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Bowel sound analysis using a common vector approach

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Abstract: *Bowel sound (BS) results from the intestinal activity and can be observed via auscultation. Many studies have been conducted for earlier, harmless, and practical detection of bowel related diseases from BS. Typically, BS is observed using microphones but because of its sudden changing character, silent periods (QP) can last a very long time in the recordings, single bursts (SB) appear vaguely, and multiple bursts (MB) can be confused with external noise. In this study, a new method in BS analysis is proposed to attenuate noise, detect BS, determine the number of occurrences, and classify differentiate BS or Non-BS signals. A common vector approach (CVA) method was used for the detection and classification of BSs. This study aims to show that the orthonormal projection matrix (Q) can be used as a reflection tool in all recordings independent of the training set, without consulting medical professionals. The results show that, in the training, the BS recognition rates were 96,1%, non-BS recognition rates were83,3%, on the other hand, Single burst (SB) and Multiple bursts (MB) recognition rates were 80,9% and 15,4%, respectively. In the tests with using unused abdominal records, 87.5% of the single bursts (SB), 35,7% of multiple bursts (MB) and 84,3% non-BS signals were recognized. The ratios of SB, MB, QP and non-BS signal parts in the signal, were respectively 2,3%, 0,3%, 92,9% and 4,5%.*

Keywords: *Bowel sound recognition, biosensors, bowel activity detection, common vectors.*

I.INTRODUCTION

Bowel sounds detection and evaluation for the intestinal activity monitoring using a stethoscope has become a preferred method. The pioneering work of Cannon [1], in the early 1900s in which he recorded abdominal sounds with a simple stethoscope is one of the earliest studies on the subject of BS. After several medical acoustic studies [2,3], Dalle [4] was the first researcher who digitized BS and used computers for its analysis. In the same year, when analyzing the effect of feeding on abdominal sounds with a 2-electret microphone stethoscope [5], it was also determined that bowel activity decreases or increases based on the motility in patients with mechanically obstructed or paralytic bowel. Similarly, intestinal activity reduces or completely ceases due to the administration of anesthesia [6,7]. Additional studies, were done using a microphone placed in the abdomen of mice [8], such as Hadjileontiadis and Panas analyzed intermittent lung sounds and explosive bowel sounds using symmetric stable α-distributions (SαS) and 2nd Order statistics [9]. Also, wavelet-based and multi-resolution noise reduction techniques [10], high-order transitions (HOC) and wavelet transform-based stationary-non-stationary (WTST-NST) filtering [11], WTST-NST filtering [12], fractal dimension (FD) analysis that can detect time location and duration of the sound [13], (fourth order statistical parameter with zero latency) kurtosis-based noise filtering (Kurtosis-based Detector (KD) for explosive BS) [14] were used. [15,16], presented an effective method for explosive character lung (ELS) and explosive bowel sound (EBS) detection using wavelet transform (WT) and fractal dimension (FD) analysis. In [17] a novel Kurtosis-based (IKD) technique was used to detect non-stationary bioacoustic signals such as lung sounds and EBS. In ongoing studies, wavelet transform and thresholding-based detection [18], and principal component analysis (PCA) [19] were used. In [20], 4-microphone sensor circuit design with a non-contact professional microphone was also used with independent component analysis (ICA), WSNT-NST filter, MFCCs (Mel frequency cepstral coefficients) and PNCCs (Power-normalized cepstral coefficients) techniques on recordings from 20 subjects [21]. Similarly, support vector machines (SVM) classification [22], Time Series Gauss Hamming distance measurements and classification algorithms (TSGHD) [23] were used. Also in various studies, power distribution parameters on the frequency spectrum of the sounds were inserted into the SVM [24], analysis were performed by decomposing logarithmic values of sound spectra into Legendre polynomial [25]. Some techniques such as the use of spectral entropy for the detection of the start and end of the BS [26], use of least mean squares (LMS) and Hilbert envelope for peak detection [27], adaptive filtering [28], higher-order statistics (HOS)-based radial basis function (RBF) [29], higher-order statistics (HOS)-based Fractal dimension algorithm [30], area based multi-channel abdominal sound monitoring [31,32], autoregressive moving average (ARMA) spectrum of recordings [33] has also been proposed. In [34], unlike other studies, researchers tried to observe sounds in 2D by simultaneous auscultating using 3 sensors from the abdominal area of patients who have irritable bowel syndrome (IBS) and non-ulcer dyspepsia (NUD).Dimoulas et al. [35,36] performed a comprehensive analysis of BS noise attenuation techniques at different SNR values using variations of wavelet-based wiener filter (WDWF). He also proposed a new preprocessing and wavelet-based BS detection techniques. In [37] researchers developed autonomous system for monitoring prolonged bowel activities by abdominal surface vibrations. In the study, a new analysis method, AIMAS (autonomous intestinal motility analysis system) were offered, which could eliminate unwanted non-stationary noise components. Also, AIMAS offers model-related analysis approaches such as time pattern distribution analysis (TPDA) and spatial-temporal pattern distribution analysis (STPDA). The study [38] proposed a hierarchical taxonomy called ASFC for abdominal voice classification analysis, which uses the properties of duration, spectral center, and bandwidth. In 2016, Dimoulas conducted a study that focused on mapping gastrointestinal motility (GIM) through topographic analysis and multi-channel recording of abdominal sounds (AS) [39]. The study was carried out using four piezoelectric microphones and a 3-axis accelerometer for fault detection. The localization is estimated analytically based on the direction of arrival (DOA) of the pressure variation generated in the microphones. The study focused on artificial sound localization performance on an artificial abdominal surface-like tissue. Experimental studies have been carried out on silent periods between BS events in order to find the optimum unit time in calculating the frequency of occurrence of bowel sounds [40]. Delfini [41] performed a 6-channel BS analysis on five volunteers and found more intense BS in the right upper and middle abdomen. Tsai CF et al. [42] first developed a stethoscope with a single-channel microphone to view real-time BS under laboratory conditions. They increased the visibility of BS by filtering frequency ranges to filter out noise. K.S. Kim et al. [43] detected BS signals with back propagation neural network (BPNN) as estimated colon transit time (eCTT). They used the simple stethoscope and mIKD algorithm which was also used in their previous work to separate BS segments of 20 healthy and 6 patient subjects.In some studies, researchers developed a noise filtering algorithm by using the acoustic properties of BS, such as Jitter and Shimmer using regression modeling [44]. In [45], an artificial neural network system were used for continuous monitoring of acoustic (shimmer and jitter) features of (multi-channel) BS samples taken from three different regions on 20 healthy and 6 patients with intestinal delay. Kölle K. et al. [46] used multivariate empirical mode decomposition (MEMD) feature with internal mode function-fractal dimension (IMF-FD) filtering which acts like band-pass filter.Recently, multi-channel BS detection studies have also been carried out. Chien C.H. et al. [47] developed a two-dimensional (2D) BS map (BSMM) technique with multichannel electronic stethoscopes to evaluate the location, intensity, and trace of GI motility on the anterior abdominal wall surface in real-time. Wang F. et al. [48] developed a flexible wireless acoustic device attached to the skin to monitor and evaluate BSs. Unlike traditional sensors, the flexible sensor, which allows patients to breathe comfortably and is designed to be least affected by breathing and muscle movement in the abdominal region, transmits the data received from MEMS microphones to mobile devices via Bluetooth connection. Ulusar et al. [49], developed a single channel real-time BS monitoring system. They used sound intensity and Hilbert transform for threshold estimation and Naïve-Bayes algorithm for classification [50]. In [51], noise attenuation was performed by using signals obtained from a second microphone positioned on top of the stethoscope. In [52,53] its wireless version with ZigBee module was designed. Similar design was also used for wireless transfer of electrocardiography (ECG) signals [54].

