Advances in Acoustic Signal Processing Techniques for Enhanced Bowel Sound Analysis

Gary Allwood, *Member, IEEE*, Xuhao Du, K. Mary Webberley, Adam Osseiran, *Senior Member, IEEE*, and Barry James Marshall

(Methodological Review)

***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 paper 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 a historical perspective are provided. The document specifically address the progress in bowel sound analysis, such as improved noise reduction, segmentation, signal enhancement, feature extraction, localization 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.**

Nomenclature

Table Abbreviations

ECM	Electret condenser microphone.
PZT	Piezoelectric transducer.
CES	Commercial electronic stethoscope.
FFT	Fast Fourier transform.
WT	Wavelet transform.
WTST-NST	Wavelet transform stationary–nonstationary filter.
AF	Adaptive filter.
WDWF	Wavelet domain Weiner filter.
FDD	Fractal dimension detector.
IKD	Iterative Kurtosis detector.
LF	Legendre fitting.
TD	Time domain.
FD	Fourier domain.
WD	Wavelet domain.
PCA	Principle component analysis.
ANN	Artificial neural network.
ARMA	Autoregressive moving average.
RBFN	Radial basis function network.
NBD	Naive Bayesian detector.

Manuscript received May 3, 2018; revised August 10, 2018; accepted September 8, 2018. Date of publication October 11, 2018; date of current version February 15, 2019. *(Corresponding author: Gary Allwood.)*

G. Allwood, X. Du, K. M. Webberley, and B. J. Marshall are with the Marshall Centre for Infectious Disease Research and Training, School of Biomedical Sciences, University of Western Australia, Perth, WA 6009, Australia (e-mail: gary.allwood@uwa.edu.au; xuhao.du@uwa.edu.au; mary.webberley@uwa.edu.au; barry.marshall@uwa.edu.au).

A. Osseiran is with the School of Engineering, Edith Cowan University, Perth, WA 6027, Australia (e-mail: a.osseiran.ecu.edu.au).

Digital Object Identifier 10.1109/RBME.2018.2874037

I. 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]. Recognizing 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].

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 analyze large data sets and through training, recognize previously hidden, higher dimensional patterns within the data. These machine learning techniques have recently been applied to identification of bowel sounds.

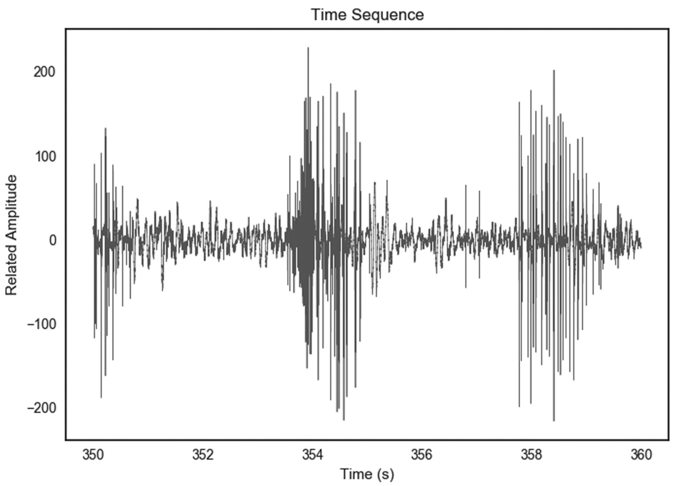


Fig. 1. Time domain acoustic signal recorded from the gut.

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 analyze 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, WT, and short time Fourier transformation (STFT) 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.

II. 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 electromechanical 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.

A. 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 44.1 kHz is shown in Fig. 1. The sensor used to detect the signal had an effective frequency response from 80 Hz to 5 kHz.

Several features can be extracted directly from the time domain signal including the signal to noise ratio (SNR), duration, and number of events. 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 below

$$\mathrm{SNR_{dB}} = 10\log_{10}\left(\frac{P_{\mathrm{signal}}}{P_{\mathrm{noise}}}\right) = P_{\mathrm{signal,dB}} - P_{\mathrm{noise,dB}}. \quad (1)$$

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. [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 analyzed. Filtering categories include Butterworth, Chebyshev, Bessel, and Elliptic, which are described in [16]. Adaptive filtering can also be used to enhance the signal by analyzing 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 improved performance in terms of signal enhancement [17]. Another useful processing technique that is usually performed in the time domain is enveloping. The envelope of an acoustic signal is a smooth line that outlines the extremes of the signal and can represent the energy of a signal with respect to time.

Before any features are extracted from the sound, it is a 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. 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.

2) 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 the 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 to 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 a bowel sound analysis including the centroid frequency, spectral bandwidth, sub-band energy, etc. The main problem with performing a FFT, however, is that most of the time domain information is lost in order to obtain the frequency components.

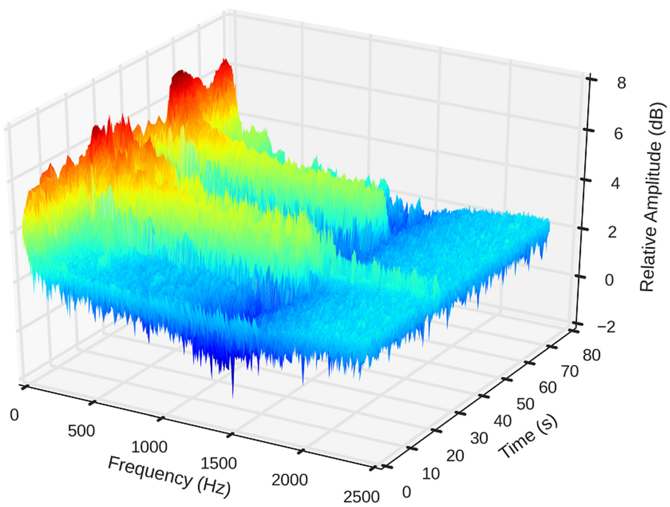


Fig. 2. Short term Fourier transform of an acoustic signal recorded from the gut.

