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Advances in Acoustic Signal Processing Techniques for Enhanced Bowel Sound Analysis

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**Abstract**—With the invention of the electronic stethoscope and other similar recording and data logging devices, acoustic signal processing concepts and methods can now be applied to bowel sounds. In this paper, the literature pertaining to acoustic signal processing for bowel sound analysis is reviewed and discussed. The article outlines some of the fundamental approaches and machine learning principles that may be used in bowel sound analysis. The advances in signal processing techniques that have allowed useful information to be obtained from bowel sounds from an historical perspective is provided. The document specifically address the progress in bowel sound analysis, such as improved noise reduction, segmentation, signal enhancement, feature extraction, localisation of sounds, and machine learn­ing techniques. We have found that advanced acoustic signal processing incorporating novel machine learning methods and artificial intelligence can lead to better interpretation of acoustic information emanating from the bowel.

**Index Terms**—Acoustics, Bowel Sound, Signal Processing.

1. INTRODUCTION

THe use of stethoscopes to listen to the heart, lungs, and bowel has been a common practice since their invention by Laennec in 1816 [1]. Scientific analysis of sounds produced by the bowel have been reported since the early 1900’s by Cannon [2]. However, observation and recording of sounds produced by the gastrointestinal tract were performed centuries earlier with Hooke proposing that it may be possible to discover the workings of the internal parts of the body by listening to the sound they make [3]. Cannon described the rhythmic sounds in the gut possibly produced by peristaltic movement of the intestines, as well as continuous random sounds that vary in intensity and location within the bowel. It is understood that many of the sounds produced in the abdomen are caused by the intestines pushing liquid and gasses through the bowel as part of the digestive process, as well as sounds produced as the material passes through valves connecting the different sections of the bowel [4]. Recognising differences in the sounds that the bowel makes may lead to a better understanding of the anatomy and physiology of the human gut [5]. Bowels sound analysis may also provide insight into the activities of the microbiome, such as gas production through fermentation [6].

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Big data analytics and artificial intelligence are emerging as powerful tools in many diverse applications from facial recognition to financial forecasting [7]. Models based on artificial intelligence algorithms have been reported useful in many areas such as structural damage detection [8], disease diagnosis [9], and civil engineering [10]. The technology has been driven by developments in computer processing power that have enabled basic computer algorithms to analyse large datasets and through training, recognise previously hidden, higher dimensional patterns within the data. These machine learning techniques have recently been applied to identification of bowel sounds.

The improvements in acoustic signal processing methods have led to improved noise reduction and signal enhancement. Dalle et al. are noteworthy because they pioneered the use of computers to analyse bowel sounds in 1975 [11]. They used the duration of the recorded bowel sounds to classify them into different types. Later, signal processing techniques like Fourier transformation, wavelet transformation, short time Fourier transformation were used for signal enhancement, identification of bowel sound types and extraction of sound features [12]-[14]. Signal processing methods in turn have culminated in the extraction of large feature sets from acoustic signals and enabled automatic detection of bowel sounds. Here, the advances in acoustic signal processing techniques in bowel sound applications are reviewed and discussed.

1. Theory- Acoustic Signal Processing and

MACHINE LEARNING FUNDAMENTALS

Sounds are produced by the mechanical deformation of an object or material that causes the surrounding medium, air or water molecules, to move. This in turn generates an energy wave that propagates through the medium before it is detected by the ear or an electro-mechanical transducer, such as a piezoelectric material. In the case of a piezoelectric transducer, the pressure wave induces a voltage that varies with time, which is known as the time domain signal. The following sections provide an overview of some of the fundamental concepts in acoustic signal processing and machine learning techniques.

1. Signal Identification and Enhancement

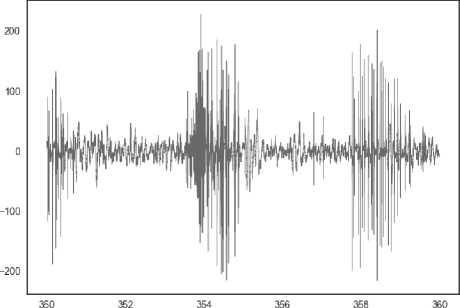
1) Time Domain Signal: The time domain signal is es­sentially the raw data obtained from a listening device that changes over time. An example of a time domain signal recorded from the bowel with a sampling rate of 44.1kHz is

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shown in Fig. 1. The sensor used to detect the signal had an effective frequency response from 80Hz to 5kHz.

Time Sequence



Time (s)

Fig. 1: Time domain acoustic signal recorded from the gut.

Several features can be extracted directly from the time do­main signal including the signal to noise ratio (SNR), duration, and number of events etc. The SNR is an important index that gives an indication of the quality of the signal. The higher the SNR, the more information that can be extracted from the signal. Usually, a sensor will have an in-built algorithm to increase the SNR in real time during data acquisition, in addition to improving the SNR in subsequent data processing. The SNR of an acoustic signal measured in decibels (dB) is given in Eq. 1.

SNRdB = 1〇1〇gio

Psignal Pnoise y

noise,dB

(1)

As bowel sounds do not occur all the time it is possible to obtain the power of the noise during a period when no bowel sounds are present. Many common statistical parameters can also be obtained from the time-domain signal such as the root mean square etc. [15]. A common first step in acoustic signal processing, in order to increase the SNR, is signal enhancement through filtering. Filtering a signal is a way to remove unwanted parts of a signal. The simplest types of filtering are low pass, high pass, and band pass filters. Low pass and high pass filters remove higher and lower frequency components of a signal, respectively, and a band pass filter removes both high and low components of a signal. The choice of threshold values depend on the type of acoustic signal being analysed. Filtering categories include Butterworth, Chebyshev, Bessel, and Elliptic, which are described in [16]. Adaptive filtering can also be used to enhance the signal by analysing the properties of the noise present. The ambient noise is recorded and input into the adaptive filter which then adjusts in response to the environmental noise over time, to give

Before any features are extracted from the sound, it is common practice to slice the acoustic recordings into small samples. Various window functions can be used to achieve this, such as rectangular, Hamming, and Hann etc. Because bowel sounds are usually bursts, where the energy versus time distribution is extremely uneven, the rectangle window function is often used. Usually a bowel sound signal will be sliced into small sample chunks before the bowel sound identification process begins.