This study aims to propose an autonomous approach to identify and determine the type of sounds in recording obtained from the abdomen region. For this, in the training set, during the listening, acquired data is passed through a series of normalization, noise reduction, and filtering. The audio events in the recordings are segmented using the signal peak values-signal energy change, SNR and Fractal dimension vector-signal energy relations of the signal. Recordings were also marked by medical experts and results were compared. The time-frequency properties of the BS were examined, feature vectors from non-overlapping time frames were extracted and, each segment was marked BS and non-BS. CVA was applied to evaluate these feature vectors in the training set. The Q projection matrix was obtained for tests belonging to all classes. In the test part, BS classification was performed using only this Q matrix without consulting the medical expert, and the results were evaluated.

II.MATERIAL AND METHODS

Bowel Sound

BSs are caused by the movement of liquid and solid foods that are pushed-compressed by the wave-like muscle contractions called a peristaltic movement of the intestine during digestion. Generally, BSs occur due to regular digestion, and vocal activity increases typically in the period after meal intake. Mostly BSs cannot be heard unless closely listened to using a stethoscope. Accordingly, in its general character, there are single or multiple sudden changes at the end of variable silence periods. These sudden changes may indicate bowel activity, as well as speech, muscle movement, the patient's spinning motion, or environmental noises like stomach, heart, muscle sounds. Typically, BSs are divided into two activity classes: single burst (SB) and multiple bursts (MB). SB is the result of short-term contractions and creates sharp sounds. The MB consists of a cluster of spawning SBs with little or no gaps. Quiet periods (QP) are observed in the absence of BS or noise. The ambient sounds in the examination room, the sliding friction of the sensors and microphones, or the noises caused by the connecting cables due to the movements of the subjects, are added to the signal even if their level is very small. Heartbeat sounds have very weak amplitudes and are mostly mixed in infants.For the first time, the BSs were modeled using the spring-mass relationship in Eq. (1) by Du [55] as shown below and other main properties of BSs are listed below.