3) 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 STFT or a WT. 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 an STFT can be used for speech recognition and noise suppression by implementing a convolutional neural network [18], [19] An example of an STFT is shown in Fig. 2.

As for the WT, 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 WTs 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 WTs 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 determine the nonlinear information from a data set without being explicitly programed. The machine learning algorithms are used to search for unknown patterns or relationships within data sets and adjust the model accordingly. Machine learning methods typically fall into the following categories.

1) Supervised learning.
2) Unsupervised learning.
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 the 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.

III. Advanced Signal Processing of Bowel Sounds

In general, the term acoustic signal processing may encompass many steps including data acquisition and preprocessing, 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 crossovers in each of the sections depending on the type of acoustic sounds being analyzed and the exact goal of the research. For example, denoising and filtering, would usually be part of a preprocessing stage, although it may also occur in later stages. Within the literature, many studies focus on specific steps, such as signal enhancement or localization, whereas other works may describe a complete sequence from acquiring a signal through to classification. An attempt has been made to categorize 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 has 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. The microphones and piezoelectric elements used in audio applications typically have an effective frequency response range from 20 Hz to 20 kHz. However, electronic stethoscopes are usually designed to pickup signals up to 1 kHz. In the case of a microphone-based stethoscope, there are three types, capaci-

TABLE I
SUMMARY OF ADVANCED SIGNAL PROCESSING STAGES DESCRIBED BY AUTHORS IN THE REVIEWED 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.

tive, 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 an 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 55 dB. An example of a piezoelectric-based stethoscope is the 3 M Littmann 3200 electronic stethoscope.

Electronic stethoscopes often resemble traditional stethoscopes, perhaps because they symbolize 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 three-dimensional 3-D printed stethoscope 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 Frank 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 into 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 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 analyzed external noise contamination caused by vibrations from handling a commercial electronic stethoscope was presented by Nelson *et al.* [32]. The work ad-

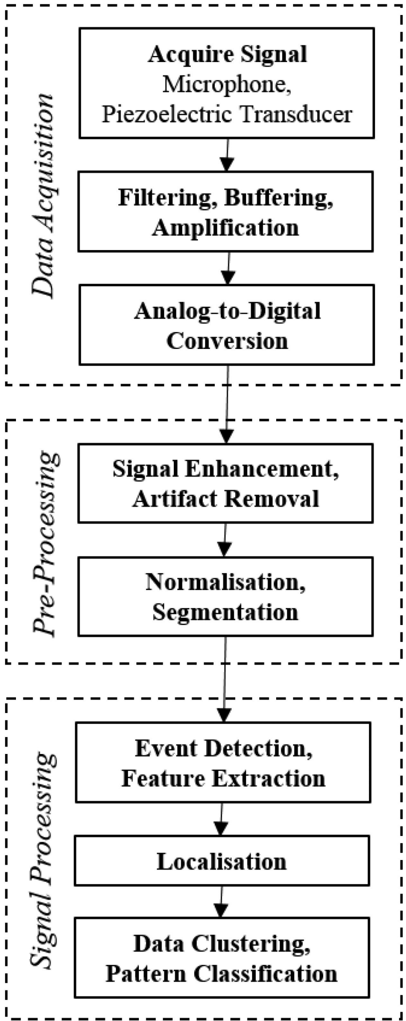


Fig. 3. Bowel sound signal processing flow chart.

dressed the physical limitations of the stethoscope design by modeling 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 tradeoff 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.* [34] 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 into 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 150 Hz, 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 localization.

B. 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 computerized postprocessing 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-min recordings were taken from eight subjects amounting to a total of 15 h 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 FFT of the acoustic signals in slices of 0.2 s. 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 4.5 ms and a mean duration of silence was 32 ms, 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 an analysis of bowel sounds recorded from eight abdominal regions simultaneously. They again performed an 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 optimize 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 obstruc-

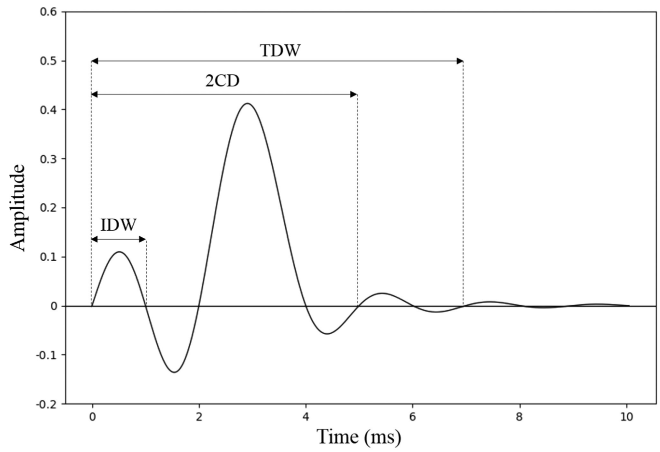


Fig. 4. Graphical representation of the time-domain features, i.e., the IDW, the 2CD, and the TDW, adapted from [40].

tions by analyzing 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 a number of detailed publications [39]–[43]. Their initial study [39] implemented the WT algorithm, based on work performed by Coifman and Wickerhauser [44], that had been developed for removing heart sounds from lung sound recordings [39]. The WT-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 prediagnosed bowel diseases. An electronic stethoscope was used to record 16 min of bowel sounds; 8 min from the right-lower abdomen, followed by 8 min 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 denoising 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 utilized 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 and Rekanos [41] used a 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 that 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 KD (IKD) that gradually separated the bowel sounds from the noise with increased precision.

