Assessing the Feasibility of Acoustic Based Seizure Detection

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***Abstract*— Objective: Long-term monitoring of epilepsy patients outside of hospital settings is impractical due to the complexity and costs associated with electroencephalogram (EEG) systems. Alternative sensing modalities that can acquire, and automatically interpret signals through easy-to-use wearable devices, are needed to help with at-home management of the disease. In this paper, a novel machine learning algorithm is presented for detecting epileptic seizures using acoustic physiological signals acquired from the neck using a wearable device. Methods: Acoustic signals from an existing database, were processed, to extract their Mel-frequency Cepstral Coefficients (MFCCs) which were used to train RUSBoost classifiers to identify ictal and non-ictal acoustic segments. A postprocessing stage was then applied to the segment classification results to identify seizures episodes. Results: Tested on 667 hours of acoustic data acquired from 15 patients with at least one seizure, the algorithm achieved a detection sensitivity of 88.1% (95% CI: 79%–97%) from a total of 36 seizures, out of which 24 had no motor manifestations, with a FPR of 0.83/h, and a median detection latency of -42s. Conclusion: The results demonstrated for the first time the ability to identify seizures using acoustic internal body signals acquired on the neck. Significance: The results of this paper validate the feasibility of using internal physiological sounds for seizure detection, which could potentially be of use for the development of novel, wearable, very simple to use, long term monitoring, or seizure detection systems; circumventing the practical limitations of EEG monitoring outside hospital settings, or systems based on sensing modalities that work on convulsive seizures only.**

***Index Terms*— Acoustics signals, epilepsy, physiological signals, seizure detection, machine learning, wearables, monitoring, digital health**

I. Introduction

EPILEPSY is a chronic and noncommunicable condition that affects the brain of those who suffer from it. More than 50 million people worldwide suffer from epilepsy [1]. The disease is characterized by the presence of seizures [2]. These seizures, which can manifest in different ways and occur at any time, are classified into different types. The unpredictability of seizures, in addition to their physical and cognitive manifestations, do have severe impacts on patients' lives. They affect their ability to work, study or perform daily tasks. Furthermore, stigmas associated with seizures and epilepsy, mostly in certain parts of the world, in some cases prevent patients from reaching out and seeking appropriate treatment.

The standard assessment method for the detection and identification of epileptic seizures involves the analysis of brain activity. This is routinely carried out using electroencephalography (EEG), a method where electrical signals generated by the brain are sensed using numerous electrodes placed at specific locations on the scalp, and these are subsequently annotated looking for epileptic activity biomarkers. The gold standard for seizure detection is video-EEG (VEEG) monitoring [3], where both the video and EEG signals are recorded. This is usually performed at specialized clinics or hospitals, under supervision of trained clinical staff.

Although VEEG can provide information on both, physical symptoms of seizures as well as the brain activity, it requires patients to be in hospital for monitoring. In addition to the in-hospital monitoring, patients are often required to keep diaries to log seizure episodes at their homes. While being helpful, this can be very subjective and unreliable. Recollections of seizure episodes by patients are based on their perception, mood, duration, trigger, and severity among other subjective factors [4]. Additionally, under-reporting of seizures is one of the major challenges faced by people with epilepsy, giving rise to an array of problems in its diagnosis, management, and treatment [5]. This can be attributed to a variety of factors, such as the loss of awareness during seizures and the forgetfulness of patients [5]. Consequently, there is a push to improve the at-home care for epilepsy patients to help with the diagnosis and management of their condition through the use of long-term monitoring systems [6].

EEG-based systems for epilepsy monitoring require a large number of electrodes, ranging from 8 to 64 [7], to be placed on the patient scalp while the recording is taking place. The large number of electrodes are essential, since the location of the source of the seizure is not normally known [8]. However, the complexity and cost of the method makes it unviable for it to be potentially deployed as a tool to be used at home by the majority of patients for long-term monitoring to assist with the long-term management of the disease.

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Alternative sensing modalities have been proposed to assist with the task of long-term seizure monitoring and detection [7], [9]. These focus on the seizure manifestations rather than the physiological signal generated at the source of the seizure, and include methods based on accelerometry, surface electromyography (sEMG), photoplethysmography (PPG), electrodermal activity (EDA), electrocardiogram (ECG), non-contact audio and video [7], [9]. Although these modalities on their own offer little value in terms of clinical diagnosis, they could potentially assist in managing the disease once this has been diagnosed.