$$P_{bs}(t) = \sum_{i=1}^{N} \frac{P_{m,i}\sin(2\pi f_{iwc}(t - \sum_{k=1}^{i} T_i))}{(t - \sum_{k=1}^{i} T_i)^b} e^{-\frac{E}{t} - \sum_{k=1}^{i} T_i} + n(t) \tag{1}$$

- BSs are non-stationary bio signals.
- Spectrum, time, amplitude, and silence duration analyzes are the most used feature fields of BS.
- 95% of the BS energy is in the frequency band 100-1000 Hz.
- Usually has a higher amplitude than ambient noise.
- Sound durations are usually between 10 ms and 1 s.

A Common Vector Approach (CVA)

According to the CVA, let the training set consist of C different classes, each containing N samples. In this case, the training set has a total of $M=NxC$ samples. i.th class, m.th sample's, feature vector is denoted by x_{mi} in d-dimensional space; within-class, between-class and total variation (scatter) matrices, S_W, S_B, S_T can be found using the following Equations. μ is the mean vector of all samples in the training set, μ_i i.th mean vector of the class, and A being the dxM dimensional matrix,

$$S_w = \sum_{i=1}^{C}\sum_{m=1}^{N}(x_m^i - \mu_i)(x_m^i - \mu_i)^T = AA^T \tag{2}$$

$$S_B = \sum_{i=1}^{C} N(\mu_i - \mu)(\mu_i - \mu)^T \tag{3}$$

$$S_T = \sum_{i=1}^{C}\sum_{m=1}^{N}(x_m^i - \mu)(x_m^i - \mu)^T = S_w + S_B \tag{4}$$

$$A = [\ x_1^1 - \mu_1 \dots x_N^1 - \mu_1 \quad x_2^1 - \mu_2 \dots x_N^C - \mu_C\ ] \tag{5}$$

Let V and V⊥ be spaces representing the difference subspace and the indifference subspace of the S_W matrix, respectively. The sum of these two spaces gives the space formed by all the d-dimensional features. Let r (r < d) linearly independent vectors be in the S_W matrix. In this case, the spaces, and the sum of these spaces,

$$V = span\ \{\ \alpha_k | S_w\alpha_k \neq 0\ , k = 1, \dots, r\} \tag{6}$$

$$V^{\perp} = span\ \{\ \alpha_k | S_w\alpha_k = 0\ , k = r+1, \dots, d\} \tag{7}$$

$$V \oplus V^{\perp} = R^d \tag{8}$$

To find the difference and indifference spaces, it is necessary to find the orthonormal vector sets that stretch these spaces. With the eigenvector analysis of S_W, the basis vectors that stretch these spaces can be found. α_k , $(k = 1, \dots, d)$are orthonormal basis vectors. In Eq. (6), vectors α_k , $(k = 1, \dots, r)$ are eigenvectors corresponding to nonzero eigenvalues of S_W and they stretch the difference subspace V. The difference subspace is stretched by *(N-1)* orthonormal basis vectors of each class. Since there are M classes, the difference subspace consists of a total of *M(N-1)* basis vectors. In other words, the size of the difference subspace is,

$$dim\, R\,(S_w) = r = M(N-1) \tag{9}$$

In Eq. (7), the vectors α_k , $(k = r+1, \dots, d)$are the eigenvectors corresponding to the zero eigenvalues of S_W and they stretch the V⊥ indifference subspace. The size of the indifference subspace is obtained by subtracting the size of the difference subspace from the total size of S_W.

$$dim\, N\,(S_w) = d - r = d - M(N-1) \tag{10}$$

The projection matrices of the S_W to the difference and indifference subspaces, respectively, are shown in Eq. (11) and (12), the projections of the samples in the training set to these spaces are as in (13).

$$Q = [\vec{\alpha}_1, \dots, \vec{\alpha}_r]P = QQ^T \tag{11}$$

$$\bar{Q} = [\vec{\alpha}_{r+1}, \dots, \vec{\alpha}_d]\bar{P} = \bar{Q}\bar{Q}^T \tag{12}$$