1. Frequency Domain Signal: Converting a signal from the time domain to the frequency domain can provide a lot of information that is not observable in the time domain. This is achieved through Fourier analysis. The time signal can be considered as a combination of many sine waves with different frequencies and amplitudes. By performing a Fourier transform it is possible calculate the amplitude of each fre­quency from the time domain signal.The fast Fourier transform (FFT) is one of the most common conversion techniques that provides information about all of the frequency components of an acoustic signal. Many features can be extracted from the frequency domain for bowel sound analysis including the centroid frequency, spectral bandwidth, sub-band energy etc. The main problem with performing a fast Fourier transform, however, is that most of the time domain information is lost in order to obtain the frequency components.
2. Time-Frequency Domain Signal: Besides the time do­main and frequency domain information, it is possible to obtain both time and frequency information simultaneously by using a short time Fourier transform (STFT) or a wavelet transform. The STFT actually provides complex information about the amplitude of an acoustic signal with respect to time and frequency in the form of a spectrogram. However, it is usually only applied to a small section of a signal. The spectrogram is a two dimensional image which is created from the one dimensional wave signal that time stamps the frequency components. It has been reported that a spectrogram created via a STFT can be used for speech recognition and noise suppression by implementing a convolutional neural network [18], [19] An example of a STFT is shown in Fig. 2.

As for the wavelet transform, it is widely used for noise suppression and has advantages over other techniques in­cluding being able to deconstruct and reconstruct complex signals with very little loss of information. There are a large array of wavelet transforms that can be implemented that provide different levels of information in the time domain and the frequency domain depending on the selection of mother wavelet. A detailed explanation of wavelet transforms is given in [20] and [21], and a review of wavelets in biomedical applications is given in [22] and [23].

*B. Machine Learning and Feature Extraction*

Machine learning is a technique that enables computers to

improved performance in terms of signal enhancement [17]. determine the non-linear information from a dataset without Another useful processing technique that is usually performed being explicitly programmed. The machine learning algo-

in the time domain is enveloping. The envelope of an acoustic rithms are used to search for unknown patterns or relationships

signal is a smooth line that outlines the extremes of the signal within data sets and adjust the model accordingly. Machine

and can represent the energy of a signal with respect to time. learning methods typically fall into the following categories:

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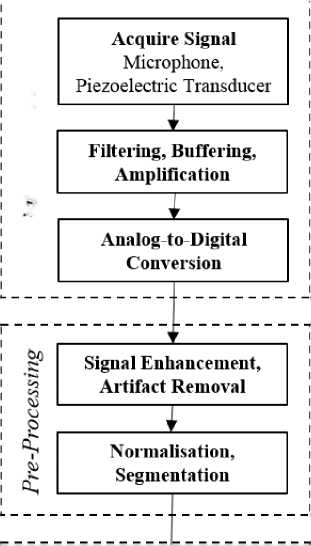
Fig. 2: Short Term Fourier Transform of an acoustic signal recorded from the gut.

1. supervised learning,
2. unsupervised learning, and
3. reinforced learning.

Each of these techniques can be used for either classification of data, or regression analysis. Supervised learning is used when the obtained data contains specific labels or solutions that are used to train the model. The model is used to map the data to the predetermined categories or solutions, and is then capable of predicting the labels or solutions of unknown data. Unsupervised learning is used when the data labels or solutions are unknown and the algorithm infers new categories or outcomes from the relationships within the data itself. Reinforced learning trains the model based on a reward and punishment system. If the model finds the correct solution to a problem it is rewarded, whereas it is punished if it obtains the wrong solution.

One of the challenges in using machine learning in acoustic signal processing applications is that acoustic signals tend to have high dimensionality, due to the high sampling rate used while recording. Thus, it is often necessary to reduce the number of dimensions by implementing a dimension reduction algorithm and extracting acoustic features.Down sampling techniques can be implemented, however the information in high frequency range is lost. Once a database of features has been developed, each feature is input into the machine learning algorithm, which generates a score to determine which features are the most significant, for a particular problem. Finally, these features are incorporated into the algorithm for training the model that is then used to make predictions about previously unseen data.

1. Advanced Signal Processing of Bowel Sounds



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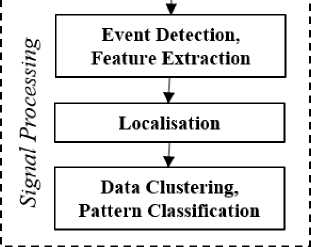


Fig. 3: Bowel sound signal processing flow chart.

cross over in each of the sections depending on the type of acoustic sounds being analysed and the exact goal of the research. For example, de-noising and filtering, would usually be part of a pre-processing stage, although it may also occur in later stages. Within the literature many studies focus on specific steps, such as signal enhancement or localisation, whereas other works may describe a complete sequence from acquiring a signal through to classification. An attempt has been made to categorise the literature into groups relating to the different stages of the overall sequence, although, as mentioned, some studies have incorporated many of the steps involved in processing bowel sounds. Table I in the appendix, summarizes to what extent each of the author’s have achieved a complete acoustic signal processing package for bowel sound analysis.

A. *Data Acquisition*

In order to record the sounds produced in the abdomen, a transducer must be designed to convert the acoustic sound energy to an electrical signal. The transducer may form the basis of an electronic stethoscope, where the main detection element is usually a microphone or a piezoelectric material.

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In general, the term acoustic signal processing may encom­pass many steps including data acquisition and pre-processing, although often signal processing refers to specific steps in the overall process. Modern bowel sound signal processing usually follows a similar sequence to that shown in the flow chart displayed in Fig. 3. However, there can be lots of

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TABLE I: Summary of Advanced Signal Processing Stages Described by Authors in the Review Article

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Author | Year | Data  Acquisition | Signal En­hancement | Feature  Extraction | Localisation | Statistical / Machine Learning | No. of pub­lications |
| Dalle et al. | 1975 | ECM | FFT | TD / FD | - | - | 1 |
| Bray et al. | 1997 | PZT | FFT | TD / FD | - | - | 1 |
| Mansy & Sandler | 1997 - 1999 | ECM | AF / HT | TD / FD | - | - | 3 |
| Hadjileontiadis et al. | 2000 - 2005 | CES | WTST-NST / FDD / IKD | TD / WD | - | - | 6 |
| Ranta et al. | 2001 - 2005 | ECM | WT | TD / WD | YES | PCA | 5 |
| Liatos et al. | 2003 | CES | WTST-NST | TD | - | - | 1 |
| Kim et al. | 2011 - 2012 | ECM | IKD | TD | - | ANN | 3 |
| Dimoulas et al. | 2006 - 2016 | PZT\* | WDWF / FDD | TD / FD / WD | YES | ANN | 5 |
| Li et al. | 2011 | ECM | AF | TD | - | - | 1 |
| Emoto et al. | 2013 | CES | - | TD | - | ARMA | 1 |
| Lin et al. | 2013 | - | AF / FDD | TD | - | RBFN | 2 |
| Ulusar et al. | 2013 - 2014 | ECM | HT | TD / FD | - | NBD | 2 |
| Yin et al. | 2015 - 2016 | - | AF / LF | TD /FD | - | ANN | 2 |

\*Many different types of sound detectors were tested, although a PZT was determined as the best.