This paper investigates, for the first time, the possibility of using physiological sounds sensed from the suprasternal notch to identify the presence of seizures. Similar to the other non-EEG modalities used for detecting seizures, acoustic sensing relies on identifying and measuring physiological changes in the cardio-respiratory system rather than the electrical activities of the brain. Hence, acoustic physiological signals were hypothesized to be relevant for the detection of seizures, as changes in cardio-respiratory function have been found during and around seizures [10], [11]; and long-term acoustic sensing could be used to quantify and characterize changes in the cardio-respiratory system, including the evolution of such characteristics around seizure episodes. As these autonomic changes occur in both focal and generalized epilepsy, they could have the potential to be used for detecting seizures and alleviate some of the issues in other modalities that only work well on specific seizure types.

The paper describes the design of a new algorithm followed by the evaluation of its performance for the detection of seizures. The algorithm was tested on an existing pseudo-anonymized database containing both, sound recordings from a small wearable device prototype and marked EEG signals. The paper is organized as follows: Section II examines the background and current non-EEG seizure detection methods. Section III describes the dataset used in this work and the proposed algorithm. In Section IV, the results and the performance evaluation are presented. This is followed by the discussion in Section V, and conclusions in Section VI.

II. Non-EEG Seizure Detection Methods

Since the gold standard for seizure detection involves using EEG, several methods have been published in literature that perform automatic detection of seizures by analyzing EEG signals. These methods have shown to achieve good results, with sensitivities in the 90% range [12]–[14]. However, as this paper focuses on alternative and complementary seizure detection methods, systems based on EEG are not described here.

Seizure detection systems based on accelerometers have been developed, in which the sensors are typically placed on the arms and/or legs in order to detect seizure characteristic movements. Studies using accelerometry as the sensing modality have shown a wide range of detection sensitivities, from 16% to 100% [15]–[33]. This wide range of sensitivities is associated to: 1- The fact that some methods have been tested with very low number of seizures (less than 11), and although they seem to achieve high sensitivity the confidence intervals are very wide [19], [26]; 2- The tradeoff with specificity which leads some methods to have higher sensitivities at the expense of a compromised false positive rate (FPR) [15], [18], [26]; 3- The fact that accelerometer-based systems rely on movements of the body location where the sensor is placed during seizures. This will vary depending, amongst others, on the type of seizure. Hence, these systems are most suitable for generalized tonic clonic seizures (GTCS). In terms of the FPRs achieved by accelerometry-based works, they ranged from 0.01/h to 0.38/h [16], [20]–[22], [25], [26], [29]–[33]. The low FPR indicates that these systems are specific and perform well in detecting seizures which have motor elements.

Electromyography (EMG) based systems, which work by sensing variations in specific muscles activity caused by seizures, have also been developed. The sensors are usually placed in locations such as the arms or legs, depending on which parts of the body are most active during seizures. The drawbacks of EMG-based systems are similar to those based on accelerometers. Since this modality for detecting seizures is movement-based, the performance of systems based on it is somewhat constrained by the position of the sensors in relation to the part of the body that moves during the seizure, the number of sensors and the type of seizures. Sensitivities ranging from 57% to 95% have been achieved [29], [34]–[38]. However, those achieving the highest sensitivities also relied on an impractically cumbersome sensing set up [36], or had very wide variability in sensitivity results depending on the center that did the study [34], [37]. The FPR reported in EMG-based studies are low, and the maximum FPR was 0.11/h [29], [34], [36]–[38]. Similar to accelerometers-based systems, although highly specific, they were tested on convulsive seizures.

During or around seizure episodes, patients can experience changes in their cardiac activity, manifesting in the form of changes in heart rate variability [11]. This has also been explored as a potential physiological modality for seizure detection. Studies of seizure detection algorithms using heart rates from ECG recordings achieved sensitivities ranging from 57% to 100% [30], [39]–[49], with FPR values as low as 0.06/h (and up to 2.11/h) [30], [40], [42], [45], [48]; but those studies reporting higher sensitivities were tested only on patients that were *a priori* known to have marked ictal autonomic changes and relied on patient specific cut-offs [43], [46]. Photoplethysmography (PPG) has also been used to try to detect cardiac changes. But in this case, the sensitivity was either significantly reduced when compared to using ECG, or it relied on signals in which sections with movement artefacts had been manually removed [42], [50].