Using the Eq. (8), the $\vec{x}_m^i$feature vectors can be parsed as follows

$$\vec{x}_m^i = \vec{y}_m^i + \vec{z}_m^i \tag{13}$$

$$\vec{x}_m^i = P\vec{x}_m^i + \bar{P}\vec{x}_m^i = \underbrace{QQ^T}_{\boxed{\textbf{Difference}\text{ subspace}}}\vec{x}_m^i + \underbrace{\bar{Q}\bar{Q}^T}_{\boxed{\textbf{Indifference}\text{ subspace}}}\vec{x}_m^i \tag{14}$$

In Eq. (5), matrix A is defined. The product of AA^Tgives the S_W the covariance matrix of size *dxd*. The A^TAproduct produces a much smaller matrix of size *MxM (M < d)*. Instead of finding the eigenvalues and eigenvectors of a *dxd* sized matrix, it is easier to find the eigen values and eigenvectors of a much smaller *MxM* sized matrix. The eigenvectors corresponding to the nonzero eigen values of this matrix form the difference subspace. To find the difference subspace of S_W , it will be sufficient to multiply these eigenvectors by A^Twhich is shown as below.

$$(AA^T - \lambda I)\vec{v} = \vec{0}$$

$$\updownarrow$$
$$(A^T A - \lambda I)\vec{\omega} = \vec{0}$$
$$\big((A^T A)A^T - (\lambda I)A^T\big)\vec{\omega} = (\vec{0})A^T$$
$$(A^T A A^T - \lambda A^T)\vec{\omega} = \vec{0}$$
$$(AA^T - \lambda I)A^T\vec{\omega} = \vec{0}$$

$$\vec{v} = A^T\vec{\omega} \tag{15}$$

As seen in Eq. (14), feature vectors $\vec{x}_m^i$ have two components, one in the difference subspace and the other in the indifference subspace. The component in the indifference subspace gives the common vector [56].

$$\vec{z}_m^i = \vec{x}_m^i - \vec{y}_m^i \tag{16}$$

$$\vec{z}_m^i = \vec{x}_{com}^i \tag{17}$$

$$\vec{x}_{com}^i = \vec{x}_m^i - P\vec{x}_m^i = \vec{x}_m^i - QQ\vec{x}_m^i \tag{18}$$
$$m = 1, \ldots, N, \quad i = 1, \ldots, C$$

$$\vec{x}_{com}^i = \bar{P}\vec{x}_m^i = \bar{Q}\bar{Q}^T\vec{x}_m^i \tag{19}$$
$$m = 1, \ldots, N, \quad i = 1, \ldots, C$$

A faster algorithm emerges with the Gram-Schmidt orthogonalization method [56]. In this method, the difference subspace of the common variation matrix defined for all classes is found by looking at the differences between the feature vectors. For this, the difference subspace of a class is found by subtracting the first feature vector of each class from the others.

$$\vec{b}_k^i = \vec{x}_{k+1}^i - \vec{x}_1^i\ , \quad k = 1, \ldots, N-1 \tag{20}$$

$$B_i = span\ \{\vec{b}_1^1, \ldots, \vec{b}_{N-1}^1\} \tag{21}$$

Since the first feature vector of the classes is referenced, *(N-1)* linear independent vectors belonging to each class are obtained. In this case, there is a total of *C(N-1)* linearly independent vectors in the difference subspace *B*. By taking the vectors that stretch the difference subspace *B*, the difference subspace of all classes can be found as in Eq. (23). Here, $D^T D$ is an invertible, positive definite matrix.

$$D = \ [\vec{b}_1^1, \ldots, \vec{b}_{N-1}^1, \vec{b}_1^2, \ldots, \vec{b}_{N-1}^C] \tag{22}$$

$$P = D(D^T D)^{-1}D^T \tag{23}$$

From here, common vectors can be obtained by projecting the feature vectors onto the indifference subspace or by subtracting their projections from the feature vectors in the difference subspace.

$$\vec{x}_{com}^i = \bar{P}\vec{x}_m^i = x_m^i - P\vec{x}_m^i = \bar{Q}\bar{Q}\vec{x}_m^i = x_m^i - QQ\vec{x}_m^i \tag{24}$$
$$m = 1, \ldots, N, \quad i = 1, \ldots, C$$

Sliding Window and Threshold

To find the feature vectors of the preprocessed time sequence, silent periods must be removed from the signal and significant audio segments must be extracted. For this, a sliding window and threshold value are determined. For the sliding window and threshold value detection, the point where the first minute of the signal falls to a maximum of 98% of the average energy curve was selected with Katz fractal dimension (Katz FD [58]) and the kurtosis value of the signal. According to Katz, assuming that a curve of length L is divided into n segments into steps ($n = L/\bar{a}$) FD does the following calculation in Eq. (25) for each loop of these segments. Where d is the distance between each loop's start and end points. Average power of the $x(i)$is shown at Eq. (26).