Table Abbreviations

|  |  |  |  |
| --- | --- | --- | --- |
| ECM | Electret Condenser Microphone | IKD | Iterative Kurtosis Detector |
| PZT | Piezoelectric Transducer | LF | Legendre Fitting |
| CES | Commercial Electronic Stethoscope | TD | Time Domain |
| FFT | Fast Fourier Transform | FD  WD | Fourier Domain |
| WT | Wavelet Transform | Wavelet Domain |
| HT | Hilbert Transform | PCA | Principle Component Analysis |
| WTST-NST | Wavelet Transform Stationary-Non-Stationary Filter | ANN | Artificial Neural Network |
| AF | Adaptive Filter | ARMA | Auto Regressive Moving Average |
| WDWF | Wavelet Domain Weiner Filter | RBFN | Radial Basis Function Network |
| FDD | Fractal Dimension Detector | NBD | Naive Bayesian Detector |

The microphones and piezoelectric elements used in audio applications typically have an effective frequency response range from 20Hz to 20kHz. However, electronic stethoscopes are usually designed to pickup signals up to 1kHz. In the case of a microphone based stethoscope, there are three types, capacitive, coil, and electret. The electret condenser microphone is typically the most common. The microphone is placed inside the tubing, somewhere between the sensor head and the ear pieces. An electronic circuit is required to power the microphone and the stethoscope usually has an additional circuit to increase the gain and filter low and high frequency noise. An example of a electret condenser microphone based stethoscope is the JABES digital electronic stethoscope manufactured by GS Technology Co., Ltd. Con­versely, a piezoelectric transducer is completely passive, and hence does not need an external power supply. It simply needs to be connected to a recording device, which usually has some electronic filtering and amplification capabilities. The specific electronics depends on the type of recording unit used however typically a bandpass filter is used to remove very low and very high frequencies and an adjustable amplifier circuit can provide a gain of up to 55dB. An example of a piezoelectric based stethoscope if the 3M Littmann 3200 electronic stethoscope.

Electronic stethoscopes often resemble traditional stetho­scopes, perhaps because they symbolise medical practitioners and healthcare professionals and therefore can psychologically help patients feel at ease [24]. However, some recent elec­tronic stethoscope designs such as the Thinklabs One digital stethoscope are more novel, using standard headphones or speakers for listening to patients or connecting them directly to a smartphone for analysis [1]. A 3D printed stethoscope

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head with a microphone and electronics built in, which can be connected to a smartphone was designed by Aguilera- Astudillo et al. [25]. Likewise, a condenser microphone based device which was connected to a microcontroller with a Blue­tooth module for wireless transmission of data was designed by Lo and Meng [26]. A similar device was also developed by Mills et al. [27] although the Bluetooth transmitter sent a signal to the receiver contained in the headset part of the stethoscope. Another design using an FM module to transmit the signals was developed by Pawar and Chaskar [28]. Yu et al. [29] designed a piezoelectric based stethoscope with a conditioning circuit built in to the stethoscope head which could be connected to a PC via a USB cable. Hill et al. [30] specifically designed an electronic stethoscope system for long-term monitoring of abdominal sounds. Their system again used a condenser microphone as the sensing element, although it was connected to a field programmable gate array (FPGA) for processing.

White [31] suggested a solution for using stethoscopes in highly hazardous or contaminated areas whilst wearing personal protective equipment. He proposed the use of the Thinklabs One stethoscope connected to wireless bone con­ducting headphones, instead of normal headphones. These types of headphones transmit the sound through the jaw bone directly to the inner ear leaving the ear canal free for communicating with patients. Moreover, the headphones do not have to be handled between auscultation times, and since they are wireless the medical practitioner can be outside of a contained area.

An informative study that analysed external noise contam­ination caused by vibrations from handling a commercial electronic stethoscope was presented by Nelson et al. [32]. The work addressed the physical limitations of the stethoscope design by modelling the influence of different insulation materials on the noise transmission through the stethoscope housing to the piezoelectric transducer. They proposed better noise isolation using dampeners, however, they noted there would be a trade-off between sensitivity and noise reduction.

A comprehensive review of electronic stethoscope technol­ogy and diagnostic techniques is given in [33]. The limitations of the current technology are discussed and future research directions are proposed.

Dimoulas et al. are one of the most significant author groups in the analysis of bowel sounds. Although, their progress will be discussed in the following sections, it is worth not­ing that Dimoulas et al. [34] also described in detail their preferred hardware for bowel sound analysis. They tested the sensitivity and frequency response of electronic stethoscopes, stethoscopes incorporating microphones, and both capacitive and piezoelectric transducers. Physical attributes such as size, shape, and weight were also taken in to consideration. Subse­quently, piezoelectric sensors were chosen due to their small size and shape, their high sensitivity and low cost, and because they were passive sensors requiring no external power. Their poor frequency response at very low frequencies, outside the range of bowel sounds which do not occur below 150Hz, was also considered an advantage, as they were less susceptible to low frequency noise. In addition, a wearable abdominal vest containing a thin metal plate and absorbing foam was used to protect the sensor from external noise and ensured they were held tight to the abdominal surface. A two channel system with one sensor in the upper right quadrant and one sensor in the lower left quadrant was initially used although a four channel system with one sensor on each quadrant of the abdomen was later implemented for improved sensitivity and localisation.