Kim *et al.* [47] suggested that the IKD 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.* [47] statistically analyzed 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 nonaudio 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 maximized 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.

WTs 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 cancelation, 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 analyze the performance of the filter in terms of noise reduction and signal enhancement.

Dimoulas *et al.* [34] highlighted the fact that many of the previous denoising algorithms were effective at removing noise from explosive bowel sounds, but they were not sufficient for denoising regularly sustained bowel sounds. The wavelet domain Weiner filter (WDWF) incorporated an exponential moving average for estimating the power of signal coefficients. Unlike an 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 WT algorithms. Four different WDWF approaches were implemented including two types of six band discrete WT (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 denoised 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 SNR 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 favorably with respect to previously developed filters. The type 2 17-band filter performed the best, although it was slightly less robust and had a higher computational cost than the type 2 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 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

$$F = [1011000010000111110\ldots] = [\underbrace{111}_{\text{BS}}1000000000\underbrace{111}_{\text{BS}}110\ldots]$$

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

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 implemented 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 were processed in 1 s chunks, which were first buffered and saved to file. A second-order Butterworth 100-Hz high-pass filter, a 1-kHz low-pass filter, and a 50-Hz 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 100 and 200 Hz. This specific frequency band was used as the majority of bowel sounds occur around 150 Hz 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 min, 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 and Rekanos [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 analyzing the distance of each data point from the center of the data set. The center of the data set was determined using a k-means clustering algorithm. The technique also used an adaptive line 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 normalized least mean square algorithm and an adaptive radial basis function with normalized 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 FD technique developed by Hadjileontiadis and Rekanos [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.

C. 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 modeling. K-fold cross validation was implemented, where 75% of the samples were used to train the algorithm and 25% were used to test its performance. A sensitivity of $86.3 \pm 6.0\%$ and a specificity of $91.0 \pm 6.1\%$ were obtained, although a small sample size was used. Overall, the modified IKD 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 from the work performed by Kim *et al.* utilizing the jitter and shimmer of the bowel sounds to characterize gastrointestinal states. An adaptive filter incorporating the least mean square algorithm was again used for noise cancelation, 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 Hadjileontiadis and Rekanos involving wavelet analysis of bowel sounds for denoising, to include segmentation and characterization. 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 denoising 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 WT was used for optimization. As such their denoising 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, localization 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 min of recordings, from six channels. Each of the features represents one dimension of the data set, and the entire data set formed a 3024×9 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 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 variances, which were ordered in terms of significance. In their study, Ranta *et al.* reduced the dimensionality of the data set by retaining the three largest components, having a variance greater than 1, meaning the resulting data set was 3-D 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 data set with the original features and therefore relate them back to clinical information. However, Ranta *et al.* proceeded to analyze the new data set 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 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 analyze 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 analyzing 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 denoising 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 performed better than traditional outlier rejection methods. As the technique could successfully detect and remove outliers it could therefore be used as a quasioptimal 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 who 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 FD technique developed by Hadjileontiadis and Rekanos to include WT coefficients. A long-term wavelet domain segmentation and summarization method was developed incorporating a WDWF and a FD pause detector (FDPD). The approach was specifically developed for long-term 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 denoising filters as well as different detection strategies. WTST-NST and WT FD denoising 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 denoising using the WDWF, signal detection, segmentation, and summarization, using envelopes representing energy with respect to time, were performed using an 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 identification of silent periods. Methods including higher order statistics, singular value decomposition, and sliding FD were effective in applications where computational cost was not a significant factor. However, for this long-term 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, localization of bowel sounds was achieved through an energy analysis.

Ulusar [14] expanded on his previous work by implementing a naive Bayesian and minimum statistics detection algorithm. The method used the same filtering as his 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 100–500 Hz.

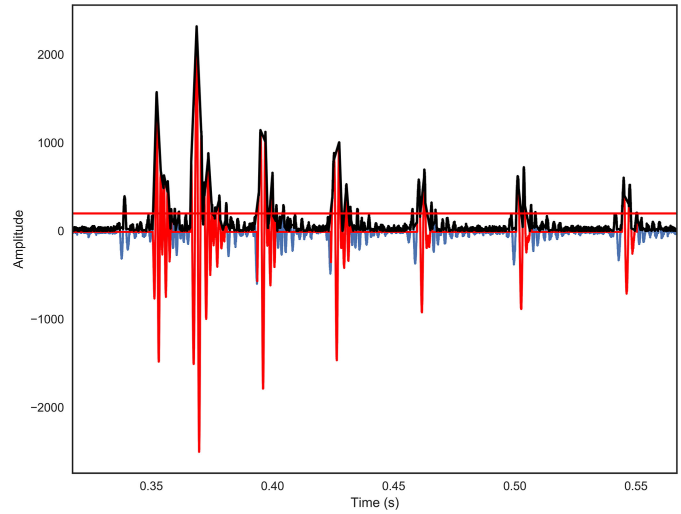


Fig. 6. Example of a time domain signal showing the burst detection threshold (horizontal red line) and the Hilbert transform envelope (black line), adapted from [14].