$$FD = \frac{\log_{10}(n)}{\log_{10}\left(\frac{d}{L}\right) + \log_{10}(n)} \tag{25}$$

$$P_{av} = 10.\log_{10}\left\{\frac{1}{N}\sum_{i=0}^{N-1} x^2(i)\right\} \tag{26}$$

After this step, the sliding window size was determined by using the signal envelope and envelope RMS. Then, the signal was cut from the points where the sliding window-threshold pair boxes, and the parts above the threshold value were named as significant signal segments. In the signal envelope, peak values at least 20 msec intervals were used according to the

RMS.

$$x_{rms} = \sqrt{\frac{1}{N}\sum_{k=0}^{N} x^2[k]} \quad (27)$$

III.RESULTS

Microphone Design and Data Acquisition

In the study, recordings were taken from the abdomen with various microphones, and recordings from our previous studies [52,53] were used. Recordings were done at a 5 kHz sampling frequency with Electret Condenser microphones, using NI-DAQ. Records were transferred wired or wirelessly to PC and processed with Matlab. Also, Raspberry Pi 3 and ESP32 were used with a single electret microphone module. The designs are shown in Figure 1.

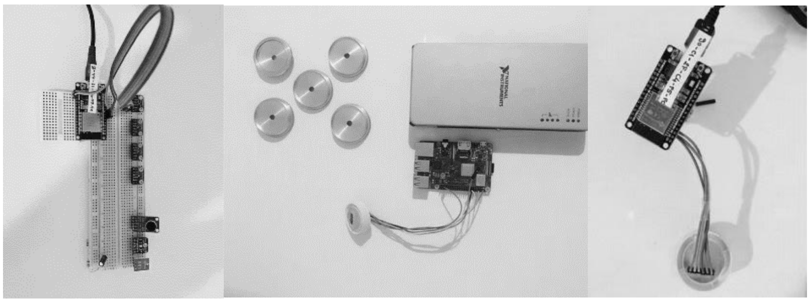

Figure 1. Types of microphones, devices, and design

The quality of the acquisition device becomes very important when acquiring bowel sounds. Although Micro electro-mechanical sensor (MEMS) microphones have much better noise performance than an equivalent size Electret Condenser (ECM) microphones, due to the sensitivity and wide frequency range, Max9814 analog ECM is preferred for the study.

Filtering

BS recordings contain noise sources such as movement-friction, breathing, stomach, heartbeat, TV, speech, and other noises. The first step of the implementation was normalization and filtering. Wavelet multiresolution decomposition and 150-600 Hz IIR band pass filter was used to filter out noise. Raw and denoised parts is shown in time-frequency representation in Figure 2. Significant sound events were extracted with Kurtosis [14] and Fractal Dimension (FD) [13] calculations of audio data.

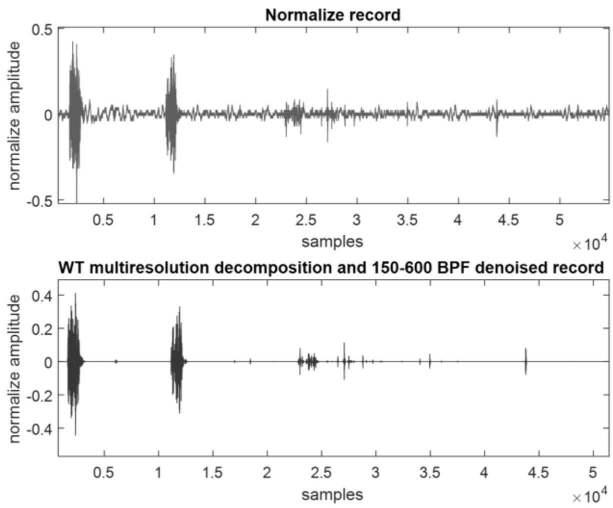

Figure 2. Unfiltered and filtered records

Application

Implementation was performed in Matlab 2021b, which consists of two main steps, training and testing. The steps are summarized as follows and shown in Table 1.

1. Filtering and normalization.
2. Determine resolution and threshold value according to Katz's fractal dimension and signal-to-noise ratio relationship, select the first local maximum where the SNR is above 98% for the optimum resolution and threshold, and segment the signal according to these values and save the segments.
3. Extract the selected features of the segments, and create clusters based on signal similarity using clustering algorithms, such as K-means. The clusters differ according to energy, zero-crossing, duration, and frequency domain features.