1. Signal Identification, Enhancement, and Extraction

Most of the documented research on the analysis of bowel sounds has involved very simple data processing, in the form of statistical analysis. Dalle et al. [11] further exploited the capability of computerised post-processing of the acoustic data by developing an algorithm for differentiation of sounds into three groups; frequent short pulses, less frequent pulses that last for a few tenths of a second, and a combination of the two. In the study, 15 minute recordings were taken from eight subjects amounting to a total of 15 hours of data. Their technique identified a bowel sound without human intervention, thus eliminating subjective errors. They defined the existence of a bowel sound as ”when the mean absolute value of a signal for a given time exceeds a predetermined level”. The program performed automatic detection of the sounds through a threshold value, as well as enveloping, and a fast Fourier transform (FFT) of the acoustic signals in slices of 0.2s. They argued that the sounds were not rhythmic in nature, but in fact obeyed Poisson's distribution. Although they reported a mean duration of sound was 4.5ms and a mean duration of silence was 32ms, it is worth noting that the results were recorded after the subject had eaten, which may account, in part for the short durations.

In 1997 Bray et al. [35] reported analysis of bowel sounds recorded from eight abdominal regions simultaneously. They again performed a FFT and calculated the number of sounds per minute at particular frequencies, in addition to the ampli­tude and duration of sounds.

In the same year, Mansy and Sandler studied the bowel sounds in sedated rats [36], [37]. Their work focused on the removal of heart sounds through adaptive filtering. Adaptive filtering had previously been found effective for removing noise from a signal where the frequency ranges overlapped, something not possible with traditional bandpass filters. A class of adaptive filtering, known as the Woodrow-Hoff least mean square adaptation algorithm was implemented due to its success in other biomedical applications. For adaptive filtering to be effective, a reference signal that correlates with the noise must be constructed. The adaptive filter cancels the noise in the primary signal by removing parts of the signal that correlate with reference noise signal. The output of the filter is continually reintroduced into the filter in order to optimise the performance. A Hilbert transform envelope was also used to provide a measure of the instantaneous amplitude for peak detection. Later they extended their work in order to classify rats with and without small bowel obstructions by analysing the duration of the sounds and the dominant frequencies present [38].

Hadjileontiadis et al. performed extensive research on bowel sound analysis from 2000 to 2005 which resulted in

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a number of detailed publications [39]-[43]. Their initial study [39] implemented the wavelet transform algorithm, based on work performed by Coifman and Wickerhauser, [44], that had been developed for removing heart sounds from lung sound recordings [39]. The wavelet transform- based stationary-nonstationary (WTST-NST) filter was used to remove the noise from the acoustic recordings of bowel sounds, but did not require a reference noise signal to do so. Furthermore, the WTST-NST filter only removed the noise in locations where it was present, leaving the original signal unchanged where possible. The study included 35 subjects, 18 healthy and 17 with pre-diagnosed bowel diseases. An electronic stethoscope was used to record 16 minutes of bowel sounds; eight minutes from the right lower abdomen, followed by eight minutes from the left lower abdomen. The work focused on demonstrating the effectiveness of the filter and did not examine the ability to diagnose any of the bowel conditions.

Using the de-noising filter and higher-order crossings-based statistics, Liatos et al. [45], were able to define normal bowel sound waveform characteristics and therefore developed a classification algorithm which could detect abnormal bowel sounds.

The subsequent study used fractal dimension (FD) analysis for detection of explosive lung sounds and bowel sounds [40]. The technique developed was capable of detecting the time, location and the duration of the sounds and the estimated FD provided information about the complexity of the sounds in terms of their waveform in the time-domain. The approach utilised known properties of the waveforms such as their initial deflection width (IDW), their two-cycle duration (2CD), and their total deflection width (TDW) as shown in Fig. 4. The developed algorithm could accurately detect the number of bowel sounds in a given sample but was not capable of extracting the sounds from the background noise. They found that the advantages of this technique were the low processing power required, the high detection rate, and the low false positive rate, and as such they found that it was an effective tool for detecting bowel sounds from long term recordings in real-time.

Another technique for extracting the bowel sounds from the background noise which was developed by Hadjileontiadis et al. [41] used an kurtosis-based detection (KD) method. Kurtosis which is a zero-lag fourth-order statistics parameter, is a measure of how non-Gaussian like a signal is. Kurtosis is typically higher in explosive bowel sounds compared to background noise. The results clearly show the algorithm was effective at detecting and extracting explosive bowel sounds without the use of a reference noise signal. The approach was successful even in cases with additive Gaussian or sym­metrically distributed noise. However, it is unclear whether it would result in false positive results from random noise contamination, such as those that have large amplitudes, or those that are very similar to bowel sounds in the structure of their waveforms. The technique again had the advantages of low processing and data storage requirements. This work was later extended further by Rekanos and Hadjileontiadis [46] to form an iterative kurtosis-based detector (IKD) that gradually

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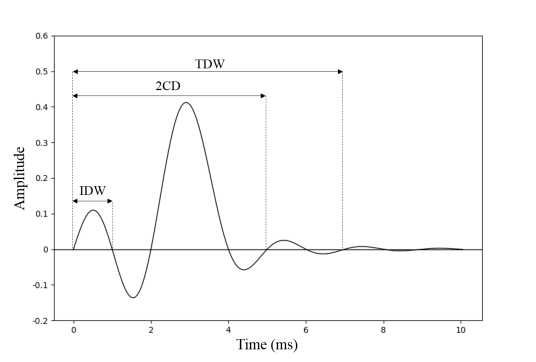


Fig. 4: Graphical representation of the time-domain features, i.e., the initial deflection width (IDW), the two-cycle duration (2CD), and the total deflection width (TDW), adapted from [40].

separated the bowel sounds from the noise with increased precision.

Kim et al. [47] suggested that the iterative kurtosis method developed by Rekanos and Hadjileontiadis had some limita­tions in the way that the threshold values were calculated based on the ratio of the standard deviation of the kurtosis and the standard deviation of the background noise. If the bowel sounds were heavily contaminated with frictional or environmental sounds then the standard deviation could be skewed resulting in an extremely low threshold value, and unwanted erroneous sounds may be detected as bowel sounds. Likewise, if the SNR was very low the threshold value may be too high and therefore some bowel sounds may not be detected. Instead of calculating the threshold values based on the standard deviation of the kurtosis Kim et al. statistically analysed a histogram of the kurtosis to obtain the threshold values using experimentally determined constants.