1) Spectral centroid.
2) Spectral bandwidth.
3) Subband normalized 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 multiburst 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 paper focused on the performance of the algorithm for determining the reintroduction of motility.

A feature-based autoregressive moving average (ARMA) method was developed by Emoto *et al.* [64] for automatic detection of bowel sounds. First, 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 characterized by the 3 dB 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.

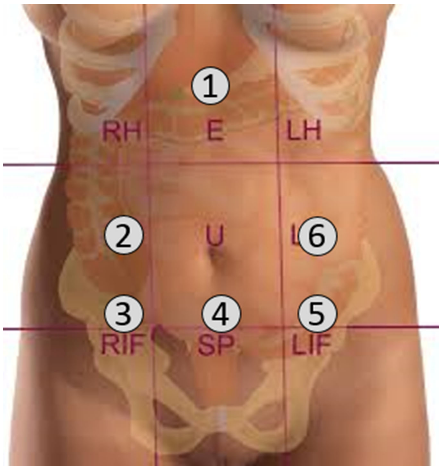


Fig. 7. Stethoscope placement on the abdomen, adapted from [66].

D. Localization

A study by Craine *et al.* [65] included the localization 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 analyzed 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 localization 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 that the abdomen was a hollow cavity and the speed of sound was therefore approximately 340 ms [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 1500 ms [68]. In addition, the abdomen is by no means completely uniform in material density. Due to these constraints, it was concluded that localization 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 localization was estimated by minimizing 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 nonabsorption models were almost equivalent. Unfortunately, their results showed that the calculated error in the localization 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 localization. Building on work by Craine *et al.* [65] and Ranta *et al.* [66], Dimoulas initially estimated the origin of abdominal sounds by analyzing abdominal sound power at each of the four sensors placed in each quadrant of the abdomen. An accelerometer was also placed on the center of the four quadrants and its localization 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 nonuniformity of the abdomen would not significantly influence the localization results. This was because the acoustic waves emanating from the abdomen would have relatively long wavelengths at frequencies below 2 kHz, given that the speed of sound through the medium was approximately 1500 ms^{-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 analyzed using machine learning visual recognition techniques.

E. 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 noteworthy 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 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.

1) *SCL*: solitary clicks.
2) *RCL*: repeated clicks.
3) *SICS*: sequences of irregularly concatenated segments.

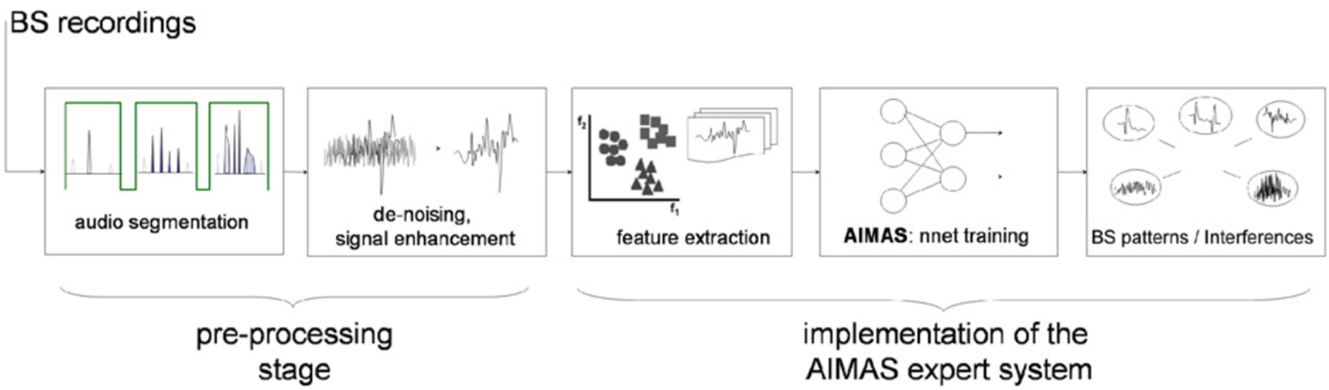


Fig. 8. Development phases of the AIMAS project, [12].

4) *CRSW*: crepitating sweeps.
5) *WSSW*: whistling sweeps.

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

1) *SP*: additive broadband noise.
2) *RESN*: respiration related noise.
3) *SN*: movement and friction noise.
4) *AN*: examination room noise.
5) *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 centers 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 0 and 1, and are usually described using non-numeric 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 a logical link between the input features and the five conditions was retained.

IV. Conclusion

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 customized 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 computerized analysis of bowel sounds, acoustic characteristics have been extracted from signals in both the time domain and the frequency domain. From the early 2000s, WTs 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 favor 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 transit distances through the body and the nonuniformity 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 characterization 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.

REFERENCES

[1] E. R. Edelman and B. N. Weber, "Tenuous tether," *New England J. Med.*, vol. 373, no. 23, pp. 2199–2201, 2015.

[2] W. B. Cannon, "Auscultation of the rhythmic sounds produced by the stomach and intestines," *Am. J. Physiology–Legacy Content*, vol. 14, no. 4, pp. 339–353, 1905.

[3] R. Hooke, "The method of improving natural philosophy," in *The Posthumous Work of Robert Hooke*. London, U.K.: Sam. Smith and Benj. Walford, 1705, p. 39.

[4] H. Baid, "A critical review of auscultating bowel sounds," *Brit. J. Nursing*, vol. 18, no. 18, pp. 1125–1129, 2009.

[5] Y. Gu, H. J. Lim, and M. A. Moser, "How useful are bowel sounds in assessing the abdomen?" *Digestive Surg.*, vol. 27, no. 5, pp. 422–426, 2010.