4. Listen to the signal and decide on BS or not. Then, save the decision vectors as BS or Non-BS.
5. Classify feature vectors by BS type. Then, extract the scatter matrix of feature vectors belonging to the same class.
6. Apply CVA to find the projection matrix Q from the eigenvectors corresponding to the zero eigenvalues of this matrix.
7. Multiply Q by the feature vectors and get the common vector for each class. For validation, multiply all feature vectors with Q and compare them with the listening data. Save the Q matrix.

Test steps are summarized as follows.
1. For the test, select a new record.
2. Perform to the new signal 1,2,3,4,5,6th steps in training.
3. Calculate the projection of the test feature vectors to the classes with the Q matrix. Then, compare the result decision vector with the training reference table or data.

Table 1. Steps of the method

Filtering	*WT denoising Multiresolution reconstruction & 150-600 Hz BPF*
Find optimum Resolution & Threshold	*Begin 10 msec window length, iteratively find optimum threshold according to 98% power of the signal. According to the optimum threshold, find the optimum window length. Use signal envelope & power & RMS*
Find Features	***Time & Spectral features of the segments*** *standard deviation, variance, maximum peak value, sound duration, number of peaks, RMS, Rssq, signal mean power, number of zero crossings, signal kurtosis value, crest factor, dynamic range, and bandwidth.*
Find BS or non-BS	*According to significant features, find the BS or non-BS and SB & MB parts**, and listen the segment-array.***
CVA_ GramSchmidt	**TRAINING with GramSchmidt-CVA** Feature Vectors for Training % Gram-Schmidt orthogonalization method
TestReal	**TEST with no-trained samples**

Window Resolution and Threshold Detection

A significant event region was extracted from signal FD, firstly by choosing window resolution, which was the lowest average BS duration (0.03 sec). The parts remaining outside the threshold were eliminated as silent periods (SP or QP). The threshold value was used to identify the significant regions of above 98% of the signal energy as shown in Figure 3.

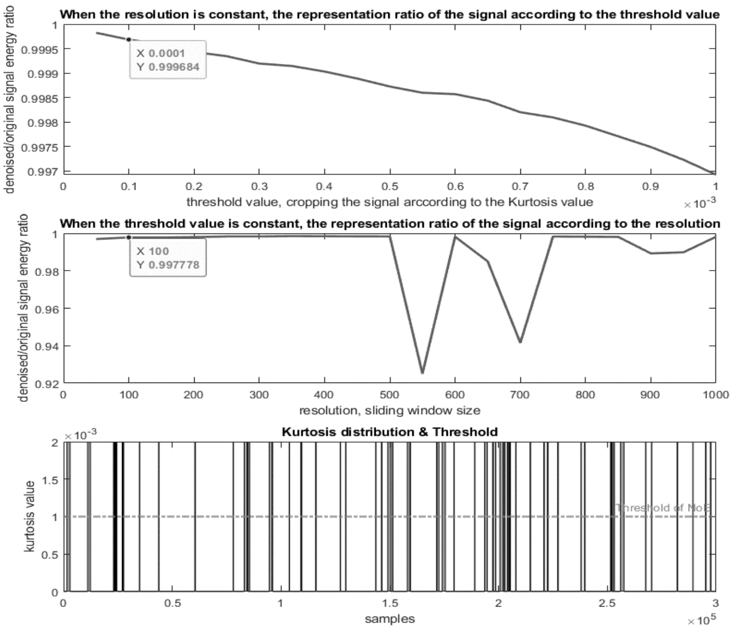

Figure 3. Optimum resolution and threshold selection

Another method to find optimum resolution and threshold is to use the average signal power and signal envelope-RMS relationship. This was a faster method, but it caused the threshold value to be high for long sequences.

Feature Extraction and Selection

In this step, the time-frequency representation of the normalized signal, filtered signal, and reconstructed signal is obtained. The feature vector set was created by calculating the time and frequency feature sets of each of the windowed segments of the signal. The feature set contained standard deviation, variance, maximum peak value, sound duration, number of peaks, RMS, Rssq, signal mean power, number of zero crossings, signal kurtosis value, crest factor, and dynamic range, and bandwidth.The first classification was made according to the distance from the mean of the feature vectors of the signal segments, then the listening data were compared with this result, and finally it was determined whether it was BS or non-BS by using CVA. A projection matrix (Q) was created in this step from the training set obtained with this analysis. For the test, records that were never used in training were selected.

Classification

1-minute parts of 10 minutes recordings have been used as training and test samples. Ten external noises were added to the records. In the test step, iteratively obtained classification results from the 1-minute unused recording pieces. Firstly, the record's quiet period (QP) was removed using the threshold value, then the signal with significant sound segments was extracted, and the sound segments in the records were shown as BS or non-BS as in Figure 4.