Dimoulas et al. [34], performed extensive analysis of previ­ous signal processing techniques for bowel sounds. The group defined a general method for noise removal from both audio and non-audio signals. The first step was transformation of the data into a different domain, such as from the time domain to the frequency or time-frequency domain, that maximised the differences in the signal and the noise. The second step was processing of the data with the goal of noise reduction or removal. The final step was then inverse transformation in order to obtain the original desired signal without noise contamination.

Wavelet transforms are examples of decomposition and reconstruction techniques which are common in acoustic sig­nal processing. A new method was introduced using wavelet analysis that incorporated a Weiner filter. Their method had the following desired attributes: improved robust noise cancella­tion, reduced signal distortion and computational cost, and the ability to perform long term recordings. Many decomposition schemes were studied using various mother wavelets in order to analyse the performance of the filter in terms of noise

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reduction and signal enhancement.

Dimoulas et al. highlighted the fact that many of the previ­ous de-noising algorithms were elective at removing noise from explosive bowel sounds, but they were not sufficient for de-noising regularly sustained bowel sounds. The wavelet domain Weiner filter (WDWF) incorporated an exponential moving average for estimating the power of signal coefficients. Unlike a STFT Weiner filter the WDWF retained an ap­proximate logarithmic frequency spacing rather than classical linear spacing and increased time resolution with respect to classical wavelet Weiner techniques. Their WDWF approach combined the efficiency of a classical Weiner filter with bark scale wavelets, and had a comparable computational cost of fast wavelet transform algorithms. Four different WDWF approaches were implemented including two types of six band discrete wavelet transform (DWT) Weiner filters and two types of 17-band wavelet packet (WP) Weiner filters. The two types differed slightly in the experimentally obtained values of their third and fourth coefficients. Joint time frequency analysis algorithms were also implemented however they underper­formed against the DWT and WP algorithms in terms of computational cost.

The performance of their filters was both qualitatively and quantitatively evaluated. For qualitative evaluation, visual ex­amination of the audio waveforms was continually performed and physicians validated the quality of the audio signals by listening to the de-noised bowel sounds. For quantitative evaluation, a signal processing environment was set up in LabVIEW where synthetic bowel sounds were constructed and then artificially contaminated with different types of noise. This was performed so that the effectiveness of noise removal from different types of signals, for each of the four developed WDWF, could be quantitatively compared. Pearson linear cor­relation was used to estimate how similar the estimated signal was to the original noise free signal. Furthermore, an effective signal to noise ratio (ESNR) was calculated after silent periods of the recordings were removed, to avoid overestimating the performance of the filter by using the traditional SNR.

All four WDWF performed favourably with respect to previously developed filters. The type two 17-band filter performed the best, although it was slightly less robust and had a higher computational cost than the type two six-band filter. Overall, the WDWFs maintained the structure of the bowel sounds, whereas most automated threshold techniques seriously degraded the shape of the signals. The WDWF approaches provided robust noise removal combined with minimal signal distortion and performed well for almost any signal unlike other techniques which were only advantageous with certain types of signals.

The study by Li et al. [48], details their simple method for automatic identification of bowel sounds. The first step was based on two assumptions: bowel sounds usually have a higher amplitude than the background noise, and bowel sounds are typically longer in duration (bowel sounds will maintain a high-energy state for longer periods). Hence, the criteria for bowel sound identification were: if the energy of the signal of the current window is above a certain threshold and the duration of the signal exceeds a threshold, then the

F = [1011000010000111110...] = [1111000000000111110...]

BS BS

Fig. 5: Checking algorithm, adapted from [48].

bowel sound condition is true, otherwise it is false. The main issue with this criteria is that it will detect any erroneous external noise, which has values above the thresholds, as bowel sounds. Their method did however, have an additional checking function whereby if the bowel sound condition was true for a single window, but the two adjacent windows were false, then the true condition was changed to false. Likewise, if the bowel sound condition for a window was false, but the two adjacent windows were true, then the false condition was changed to true. An example is shown in Fig. 5. The researchers then implement an adaptive filter for noise reduction. However, rather than using a reference noise signal, as in traditional adaptive filters, they used a new method developed by Sasaoka et al. [49] where two types of adapted line enhancers estimated the noise and the desired signal, followed by a noise reconstruction filter. The delayed input signal was then used as the reference signal. Once the bowel sounds had been identified statistical features were then extracted.

Ulusar et al. [50] developed a real-time bowel sound mon­itoring system using a modified stethoscope incorporating a microphone and a data acquisition card. The recoded data was processed in one second chunks which were firstly buffered and saved to file. A second order Butterworth 100Hz high pass filter, a 1kHz low pass filter, and a 50Hz notch filter were then applied to each segment. As the study focused on determining when bowel motility had returned after abdominal surgery, their algorithm used a statistical method based on the power of the signal between 100Hz and 200Hz. This specific frequency band was used as the majority of bowel sounds occur around 150Hz and most of the noise contamination was typically above this range. The additional parameters were empirically chosen so that, if at least two bowel sounds were recorded in each sample continuously for a period of 20 minutes, an alarm would be triggered indicating that motility had returned. Their simple algorithm, required very low computation and performed well, although again a small sample size was used to test its performance.

Lin et al. [51] used higher order statistics, in a similar way to Hadjileontiadis et al. [41], in conjunction with a radial basis function network, for separating bowel sounds from external noise. These methods rely on the fact that bowel sounds are mainly non-Gaussian and the background noise is either Gaussian or symmetrically distributed. A radial basis function network is a type of artificial neural network that uses a radial basis function, in this case a Gaussian function, to calculate a surface in a higher dimensional space. This can be used to determine the best fit to a set of training data, by analysing the distance of each data point from the centre of the dataset. The centre of the dataset was determined using a k-means clustering algorithm. The technique also used an adaptive line

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enhancement scheme incorporating a delayed input signal as the reference signal, just as Li et al. [48] had done. The quality of the filter was compared against an adaptive filter with normalised least mean square algorithm and an adaptive radial basis function with normalised least mean square algorithm. Their new algorithm performed significantly better than the others when bowel sounds were contaminated with a number a different types of artificial noise. The performance of the algorithms were also tested using real noise contaminated bowel sounds, which were then assessed by physicians. Us­ing analysis of variance from the results obtained from the physicians the new algorithm was shown to perform best at enhancing the noisy bowel sounds. However, the algorithm required significantly more computation time.