[6] C. Huttenhower *et al.*, "Structure, function and diversity of the healthy human microbiome," *Nature*, vol. 486, no. 7402, pp. 207–214, 2012.

[7] S. Sagiroglu and D. Sinanc, "Big data: A review," in *Proc. Int. Conf. Collaboration Technol. Syst.*, 2013, pp. 42–47.

[8] W. Fuan, J. Hongkai, S. Haidong, D. Wenjing, and W. Shuaipeng, "An adaptive deep convolutional neural network for rolling bearing fault diagnosis," *Meas. Sci. Technol.*, vol. 28, no. 9, 2017, Art. no. 095005.

[9] X. Du, G. Allwood, K. M. Webberley, A. J. Inderjeeth, A. Osseiran, and B. J. Marshall, "Tu2017-non-invasive diagnosis of irritable bowel syndrome via novel bowel sound features: Proof of principle," *Gastroenterology*, vol. 154, no. 6, pp. S-1370–S-1371, 2018.

[10] C. Qi, A. Fourie, X. Du, and X. Tang, "Prediction of open stope hangingwall stability using random forests," *Natural Hazards*, vol. 92, no. 2, pp. 1179–1197, 2018.

[11] D. Dalle, G. Devroede, R. Thibault, and J. Perrault, "Computer analysis of bowel sounds," *Comput. Biol. Med.*, vol. 4, nos. 3/4, pp. 247–256, 1975.

[12] C. Dimoulas, G. Kalliris, G. Papanikolaou, V. Petridis, and A. Kalampakas, "Bowel-sound pattern analysis using wavelets and neural networks with application to long-term, unsupervised, gastrointestinal motility monitoring," *Expert Syst. With Appl.*, vol. 34, no. 1, pp. 26–41, 2008.

[13] C. A. Dimoulas, G. Papanikolaou, and V. Petridis, "Pattern classification and audiovisual content management techniques using hybrid expert systems: A video-assisted bioacoustics application in abdominal sounds pattern analysis," *Expert Syst. With Appl.*, vol. 38, no. 10, pp. 13082–13093, 2011.

[14] U. D. Ulusar, "Recovery of gastrointestinal tract motility detection using naive Bayesian and minimum statistics," *Comput. Biol. Med.*, vol. 51, pp. 223–228, 2014.

[15] F. Hemmati, W. Orfali, and M. S. Gadala, "Roller bearing acoustic signature extraction by wavelet packet transform, applications in fault detection and size estimation," *Appl. Acoust.*, vol. 104, pp. 101–118, 2016.

[16] A. Matzik and S. Anwar, "Review of electrical filters," *Int. J. Innovative Sci., Eng. Technol.*, vol. 3, no. 4, pp. 543–556, 2016.

[17] B. Farhang-Boroujeny, *Adaptive Filters: Theory and Applications*. New York, NY, USA: Wiley, 2013.

[18] H. Zhang, I. McLoughlin, and Y. Song, "Robust sound event recognition using convolutional neural networks," in *Proc. IEEE Int. Conf. Acoust., Speech, Signal Process.*, 2015, pp. 559–563.

[19] L. Zhang, Y. Wei, S. Wang, D. Pan, S. Liang, and T. Xu, "Specific two words lexical semantic recognition based on the wavelet transform of narrowband spectrogram," in *Proc. 1st Int. Conf. Electron. Instrum. Inf. Syst.*, 2017, pp. 1–6.

[20] J. C. Goswami and A. K. Chan, *Fundamentals of Wavelets: Theory, Algorithms, and Applications*, vol. 233. New York, NY, USA: Wiley, 2011.

[21] L. Chun-Lin, "A tutorial of the wavelet transform," National Taiwan University, Taipei, Taiwan, 2010.

[22] M. Unser and A. Aldroubi, "A review of wavelets in biomedical applications," *Proc. IEEE*, vol. 84, no. 4, pp. 626–638, Apr. 1996.

[23] Z. Peng and F. Chu, "Application of the wavelet transform in machine condition monitoring and fault diagnostics: A review with bibliography," *Mech. Syst. Signal Process.*, vol. 18, no. 2, pp. 199–221, 2004.

[24] M. Jiwa, S. Millett, X. Meng, and V. M. Hewitt, "Impact of the presence of medical equipment in images on viewers perceptions of the trustworthiness of an individual on-screen," *J. Med. Internet Res.*, vol. 14, no. 4, 2012.

[25] C. Aguilera-Astudillo, M. Chavez-Campos, A. Gonzalez-Suarez, and J. L. Garcia-Cordero, "A low-cost 3-d printed stethoscope connected to a smartphone," in *Proc. IEEE 38th Ann. Int. Conf. Eng. Med. Biol. Soc.*, 2016, pp. 4365–4368.

[26] P.-W. L. Frank and M. Q.-H. Meng, "A low cost bluetooth powered wearable digital stethoscope for cardiac murmur," in *Proc. IEEE Int. Conf. Inf. Autom.*, 2016, pp. 1179–1182.

[27] G. A. Mills, T. A. Nketia, I. A. Oppong, and E. E. Kaufmann, "Wireless digital stethoscope using bluetooth technology," *Int. J. Eng. Sci. Technol.*, vol. 4, no. 8, 2012.

[28] C. K. Pawar and U. M. Chaskar, "Fm based electronic digital stethoscope using DSP," in *Proc. Int. Conf. Control, Instrum., Commun. Comput. Technol.*, 2014, pp. 538–542.

