthy subject. The subject ate breakfast consisting of musli, fruits and dairy about 4.5 hours to 5 hours before a lunch was given. The recording started approximately 30 minutes into the total 90 minutes recorded for each subject. The selected signals analyzed in this report is from the first 30 minutes of the recording, while the subject was still fasting. This subject sat reclined on a chair and the microphone was fixed in the upper right quadrant of the abdomen. After fixation of the microphone by medical tape, the microphone was covered by clothes.

#### B. Recording

The data was recorded with a Sennheiser MKE2 P-C condenser microphone, fixed in the chest-piece of a classical stethoscope. Single-channel 24-bit audio signals with a sampling frequency of 32 000 Hz using a digital audio recorder 722. Analysis of the data was done using MATLAB 2018a [13].

## C. Pre-processing

When reading the signal into Matlab, the sampling rate is read as  $\approx 44100$  samples per second. A recent study shows that only 0.5 % of the signal's power spectrum density occurs at frequencies above 2000 Hz [11] and that the majority of the power spectrum density of bowel sounds is located between 100 Hz and 500 Hz. However in earlier research there have been found bowel sounds with frequency up to 3000 Hz [10]. The raw signals are therefore downsampled to  $\approx 6000$  Hz, a power of 7 less than the original sampling frequency. This is done using matlab's decimate function which uses a low pass Chebyshev Type I infinite impulse response filter of order 8. Early stage analysis showed the computing amount too large with the original sampling rate. Because the largest frequencies do not exceed 3000 Hz, there is roughly no loss of information by the Nyquist frequency theorem.

# III. METHODOLOGY

The analysis of the bowel sounds consisted of a number of data analysis methods, each of them presented below with the corresponding resulting plots. The raw signal is presented in Figure 1. The signal is clearly contaminated by noise, however bowel sounds are recognizable by strong spikes. The largest spike is an unfortunate sneeze. There are also quite a bit of smaller spikes, these could be bowel sounds but can also be sounds resulting from movement or friction around the microphone. Statistical classification of whether a spike is or is not a bowel sound is not a part of this report, such that all bowel sounds analyzed are already confirmed sounds given with the data set. It is therefore assumed that the combination of abnormally high amplitude and frequency characterizes bowel sounds.

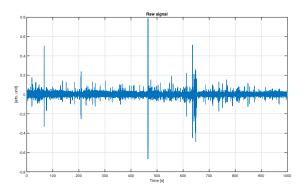


Fig. 1. Raw Signal

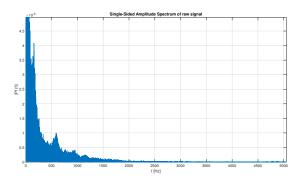


Fig. 2. FFT of raw signal

# A. Fast Fourier Transform and Short Time Fourier Transform

A Fast Fourier Transform (FFT) was used used to characterize the magnitude and phase of the signal. The signal is transformed from the time domain to the frequency domain. FFT computes the discrete Fourier transform (DFT) by factorizing the DFT matrix into a product of sparse factors, thereby reducing the complexity of the DFT from  $O(n^2)$  to O(nlogn) which n as the data size.

In addition to FFT, Short Time Fourier Transform (STFT) was used. The FT is not very effective for signals where the spectra fluctuate in time which is often the case in bowel sounds. This is displayed in Figure 2. The STFT computes

the Fourier spectra using a sliding temporal window that determines the time resolution of the resulting spectra.

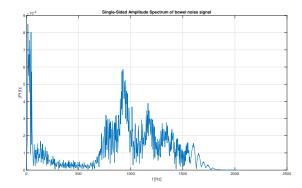


Fig. 3. FFT of 0.3 seconds of bowel sounds.

#### B. Power Spectrum

Power spectrum or power spectral density plot shows how the energy of a signal is distributed over frequency components found in the signal.

To more precisely account for noise and rapid fluctuations in the data a windowing estimation is used to better approximate the signal's actual power spectral density. To account for the signal not having finite total power, an estimate is used, called a periodogram. This is done by splitting the data into overlapping segments, calculating a periodogram for each segment using discrete fourier transform and then averaging over all periodograms to obtain a smoother estimate of the power spectral density.

#### C. Spectrogram

Looking at Figure 3, there is no information about at what time the frequencies occur. A time-spectral-density plot, more known as a spectrogram is therefore needed. This plot provides information about the frequency distribution over time [12].

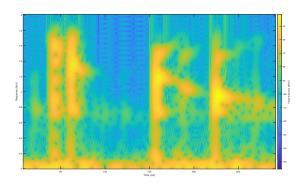


Fig. 4. Spectrogram of 0.3s of bowel sounds. Windows size 64.