In 2015, the same group [52] applied their higher order statistics method to the fractal dimension technique developed by Hadjileontiadis et al. [40]. Again their method showed increased performance with respect to the original algorithm, particularly in the form of less false positive results, and was more robust when the bowel sounds were contaminated with different types of noise at varying levels. However, there was again an increased computational cost resulting in more than twice the amount of time required to compute the algorithm. There was unfortunately no comparison of the performance of this algorithm with their previous work using a radial basis function.

1. Feature Extraction and Machine Learning

In the same study as mentioned earlier Kim et al. [47] used three sensors positioned at different colonic locations and specifically used the jitter and shimmer of individual bowel sounds as features to estimate bowel motility through colonic transit time. The jitter and the shimmer are a measure of how the period and the amplitude of the fundamental frequency varies over time, respectively. As multiple channels and time segments were used, a total of 21 features were extracted and the most significant features were determined using regression modelling. K-fold cross validation was implemented, where 75% of the samples were used to train the algorithm and 25% wereused to test it’s performance. Asensitivity of 86.3士6.0% and a specificity of 91.0 士 6.1% were obtained, although a small sample size was used. Overall, the modified iterative kurtosis detector algorithm had improved performance with respect to the original algorithm.

In subsequent work, Kim et al. [53], [54] used the same detection and feature extraction method, including jitter and shimmer features, although they implemented an artificial neural network rather than a regression model to estimate bowel motility. The correlation coefficients for both models were similar, although the backpropagation neural network [55] had lower estimation errors than the regression model.

Yin et al. [56] followed on directly ^om the work performed by Kim et al. utilising the jitter and shimmer of the bowel sounds to characterise gastrointestinal states. An adaptive filter incorporating the least mean square algorithm was again used for noise cancellation although in this case Yin et al. used a dual adaptive filter with two separate signals for removal of the external and the internal noise. A total of 420 features from both the time domain and the frequency domain were used to train the algorithm and a back propagating neural network was implemented for classification. The algorithm was used to classify digestion into three distinct states; the initial digestive state where the stomach was full, the inter­digestive state, and the final state where the stomach was empty. They later extended the work to include Legendre fitting of logarithmic bowel sound spectra [57]. The technique extracted the number of bowel events per minute which was then used to quantitatively estimate bowel activity.

In 2001, Ranta et al. [58] expanded on work by Hadjileon- tiadis et al. involving wavelet analysis of bowel sounds for de- noising, to include segmentation and characterisation. Ranta et al. explicitly explained the need for objective and quan­titative descriptions of bowel sounds rather than subjective statements or labels such as ”gurgling sounds or clicks”. After implementing the de-noising algorithm the bowel sounds were identified through segmentation of the signal using a method which was applied to the wavelet coefficients. Wavelet decom­position was then used to extract features of the bowel sounds including the duration of the sound and the power distribution within each frequency band. A fixed point approach, based on the orthogonality of the wavelet transform was used for optimisation. As such their de-noising algorithm performed four times faster than the original algorithm developed by Hadjileontiadis et al. by removing the threshold iteration of the wavelet coefficient vector [59]. It was proposed that this method of feature extraction could lead to classification of the bowel sounds, and because multiple microphones were used simultaneously, localisation of the bowel sound could also be achieved.

Ranta et al. [60], continued to develop new techniques for improved interpretation of bowel sound features. Based on the methods mentioned earlier, they extracted nine features from each of the 168 minutes of recordings, from six channels. Each of the features represents one dimension of the dataset, and the entire dataset formed a 3024 x 9 matrix. The first step in improved interpretation was to create a correlation matrix in order to remove any redundancy in the data. Principle component analysis (PCA) was then used to transform the matrix into a new matrix containing the same number of dimensions described by uncorrelated principle components. The principle components each represented variance which were ordered in terms of significance. In their study, Ranta et al. reduced the dimensionality of the dataset by retaining the three largest components, having a variance greater than one, meaning the resulting dataset was 3 dimensional and still maintained over 70% of the variance of the data.

The main problem with dimension reduction techniques is that it is extremely difficult to correlate the reduced dimension dataset with the original features and therefore relate them back to clinical information. However, Ranta et al. proceeded to analyse the new dataset in order to understand the physical meaning of the new features. A correlation between the original features and the new ones was made using correla­tion circles. The first component was hence interpreted as a measure of the sound level, the second was interpreted as a

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measure of sparsity, and the third was interpreted as a measure of pitch for each minute of data. As each of the stethoscopes corresponded to specific regions of the abdomen it was then possible to analyse the differences in each region by projecting the data onto principle planes generated by the three main principle components. Finally, the following conclusions were drawn from analysing the variation in the component values over time, region 3 produced higher frequency sounds, and more bowel sound were produced in region 4 than in the other regions.

In 2005, the same group reported a technique used for detection and removal of outliers, which was related to the previously discussed de-noising algorithm [61]. They showed that under certain conditions, the developed technique was a parameter free method for threshold computation which adapted to the shape of the distribution of the data. Moreover, under Gaussian conditions it performs better than traditional outlier rejection methods. As the technique could successfully detect and remove outliers it could therefore be used as a quasi optimal method for identifying data close to the mean, which is useful in some clustering algorithms.

More recently in 2010, Ranta et al. reported a more compre­hensive description of their complete methodology for anal­ysis of bowel sounds [62]. They detailed extensive statistical data analysis and evaluation of their method and results, as well as, the drawbacks of the hardware. Verification of the quality of the recordings, in terms of clinical interpretation, was performed by experienced medical practitioners whom listened to sampled recordings. Ranta et al. ”conclude that the frequency response of the instrumentation does not distort the physiological information carried by the abdominal sounds”. Perhaps one of the most interesting outcomes from the work performed by Ranta et al. was their ability to give their results physical meaning, such as locations of increased activity etc. even when using dimension reduction algorithms. This was achieved by using guided feature selection, linking the most significant principle components to the most correlated original features.