[29] F. Yu, A. Bilberg, and F. Voss, "The development of an intelligent electronic stethoscope," in *Proc. IEEE/ASME Int. Conf. Mechatronic Embedded Syst. Appl.*, 2008, pp. 612–617.

[30] J. M. Hill, A. Maloney, K. Stephens, R. Adrezin, and L. Eisenfeld, "Stethoscope for monitoring neonatal abdominal sounds," *Int. J. Modern Eng.*, vol. 9, no. 1, pp. 5–11, 2008.

[31] S. J. White, "Auscultation without contamination: A solution for stethoscope use with personal protective equipment," *Ann. Emergency Med.*, vol. 65, no. 2, pp. 235–236, 2015.

[32] G. Nelson, R. Rajamani, and A. Erdman, "Vibro-acoustic model of a piezoelectric-based stethoscope for chest sound measurements," *Meas. Sci. Technol.*, vol. 26, no. 9, 2015, Art. no. 095701.

[33] S. Leng, R. San Tan, K. T. C. Chai, C. Wang, D. Ghista, and L. Zhong, "The electronic stethoscope," *Biomed. Eng. Online*, vol. 14, no. 1, 2015, Art. no. 66.

[34] C. Dimoulas, G. Kalliris, G. Papanikolaou, and A. Kalampakas, "Novel wavelet domain wiener filtering de-noising techniques: application to bowel sounds captured by means of abdominal surface vibrations," *Biomed. Signal Process. Control*, vol. 1, no. 3, pp. 177–218, 2006.

[35] D. Bray, R. Reilly, L. Haskin, and B. McCormack, "Assessing motility through abdominal sound monitoring," in *Proc. IEEE 19th Annu. Int. Conf. Eng. Med. Biol. Soc.*, 1997, vol. 6, pp. 2398–2400.

[36] H. A. Mansy and R. H. Sandler, "Bowel-sound signal enhancement using adaptive filtering," *IEEE Eng. Med. Biol. Mag.*, vol. 16, no. 6, pp. 105–117, Nov./Dec. 1997.

[37] H. A. Mansy and R. H. Sandler, "Choice of operating parameters in heart sound removal from bowel sounds using adaptive filtering," in *Proc. 19th Ann. Int. Conf. Eng. Med. Biol. Soc.*, 1997, vol. 3. pp. 1398–1401.

[38] H. A. Mansy and R. H. Sandler, "Detection and analysis of gastrointestinal sounds in normal and small bowel obstructed rats," *Med. Biol. Eng. Comput.*, vol. 38, no. 1, pp. 42–48, 2000.

[39] L. J. Hadjileontiadis, C. N. Liatsos, C. C. Mavrogiannis, T. A. Rokkas, and S. M. Panas, "Enhancement of bowel sounds by wavelet-based filtering," *IEEE Trans. Biomed. Eng.*, vol. 47, no. 7, pp. 876–886, Nov./Dec. 2000.

[40] L. J. Hadjileontiadis and I. T. Rekanos, "Detection of explosive lung and bowel sounds by means of fractal dimension," *IEEE Signal Process. Lett.*, vol. 10, no. 10, pp. 311–314, Oct. 2003.

[41] L. J. Hadjileontiadis and I. T. Rekanos, "Enhancement of explosive bowel sounds using kurtosis-based filtering," in *Proc. 25th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, 2003, vol. 3, pp. 2479–2482.

[42] L. J. Hadjileontiadis, "Wavelet-based enhancement of lung and bowel sounds using fractal dimension thresholding-part I: Methodology," *IEEE Trans. Biomed. Eng.*, vol. 52, no. 6, pp. 1143–1148, Jun. 2005.

[43] L. J. Hadjileontiadis, "Wavelet-based enhancement of lung and bowel sounds using fractal dimension thresholding-part II: Application results," *IEEE Trans. Biomed. Eng.*, vol. 52, no. 6, pp. 1050–1064, Jun. 2005.

[44] R. R. Coifman and M. V. Wickerhauser, "Experiments with adapted wavelet de-noising for medical signals and images," in *Time Frequency and Wavelets in Biomedical Signal Processing*. New York, NY, USA: Wiley, 1995.

[45] C. Liatsos, L. J. Hadjileontiadis, C. Mavrogiannis, D. Patch, S. M. Panas, and A. K. Burroughs, "Bowel sounds analysis: A novel noninvasive method for diagnosis of small-volume ascites," *Digestive Diseases Sci.*, vol. 48, no. 8, pp. 1630–1636, 2003.

[46] I. T. Rekanos and L. J. Hadjileontiadis, "An iterative kurtosis-based technique for the detection of nonstationary bioacoustic signals," *Signal Process.*, vol. 86, no. 12, pp. 3787–3795, 2006.

[47] K. S. Kim, J. H. Seo, S. H. Ryu, M. H. Kim, and C. G. Song, "Estimation algorithm of the bowel motility based on regression analysis of the jitter and shimmer of bowel sounds," *Comput. Methods Programs Biomed.*, vol. 104, no. 3, pp. 426–434, 2011.

[48] M. Li, X. Wang, and J. Yang, "Research on auto-identification method to the typical bowel sound signal," in *Proc. 4th Int. Conf. Biomed. Eng. Informat.*, 2011, vol. 2, pp. 845–849.

[49] N. Sasaoka, K. Sumi, Y. Itoh, and K. Fujii, "A new noise reduction system based on ale and noise reconstruction filter," in *Proc. IEEE Int. Symp. Circuits Syst.*, 2005, pp. 272–275.