#### D. Hilbert Huang Transform

The Hilbert Huang transform [8] is the combination of Hilbert Spectral Analysis and Empirical Mode Decomposition

The Hilbert transform is used to find the analytic representation of a signal,

$$z(t) = f(t) + j\hat{f}(t) = A(t)e^{j\phi(t)}$$
(1)

Where A(t) is the envelope and  $\omega(t)=\frac{\partial \phi}{\partial t}$  is the instantaneous frequency. This is conditioned on f(t) and its Hilbert transform H(f(t)) together create a strong analytical signal. The instantaneous frequency is useful because by expressing frequency as a rate of change in phase, the frequency can vary with time.

Empirical Mode Decomposition is based on having a multimodal signal, meaning there are fast oscillations on top of the slower oscillation. The locally fastest oscillations are called the Intrinsic Mode Functions (IMF). These are found by a process called sifting.

- 1) Extract the Local Maxima and Minima
- Construct an Upper and Lower Envelope by connecting all the maxima through cubic spline lines and connecting all the minima the same way
- 3) Subtract the envelope mean from the signal repeatedly
- 4) Subtract the IMF from the original signal

Repeat this process until the number of extrema of the residue is  $\leq 1$  or the mean value of the upper and lower envelope must be equal to zero at any point. The IMFs found by the EMD is lossless and can therefore be summed together to form the original signal. In addition the IMFs represent the frequencies from the highest to the lowest.

Combining EMD and the HT, finding the Hilbert transform of the IMF yields information of the instantaneous frequencies. Figure 5 shows 5 IMFs of the 0.3 second long cluster of bowel sounds while Figure 10 shows 3 IMFs for a specific burst.

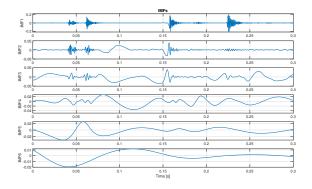


Fig. 5. EMD of 0.3s of bowel sounds

#### E. Filtering

Looking at Figure 2 we find that there is a lot of frequencies with large magnitudes below what is generally known as the "hearing" frequency, 20 Hz. After decomposing the signal with EMD we also discovered the signal noise very low frequent. Therefore a high-pass 5th order Butterworth filter [9] was implemented with a cut-off frequency of 100 Hz. This led to the audio signal becoming more visible and interpretable.

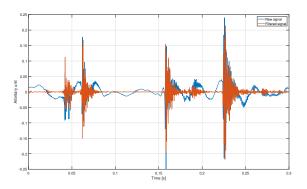


Fig. 6. Filtered and raw signal. Cutoff frequency is 100Hz.

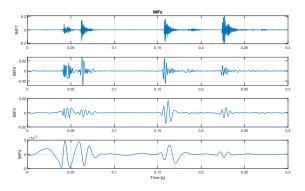


Fig. 7. IMF 1-4 of filtered signal

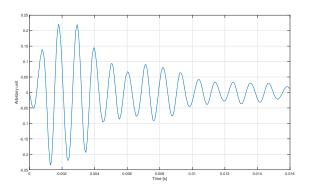


Fig. 8. Last burst of the filtered signal.

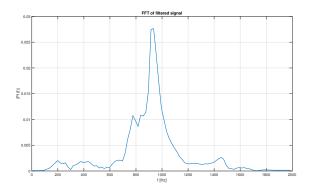


Fig. 9. FFT of the last burst.

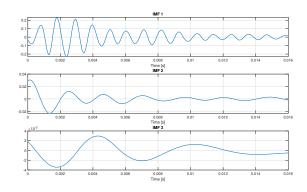


Fig. 10. IMFs of the last burst.

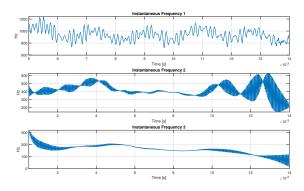


Fig. 11. Instantaneous frequencies of the IMFs.

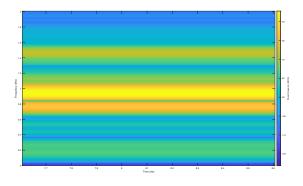


Fig. 12. Spectrogram of the last burst

#### IV. DISCUSSION

The result of the FFT of the entire signal (Figure 2) shows that most of the frequencies lie between 0 and 2000 Hz. This is as discussed earlier within what is common for bowel signals [11]. Looking at a much smaller period of time, the FFT of a 0.3 seconds long cluster (Figure 3) showed a large concentration of frequencies from about 600 Hz to approximately 1700 Hz. From there on there is a concentration with a larger magnitude from 0 to 250 Hz, which is assumed to be and later proven to be noise.