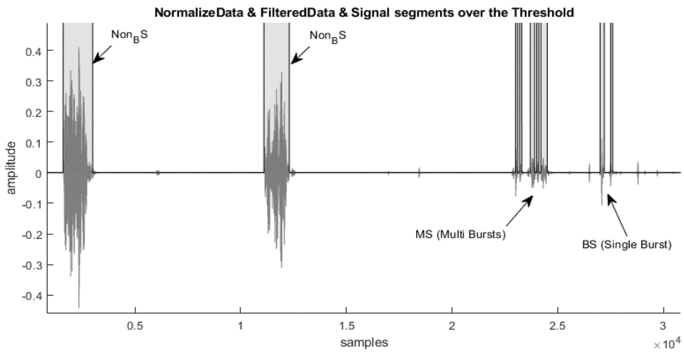

Figure 4. Segmentation and classes

When K-means clustering was used, feature vectors were divided into three classes for classification. In the training set, the feature vectors were first classified according to their distance from the mean with the k-means method, then the listening data were compared with this result, and finally Q projection matrix was trained with the CVA. By applying CVA to the features for each class, the Q projection matrix is reflected to the one average common vector. Q matrix also can be obtained from another record of sufficient length by repeating the same operations. Finally, the classification results are shown in Figure 5.

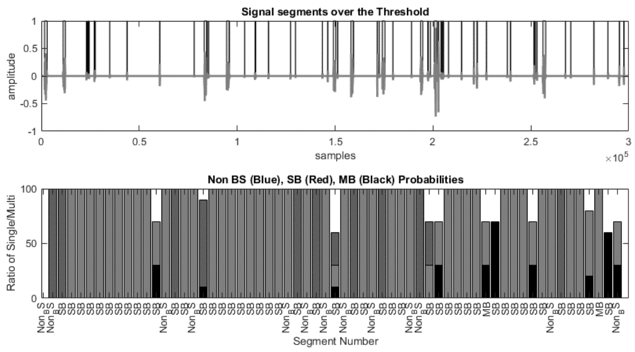

Figure 5. Signal segments and classification results

Results

The training results were compared with the reference classification results. The findings show that 96,1% of BS was assigned to the correct class. Similarly, 83,3% of non-BS was the same too. Single burst (SB) and Multiple bursts (MB) recognition rates were 80,9% and 15,4%, respectively. The ratios of SB, MB, QP and non-BS signal parts in the signal, respectively 2,3%, 0,3%, 92,9% and 4,5%. The numbers of these classes in the sound event were also indicated as shown in Table 2.

Table 2. Training set classification results

BS types	% Ratio in Signal	Training (Reference)	Training with CVA	Training RecognitionRate
QP	92,9%	0	0	-
BS	2,6%	49	51	**96,1%**
SB	2,3%	47	38	**80,9%**
MB	0,3%	2	13	15,4%
Non-BS	4,5%	12	10	**83,3%**
Not_Recognized	0,0%	0	0	-

In the test, similarly, the accuracy was calculated by classifying the classes according to their proximity in the same way and comparing them with the reference data. The unused signal's feature vectors were multiplied by the Q projection matrix obtained in training, then the nearest class was traced, and the accuracy was checked by comparing the classification result with the reference data. In the test, the results in Table 3. were obtained.

Table 3. Test set recognition results

TEST with CVA		BS: **SB** *Test/Reference*	BS: **MB** *Test/Reference*	**Non-BS** *Test/Reference*	**Not_Recognized** *Test/Reference*
TEST 1	*Used in Training*	35/47	2/13	10/12	0/3
TEST 2	*Unused*	60/64	9/15	10/12	1/1
TEST 3	*Unused*	41/49	2/14	8/14	0/2
TEST 4	*Unused*	42/53	4/16	9/9	0/1
TEST 5	*Unused*	23/23	2/7	3/10	2/4
TEST 6	*Unused*	33/35	3/4	10/10	1/2
TEST 7	*Unused*	50/55	4/10	10/13	0/2
TEST 8	*Unused*	50/69	2/27	10/15	0/1
TEST 9	*Unused*	45/49	2/10	10/13	0/1
TEST 10	*Unused*	49/52	5/7	10/11	0/4
TEST 11	*Non_BS record*	-	-	10/10	0/0
TEST 12	*Non_BS record*	-	-	10/10	0/0
TEST 13	*Non_BS record*	-	-	8/10	0/2
TEST 14	*Non_BS record*	-	-	9/10	0/1
TEST 15	*Non_BS record*	-	-	10/10	0/0
TEST 16	*Non_BS record*	-	-	9/10	0/1
TEST 17	*Non_BS record*	-	-	9/10	0/1
TEST 18	*Non_BS record*	-	-	10/10	0/0
TEST 19	*Non_BS record*	-	-	9/10	0/1
TEST 20	*Non_BS record*	-	-	8/10	0/2

According to the test results, after quite periods (QP) are discarded from the signal, 87.5% of the single bursts (SB), 35,7% of multiple bursts (MB) and 84,3% of non-BS signals were recognized overall, which were shown in Table 4.