[50] U. D. Ulusar, M. Canpolat, M. Yaprak, S. Kazanir, and G. Ogunc, "Real-time monitoring for recovery of gastrointestinal tract motility detection after abdominal surgery," in *Proc. 7th Int. Conf. Appl. Inf. Commun. Technol.*, 2013, pp. 1–4.

[51] B.-S. Lin, M.-J. Sheu, C.-C. Chuang, K.-C. Tseng, and J.-Y. Chen, "Enhancing bowel sounds by using a higher order statistics-based radial basis function network," *IEEE J. Biomed. Health Informat.*, vol. 17, no. 3, pp. 675–680, May 2013.

[52] M.-J. Sheu, P.-Y. Lin, J.-Y. Chen, C.-C. Lee, and B.-S. Lin, "Higher-order-statistics-based fractal dimension for noisy bowel sound detection," *IEEE Signal Process. Lett.*, vol. 22, no. 7, pp. 789–793, Jul. 2015.

[53] K.-S. Kim, J.-H. Seo, and C.-G. Song, "Non-invasive algorithm for bowel motility estimation using a back-propagation neural network model of bowel sounds," *Biomed. Eng. Online*, vol. 10, no. 1, 2011, Art. no. 69.

[54] K.-S. Kim, H.-J. Park, H. S. Kang, and C.-G. Song, "Awareness system for bowel motility estimation based on artificial neural network of bowel sounds," in *Proc. 4th Int. Conf. Awareness Sci. Technol.*, 2012, pp. 185–188.

[55] L. Fausett and L. Fausett, *Fundamentals of Neural Networks: Architectures, Algorithms, and Applications*. Englewood Cliffs, NJ, USA: Prentice-Hall, 1994.

[56] Y. Yin, W. Yang, H. Jiang, and Z. Wang, "Bowel sound based digestion state recognition using artificial neural network," in *Proc. IEEE Biomed. Circuits Syst. Conf.*, 2015, pp. 1–4.

[57] Y. Yin, H. Jiang, W. Yang, and Z. Wang, "Intestinal motility assessment based on legendre fitting of logarithmic bowel sound spectrum," *Electron. Lett.*, vol. 52, no. 16, pp. 1364–1366, 2016.

[58] R. Ranta, C. Heinrich, V. Louis-Dorr, D. Wolf, and F. Guillemin, "Wavelet-based bowel sounds denoising, segmentation and characterization," in *Proc. 23rd Ann. Int. Conf. IEEE Eng. Med. Biol. Soc.*, 2001, vol. 2, pp. 1903–1906.

[59] R. Ranta, C. Heinrich, V. Louis-Dorr, and D. Wolf, "Interpretation and improvement of an iterative wavelet-based denoising method," *IEEE Signal Process. Lett.*, vol. 10, no. 8, pp. 239–241, Aug. 2003.

[60] R. Ranta, V. Louis-Dorr, C. Heinrich, D. Wolf, and F. Guillemin, "Principal component analysis and interpretation of bowel sounds," in *Proc. 26th Ann. Int. Conf. IEEE Eng. Med. Biol. Soc.*, 2004, vol. 1, pp. 227–230.

[61] R. Ranta, V. Louis-Dorr, C. Heinrich, and D. Wolf, "Iterative wavelet-based denoising methods and robust outlier detection," *IEEE Signal Process. Lett.*, vol. 12, no. 8, pp. 557–560, Aug. 2005.

[62] R. Ranta, V. Louis-Dorr, C. Heinrich, D. Wolf, and F. Guillemin, "Digestive activity evaluation by multichannel abdominal sounds analysis," *IEEE Trans. Biomed. Eng.*, vol. 57, no. 6, pp. 1507–1519, Jun. 2010.

[63] C. Dimoulas, G. Kalliris, G. Papanikolaou, and A. Kalampakas, "Long-term signal detection, segmentation and summarization using wavelets and fractal dimension: A bioacoustics application in gastrointestinal-motility monitoring," *Comput. Biol. Med.*, vol. 37, no. 4, pp. 438–462, 2007.

[64] T. Emoto *et al.*, "ARMA-based spectral bandwidth for evaluation of bowel motility by the analysis of bowel sounds," *Physiological Meas.*, vol. 34, no. 8, pp. 925–936, 2013.

[65] B. L. Craine, M. L. Silpa, and C. J. O'toole, "Two-dimensional positional mapping of gastrointestinal sounds in control and functional bowel syndrome patients," *Digestive Diseases Sci.*, vol. 47, no. 6, pp. 1290–1296, 2002.

[66] R. Ranta, V. Louis-Dorr, C. Heinrich, D. Wolf, and F. Guillemin, "Towards an acoustic map of abdominal activity," in *Proc. 25th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, 2003, vol. 3, pp. 2769–2772.

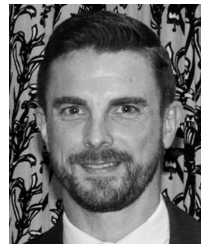
[67] C. Garner and H. Ehrenreich, "Non-invasive topographic analysis of intestinal activity in man on the basis of acustic phenomena," *Res. Exp. Med.*, vol. 189, no. 2, pp. 129–140, 1989.

[68] P. N. Wells and H.-D. Liang, "Medical ultrasound: imaging of soft tissue strain and elasticity," *J. Roy. Soc. Interface*, vol. 8, no. 64, pp. 1521–1549, 2011.

[69] C. A. Dimoulas, "Audiovisual spatial-audio analysis by means of sound localization and imaging: A multimedia healthcare framework in abdominal sound mapping," *IEEE Trans. Multimedia*, vol. 18, no. 10, pp. 1969–1976, Oct. 2016.