However the Power Spectrum given by the FFT does not tell us how the frequencies are distributed for the entire cluster and a Spectrogram (Figure 4) is therefore used. Although difficult to get precise information on frequency and time, there are four clear bursts of sound with corresponding frequency limits from about 700 Hz to 1600 Hz. The main take from this plot is however the constant noise contributing throughout the entire period of time with frequencies below 150 Hz.

The cluster was then decomposed using EMD to learn about the higher frequencies that make up the sound. Figure 5 shows the 6 resulting IMFs where it is clear that the noise has less frequency then the sound. Summing up the first 2-3 IMFs gave a much clearer sound signal. Therefore it was suggested to high-pass filter the signal with a Butterworth signal (Figure 6). This gave an a lot more clear image of the different bursts in the cluster. The corresponding IMFs (Figure 7) are still largely affected by mode mixing but there are clear breaks between bursts. To explore this further the EMD was used on the last burst in the cluster, Figure 8. The Power Spectrum of the last burst (Figure 9) shows a clear distribution of frequency around about 900 Hz. Although the IMFs (Figure 10) of the last bursts does not give us much more, the instantaneous frequencies of the IMFs (Figure 11) shows frequencies  $\approx 900$  Hz, 400Hz and 200Hz. The 200Hz is weak in Power Spectrum and could be background noise. IF1 seems to include several frequency components and by looking at the Spectrogram in figure 12 one can see that these could be in the area around 1400Hz, 900Hz and 800Hz. A very high frequency can also be seen on IF1, this could be the sampling rate frequency. It is not clearly visible from the IMF's in figure 10 that there are mode mixing tendencies but from IF1 in figure 11 it can be seen that there are mode mixing and an attempt to solve this by masking was tried out but did not give any satisfactory results.

#### V. CONCLUSIONS

First, by applying Spectrogram, Power Spectrum and EMD on the 0.3 second bowel sound signal the low frequency noise is identified and removed from the signal by a high pass filter with cutoff frequency at 100Hz. Then a closer look at the last burst in the 0.3 seconds bowel sound signal is conducted by applying the same methods. Here the Instantaneous Frequencies of the IMF's and the Spectrogram show that the last burst consists of frequency components around 1400Hz, 900Hz, 800Hz, 400Hz and 200Hz. Where the 200Hz is assumed to be background noise. A natural

step for further research will be to find a solution to the mode mixing problem to give a more accurate prediction on which frequencies the signal consists of. The problem can also be extended to include classification of the sounds, thereby giving more context to the origin and behaviour of the audio signal.

#### REFERENCES

- [1] Healthline. 2017. Abdominal (bowel) sounds. Accessed: 2018- 11-17. https://www.healthline.com/health/ abdominalsounds#other-symptoms.
- [2] Cannon, W. B. 1905. Auscultation of the rhythmic sounds produced by the stomach and intestines. American Journal of Physiology-Legacy Content, 14(4), 339353.
- [3] Gu, Yuqi, Lim, Hyun Ja, Moser and Michael A.J, How Useful Are Bowel Sounds in Assessing the Abdomen? Digestive Surgery, November 2010, 27(5), 422-426
- [4] Ozawa, T., Saji, E., Yajima, R. et al., Reduced bowel sounds in Parkinsons disease and multiple system atrophy patients. Clin Auton Res (2011) 21, 181.
- [5] M. Molinas, Lecture 4 Introduction to Hilbert Huang Transform -HHT, Norway, 2018.
- [6] Klle, K. Towards a Safe Artificial Pancreas: Meal Detection and the Intraperitoneal Route, Norway, 2018.
- [7] Bray, D., Reilly, R., Haskin, L., & McCormack, B. 1997. Assessing motility through abdominal sound monitoring. In Engineering in Medicine and Biology Society, 1997. Proceedings of the 19th Annual International Conference of the IEEE, volume 6, 23982400. IEEE.
- [8] Huang, N.E., Shen, Z., Long, S.R., Wu, M.C., Shih, H.H., Zheng, Q., Yen, N.-C., Tung, C.C., Liu, H.H.: The empirical mode decomposition and the hilbert spectrum for nonlinear and non-stationary time series analysis. Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences 454(1971), 903995 (1998)
- [9] Butterworth, S. 1930. On the theory of filter amplifiers. Wireless Engineer, 7(6), 536541.
- [10] D. Dalle, G. Devroede, R. Thibault, et al., Computer analysis of bowel sounds. Computers in Biology and Medicine, vol. 4, no. 3-4, pp. 247256, 1975.
- [11] R. Ranta, V. Louis-Dorr, C. Heinrich, et al., Digestive activity evaluation by multichannel abdominal sounds analysis. IEEE Transactions on Biomedical Engineering, vol. 57, no. 6, pp. 15071519, 2010
- [12] M. Molinas, Lecture 1 Understanding Frequency, Norway, 2018.
- [13] www.mathworks.com.