Dimoulas et al. [63] extended the fractal dimension tech­nique developed by Hadjileontiadis et al. to include wavelet transform coefficients. A long term wavelet domain segmen­tation and summarisation (LT-WDSS) method was developed incorporating a WDWF and a fractal dimension pause detector (FDPD). The approach was specifically developed for long­term recordings, in addition to detecting regularly sustained bowel sound rather than just explosive bowel sounds. The researchers comprehensively compared the performance of many different types of de-noising filters as well as differ­ent detection strategies. WTST-NST and wavelet transform fractal dimension (WTFD) de-noising techniques were inap­propriate for long-term unsupervised processing as they could distort the shape and structure of the signals, and required increased computation. In conjunction with de-noising using the WDWF, signal detection, segmentation and summarisation, using envelopes representing energy with respect to time, were performed using a FDPD. Both time and frequency domain features, such as short-term energy level, signal strength and zero crossing rate are commonly used for signal detection and

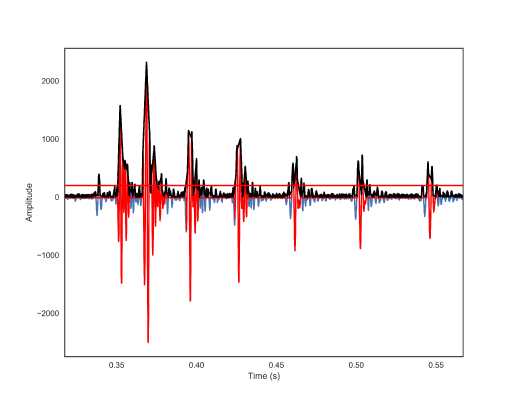


Fig. 6: An example of a time domain signal showing the burst detection threshold (horizontal red line) and the Hilbert transform envelope (black line), adapted from [14].

identification of silent periods. Methods including higher order statistics, singular value decomposition, and sliding fractal dimension were effective in applications where computational cost was not a significant factor. However, for this long­term application, the FDPD was implemented since it was more sensitive than energy-based comparison methods, more adaptive, and did not require threshold selection. Finally, as four sensors were used, localisation of bowel sounds was achieved through energy analysis.

Ulusar et al. [14] expanded on their previous work by im­plementing a naive Bayesian and minimum statistics detection algorithm. The method used the same filtering as their earlier work and the background noise power was estimated using minimum statistics during quiet periods. The magnitude of the noise and a Hilbert transform envelope were used to determine the adaptive burst detection threshold in a similar way to Mansy and Sandler’s technique [38]. Fig. 6 shows an example of a time domain signal with the burst detection threshold. The following three spectral features were then extracted from a frequency band of 100Hz - 500Hz:

* Spectral Centroid,
* Spectral Bandwidth, and
* Sub-Band Normalised Energy.

Mathematical definitions of the features are given in [14]. A naive Bayesian method was then used to classify the signals into quiet periods, additive broadband noise, movement and frictional noise, and examination room noises, as well as single burst, and multi-burst bowel sounds. The naive Bayesian approach assumes that each of the features are statistically independent and calculates the probability distribution of each class during training. The naive Bayesian method was used in this real-time monitoring application as it was easy to interpret and modify and had low computational cost. The remainder of the article focused on the performance of the algorithm for determining the reintroduction of motility.

A feature-based autoregressive moving average (ARMA)

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method was developed by Emoto et al. [64] for automatic detection of bowel sounds. Firstly, an objective definition of a bowel sound was ascertained. In their study, they argued that bowel sounds were periodic signals which were amplitude modulated and had ’’beat tone like frequency properties” [64]. The average of the frequencies of the mixed waves was therefore defined as the beat-related frequency (BRF) and a bowel sound was defined as ”an episode containing sound with detectable periods of the BRF”. Subsequently, the BRF was detected as a sharp spectral peak in the ARMA spectrum that could be characterised by the 3dB bandwidth at the peak frequency. Hence, automatic detection of bowel sounds was achieved. They then proceeded to correlate the sound to sound interval with bowel motility.

1. Localisation

A study by Craine et al. [65] included the localisation of sounds emitted from the bowel. The area of the bowel was separated into four quadrants and three electronic stethoscopes were used to simultaneously record and triangulate the bowel sounds. Whilst the study statistically analysed the frequency of the bowel sounds generated, it was difficult to make any convincing conclusions as the sample size was very small.

Ranta et al. [66], explored localisation of bowel sounds using six different stethoscope locations as shown in Fig. 7. They first examined the ability to measure the location of the origin of a bowel sound based on the time of arrival. A previous study had assumed the abdomen was a hollow cavity and the speed of sound was therefore approximately 340ms [67]. This assumption is obviously inaccurate as it is understood that the abdomen mainly consists of soft tissue and the speed of sound through the tissue is approximately 1500ms [68]. In addition, the abdomen is by no means completely uniform in material density. Due to these constraints it was concluded that localisation using time of arrival techniques was difficult to implement as the distances between the source and the detectors were too small.

The researchers proposed two alternative methods, a non­absorbent and an absorbent model, based on triangulation using sound intensity. However, the models still assumed an isotropic environment within the abdomen. In both cases, the localisation was estimated by minimising a cost function re­lated to difference between the power received at the detectors and the power of the source. However, it was shown that at small propagation distances, as in this case, the absorption and non-absorption models were almost equivalent. Unfortunately, their results showed the calculated error in the localisation was relatively large and therefore highly inaccurate. They concluded that the aforementioned techniques could not be used for bowel sound location and that, simply assigning each sound to a specific detector with largest recorded intensity and eliminating it from the others, was the simplest and most precise method.

In 2016 Dimoulas [69] reported the results of a study that focused on abdominal sound localisation. Building on work by Craine et al. [65] and Ranta et al. [66], Dimoulas initially estimated the origin of abdominal sounds by analysing

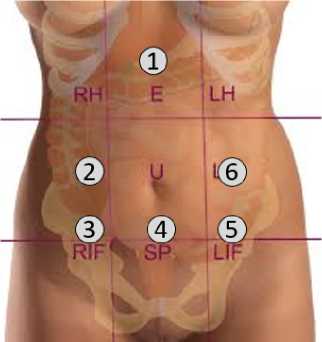


Fig. 7: Stethoscope placement on the abdomen, adapted from [66].

abdominal sound power at each of the four sensors placed in each quadrant of the abdomen. An accelerometer was also placed on the centre of the four quadrants and it’s localisation performance was compared against the performance of the four sensors. Sound field maps were generated from the sound energy data using the inverse square law.

Agreeing with the earlier work by Ranta et al., Dimoulas proposed that the non-uniformity of the abdomen would not significantly influence the localisation results. This was because the acoustic waves emanating from the abdomen would have relatively long wavelengths at frequencies below 2kHz, given that the speed of sound through the medium was approximately 1500ms-1. Moreover, the absorption of the waves would be insignificant at such short distances.