[70] R. Ranta *et al.*, "A complete toolbox for abdominal sounds signal processing and analysis," in *Proc. 3rd Eur. Med. Biol. Eng. Conf.*, 2005.

[71] B. H. Kumar, "A fuzzy expert system design for analysis of body sounds and design of an unique electronic stethoscope (development of hilsa kit)," *Biosensors Bioelectron.*, vol. 22, no. 6, pp. 1121–1125, 2007.



Gary Allwood (M'10) was born in Southport, England, in 1982. He received the Bachelor's of Science degree with majors in physics and mathematics and a minor in engineering in 2007 from Edith Cowan University, Joondalup, WA, Australia. In 2010, he received the Master's (first class hons.) degree in physics, and the Ph.D. degree in engineering in 2015 from Edith Cowan University.

He is a qualified Control Systems Engineer with experience in mining and services sectors and is currently a Research Associate with the School of Biomedical Sciences, University of Western Australia, Crawley, WA, Australia. His research interests include optoelectronics, photovoltaics, theoretical physics, and biomedical engineering.

Dr. Allwood is a member of the Society of Photo Instrumentation Engineers, the Optical Society of America, and the Australian Optical Society.

Xuhao Du was born in Guangzhou, China, in 1991. He received the B.Sc. degree in physics and acoustics from Nanjing University, Nanjing, China, in 2014. Since 2015, he has been working toward the Ph.D. degree in mechanical engineering with the University of Western Australia, Crawley, WA, Australia.

He is currently a Research Officer with the Marshall Centre, School of Biomedical Sciences, University of Western Australia. His research interests include noise reduction, bioacoustics, psychoacoustics, architectural acoustics, and machine learning.

K. Mary Webberley was born in the U.K. She received the B.A. (Hons.) degree in the natural sciences (biological) in 1994, the M.A. degree in 1998 and the Ph.D. degree in natural sciences in 2000, all from the University of Cambridge, Cambridge, UK.

She currently works as a Project Manager with the Marshall Centre, School of Biomedical Sciences, University of Western Australia, Perth, WA, Australia. Her current research interest include the noninvasive diagnosis of irritable bowel syndrome, as part of the Noisy Guts Project. She has held positions at the University College London, London, U.K., Queen Mary, University of London, London, U.K. and the School of Animal Biology, University of Western Australia. Her previous area of study was the ecology and evolutionary biology of insect mating systems including the population dynamics of sexually transmitted parasites. More recently, she has also worked on the gastric pathogen Helicobacter pylori.

Adam Osseiran (SM'05) received the B.S. degree in 1981 and the M.S. degree in 1983 both in electrical engineering from the University of Joseph Fourier, Grenoble, France, and the Ph.D. degree in microelectronics in 1986 from the National Polytechnic Institute of Grenoble, Grenoble, France.

In 1987, he joined Swiss Federal Institute of Technology, Lausanne, Switzerland, as a Research Fellow. In 1999, he joined a US start-up Company, and participated in its growth. In 2000, he became the Technical Director with Integrated Measurement Systems specialized in the design for test and built-in self-test techniques for integrated circuits. In September 2002, he became the Director of the National Networked Teletest Facility in Perth-Australia and Associate Professor with the School of Engineering, Edith Cowan University. He holds seven patents in the field of design of CMOS structure dedicated to optoelectronics image sensors for automotive applications, systems, and sensors for environmental monitoring and in the field of display architecture. He was the Editor of a book: *Analog and Mixed-Signal Boundary-Scan, A guide to the IEEE 1149.4 Test Standard* (Kluwer Academic Publisher, 1999). He is the co-editor of a book entitled: *VLSI-SOC: From Systems to Silicon* (Springer, September 2007).

Dr. Osseiran was the Chair of the International Working Group of the IEEE Std. 1149.4 Mixed-Signal Test Bus Standard from 2000 to 2005. He received six certificates of appreciation, a Continuing Service Award and a Meritorious Service Award from the IEEE and the Computer Society for his contributions and numerous services to the engineering community. He was the Chairperson of the Western Australian IEEE Section for 2015 and 2016. He is the Vice Chair of the Test Technology Technical Council Asia.

Barry James Marshall was born in Kalgoorlie, Western Australia. He received the Bachelor's of Medicine, Bachelor's of Surgery degree in 1975 from the University of Western Australia, Perth, WA, Australia.

He was a Registrar with numerous hospitals in Western Australia from 1976 to 1984. From 1986 to 2007, he held multiple positions with the University of Virginia, including being a Research Fellow and a Professor of medicine. He became the Founder and Director of TRI-MED, a diagnostics company and ONDEK, a biotechnology company in Western Australia, in 1996 and 2005, respectfully. Since 1997, he has been an Honorary Clinical Professor in medicine and pharmacology and Senior Principal Research Fellow with the University of Western Australia. He was a Visiting Professor Francis R & Helen M. Pentz Professor of science with Penn State University from 2006 to 2013. He has been the Director of the Marshall Centre for Infectious Diseases Research and Training and the Ambassador for Life Sciences for Western Australia since 2006 and 2007, respectively. His research interests has expanded to embrace new technologies including next generation sequencing, and genomic analysis.

Dr. Marshall has received a number of honorary doctorates and awards including the Nobel prize for physiology or medicine. He is Co-Patron at the Ear Science Institute of Australia, member of the Australian Inventors Association and WA Technology and Industry Advisory Council, Scientific Advisor for the Australian Doctors for Africa, and Medical Patron with Harry Perkins Institute of Medical Research.