Table 4. The test set recognition rates

TEST with CVA		BS: **SB** Test RECOGNITION RATE	BS: **MB** Test RECOGNITION RATE	**Non-BS** Test RECOGNITION RATE
TEST 1	*Used in Training*	74,5%	15,4%	83,3%
TEST 2	*Unused*	**93,8%**	60,0%	83,3%
TEST 3	*Unused*	83,7%	14,3%	57,1%
TEST 4	*Unused*	79,2%	25,0%	**100,0%**
TEST 5	*Unused*	**100,0%**	28,6%	30,0%
TEST 6	*Unused*	**94,3%**	**75,0%**	**100,0%**
TEST 7	*Unused*	**90,9%**	40,0%	76,9%
TEST 8	*Unused*	72,5%	7,4%	66,7%
TEST 9	*Unused*	**91,8%**	20,0%	76,9%
TEST 10	*Unused*	**94,2%**	**71,4%**	**90,9%**
TEST 11	*Non_BS record*	-	-	**100,0%**
TEST 12	*Non_BS record*	-	-	**100,0%**
TEST 13	*Non_BS record*	-	-	80,0%
TEST 14	*Non_BS record*	-	-	**90,0%**
TEST 15	*Non_BS record*	-	-	**100,0%**
TEST 16	*Non_BS record*	-	-	**90,0%**
TEST 17	*Non_BS record*	-	-	**90,0%**
TEST 18	*Non_BS record*	-	-	**100,0%**
TEST 19	*Non_BS record*	-	-	**90,0%**
TEST 20	*Non_BS record*	-	-	80,0%
Test RECOGNITION RATE Overall		**87,5%**	**35,7%**	**84,3%**

IV.CONCLUSION

In this study, a comprehensive literature review was performed, almost all studies and methods for the detection of BS were examined. The microphone types used in BS detection were examined, and the recordings were obtained with different hardware such as NI-DAQ, Raspberry Pi and ESP32. BS detection processes such as signal acquisition, preprocessing, denoising, feature extraction, classification, and Q projection matrix with discriminative CVA sections, were implemented. Training and test sections were carried out with the new method, and results were shown.

Because of the BSs burst like character, it has become more apparent that it could occur at different amplitudes and durations. Therefore, the BS detection was directly affected by the threshold value and the sliding window size. With the low threshold values, it is possible to detect small sound events. On the contrary, with high threshold values many BS events are missed. The window size used to accurately detect sound events in the signal depended on criteria such as average signal strength, fractal size of the signal, snr and signal envelope.

With the discriminative CVA, all classes' feature vectors were projected to a linear independent orthonormal basis.

Thanks to the method, the small differences between the vectors in the same class were removed. A single common vector representing each class remained. Small changes in sounds for the same class did not change the common vector of the class.

In the training, the recognition rates were 96,1% BS, and 83,3% non-BS. Single burst (SB) and Multiple bursts (MB) recognition rates were 80,9% and 15,4%, respectively. The ratios of SB, MB, QP and non-BS signal parts in the signal, respectively 2,3%, 0,3%, 92,9% and 4,5%. In the tests, after quite periods (QP) are discarded from the signal, 87.5% of the single bursts (SB), 35,7% of multiple bursts (MB) and 84,3% non-BS signals were recognized. As a result, to obtain a more accurate recognition rate, the filtering step of the signal, the choice of threshold-resolution value for segmentation, the selection of features steps, classification, and clustering algorithm were very important. The most characteristic features in the signal were representing the classes in the best way. It's very valuable in the classification that the common vectors be linearly independent between the classes optimized the recognition performance by creating perpendicular bases, so it assigned the test sample of each class to the most accurate class.

The results showed that the orthonormal feature matrix Q obtained using discriminative CVA could be a projection tool for abdominal recordings. Furthermore, this property showed that the Q projection matrix, which was well trained with discriminative CVA with the help of medical experts, could classify BS and non-BS without additional assistance.

V.FUTURE WORK

In future studies, it is aimed to obtain a multi-channel BS wirelessly and analyze it together with the proposed methods and Beam forming techniques to create an ultrasound-like BS map.

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