Dimoulas used a physical model consisting of artificial sound sources, six sensors, and layers of different materials, as well as software simulations to validate the obtained results. Overall Dimoulas proposed that the addition of sound field imaging techniques could lead to more sophisticated analysis of abdominal sounds, potentially allowing them to be analysed using machine learning visual recognition techniques.

1. Complete Signal Processing Systems

All of the earlier work by Ranta et al. culminated in ”a complete toolbox for abdominal sounds signal processing and analysis” [70]. This included a description of the physical instrumentation and some of the potential issues associated with multichannel recordings, as well as, all of the signal processing, feature extraction, and data analysis steps. One of the note-worthy sections of the procedure was the elimination of artifacts. A detailed discussion of the limitations of the signal processing techniques, in terms of removing unwanted artifacts that overlapped the frequency of the bowel sounds, was given. Moreover, they defined qualitative criteria for elim­inating unwanted signals resulting from friction, movement, and heart beats and respiration.

An autonomous intestinal motility analysis system (AIMAS) was developed for long-term unsupervised monitoring of bowel sounds by Dimoulas et al. [12]. This

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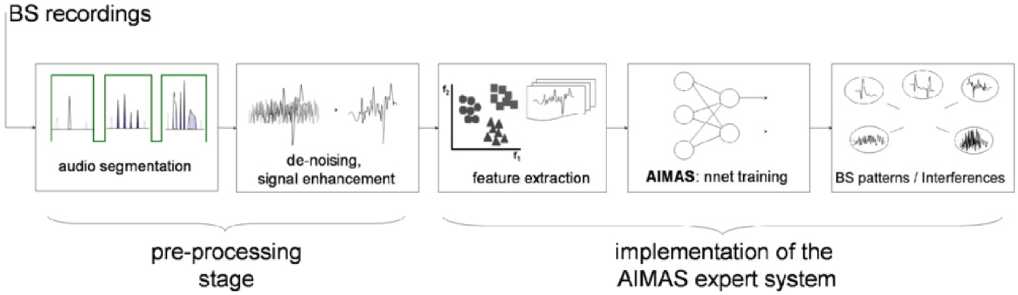


Fig. 8: Development phases of the AIMAS project, [12].

approach used wavelets and neural networks incorporating time domain and frequency domain features, and wavelet parameters. A block diagram showing the different stages of the signal processing is displayed in Fig. 8. The implemented wavelet neural network gave an accuracy of almost 95%, although the author’s stated that ”it is estimated that AIMAS performance can be further extended”.

In their more recent work Dimoulas et al. [13] developed a hybrid expert system (HES) used for abdominal sound pattern classification. Initially, an abdominal sound pattern analysis scheme was implemented so that the desired signals and the noise could be classified into specific groups. The abdominal sound pattern taxonomy resulted in the following bowel sound groups:

* SCL: solitary clicks,
* RCL: repeated clicks,
* SICS: sequences of irregularly concatenated segments,
* CRSW: crepitating sweeps, and
* WSSW: whistling sweeps.

A complete description is given in Table 2 in [13]. Addi­tionally, the different types of noise were separated into the following groups:

* SP: additive broadband noise,
* RESN: respiration related noise,
* SN: movement and friction noise,
* AN: examination room noise, and
* IHS: heartbeat related noise.

The HES AIMAS was then used to classify all of the recorded abdominal sounds. Standard machine learning techniques were then used to split the data up in order to train and test the algorithm, and the performance was validated using k-fold cross validation. The samples were randomly split into train and test data sets which was repeated k-times until a local test error minimum was found, resulting in trained centres with minimum error. An overall classification accuracy of 94.3% was reported.

Kumar [71], took a different approach to bowel sound analysis (in addition to lung and heart sounds) using fuzzy logic. Fuzzy logic systems are useful for obtaining information where the variables in the system do not take on exact values. Instead the variables are assigned a truth value, somewhere between zero and one, and are usually described using non­numeric linguistic terms. For example a temperature variable may be described in terms of hot, warm, cool, or cold. These types of variables are described by corresponding membership functions. A set of rules are then applied to the membership functions which are interpreted by a computer as the control logic. Kumar defined input variables including the presence or absence of sound and duration of bowel sounds. Depending on the probabilities of the input variables, a prediction whether the subject had paralysis, peritonitis, perforation, large intestinal obstruction, small intestinal obstruction or a normal condition could be made. The advantage of this system was that and logical link between the input features and the five conditions was retained.

IV. Conclusions

After reviewing the literature pertaining to acoustic sig­nal processing techniques for analysis of bowel sounds, the following conclusions have be drawn. Data acquisition has been achieved through the use of customised sensors using electret condenser microphones and piezoelectric transducers, in addition to commercial electronic stethoscopes. The choice of which has depended on the constraints of the research aims, such as cost and acquisition time. Although, as demonstrated by Dimoulas et al., piezoelectric transducers generally satisfy the requirements whilst needing minimal additional electron­ics.

Following computerised analysis of bowel sounds, acoustic characteristics have been extracted from signals in both the time domain and the frequency domain. From the early 2000s wavelet transforms have enabled more complex features to be extracted. These advanced feature extraction techniques have corresponded with the introduction of machine learning methods in the analysis of bowel sounds. Furthermore, higher order statistical analysis and adaptive filtering has contributed to better signal enhancement. However, more recently some researchers have abandoned some of the more complex signal processing methods in favour of simplified approaches which require lower processing time and are easier to interpret.

An attempt has been made by a few researchers to determine the location of the origin of sounds produced in the abdomen. However, progress has been limited due to the high speed and long wavelength of the acoustic waves, as well as, the short

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transit distances through the body and the non-uniformity of the bowel.

Different machine learning methods such as decision trees, dimension reduction, and clustering algorithms have been applied to bowel sounds. Although, artificial neural networks including back-propagation and radial basis function networks have often been implemented for characterisation of bowel sounds.

One of the most significant research groups in bowel sound signal processing is Hadjileontiadis et al. The group has pro­duced six publications in this field and have made substantial progress in noise reduction and signal enhancement of bowel sounds resulting from analysis of acoustic signals in both the time domain and the wavelet domain. Currently, the best and most complex analysis of signal processing techniques for abdominal sounds has been performed by Kim et al., Ranta et al., and Dimoulas et al. Each of these groups have expanded on the initial work by Hadjileontiadis et al. as well as others, to produce a number of detailed approaches for analysis of bowel sounds, including a constructive critique of methods used by other researchers.

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