Another sensing modality that has been used to capture and automatically identify seizures is based on non-contact bed movement sensing, during sleep. A wide range of sensitivities (2.2% to 89%) have been reported [51]–[53], even in evaluations involving the same devices [51], [52]. These differences can be explained by the different types of seizures occurring in the evaluation datasets. In [52], it was reported that the number of false positives was 21 in 3741 hours of recordings, which is an equivalent overall FPR of 0.006/h (or 0.14/24h).

Non-contact audio-based seizure detection methods have also been explored. The operation of these systems is based on trying to detect environmental sounds associated to seizures, such as those resulting from moving on top of a mattress [54]. The sensitivities reported were considerably lower than in other sensing modalities, ranging from 4.3% to 62.5% [53]–[55]. The FPR could be calculated from the results reported (total false positives and recording duration were 269 and 1528 hours respectively), giving an overall FPR of 0.18/h [54].

Non-contact detection using video has also been explored [56]–[58], but whilst these approaches seem to offer good performance for convulsive seizures, the latter dramatically drops for other motor seizures or seizures with minor motor manifestations. In terms of the FPR reported, these were 0.78/night [56] and 0.05/night [57]. The duration per night was defined as 8 hours in the former, which is an equivalent of 0.10/h.

Another sensing modality that has been used for seizure detection, albeit not on its own, is the electrodermal activity (EDA). The nervous autonomic response during a seizure can cause increased sweating, reducing skin resistance. This approach proved to achieve good sensitivity (92% to 95%) and FPRs (0.03/h to 0.05/h), but were evaluated on tonic-clonic seizures [59]–[61].

Overall, the performance of different sensing approaches can be improved, at least for certain metrics, when combined together. For example, by combining the data from accelerometers and EMG, a higher sensitivity was achieved in [29] (90.9% sensitivity for the combined approach, versus 86% for accelerometry alone, and 82% for EMG alone; together with a reduced FPR of 0.45/12hr versus the individual 1.94/12h and 0.6/12h). In [30], accelerometry and ECG features were combined, and a better sensitivity was achieved (71% combined versus 56% for accelerometry and 60% for ECG), but at the expense of higher FPR (5.9/night versus 2.3/night and 4.3/night).

Despite the large body of work in the research community looking into different unobtrusive methods involving sensing of a variety of non-brain physiological signals to identify seizures, there has never been any report investigating the possibility of using internal physiological sounds for this purpose. The rationale to investigate this is that physiological functions are known to change around the ictal period, and consequently those changes will likely manifest in variations in the sounds (if any) generated by the organs involved. For example, changes in respiration can occur in focal as well as generalized seizures [10]. Some of these changes include tachypnoea (increase in breathing rate), bradypnea (decrease in breathing rate), respiratory pauses (interrupted breathing lasting less than 15s), apnea (interrupted breathing lasting at least 15s), coughing and the presence of adventitious sounds [11]. And changes in heart rate, which are also known to occur in and around ictal periods [11], also manifest with different cardiac sounds. This hypothesis formed the basis of the work described in this paper.

III. Materials and Methods

A. Database

The signals used in this work were from an existing anonymized research database that had been originally created as part of a study carried out at the National Hospital for Neurology and Neurosurgery (NHNN), London, UK (approved by the UK Health Research Authority, with REC reference number 16/WA/0319). The inclusion criteria for the original study were as follows: patients between the ages of 18 and 70, with focal epilepsy, undergoing pre-surgical assessment, and having a minimum of two seizure episodes a week. Patients not fluent in english, having special communication needs, or being allergic to the sensor's adhesive dressing were excluded.

In the study, internal physiological body sounds were acquired using a custom-made wearable device whilst patients were being monitored with video and EEG as part of the conventional hospital pathway. The sensor was attached to the anterior neck with double-sided adhesive, after the standard monitoring equipment were set up. A receiver mobile device was placed within two meters of the patient. The sensor used was a smaller variant of the one previously published in [62] and was placed on the patient as shown in Fig. 1.

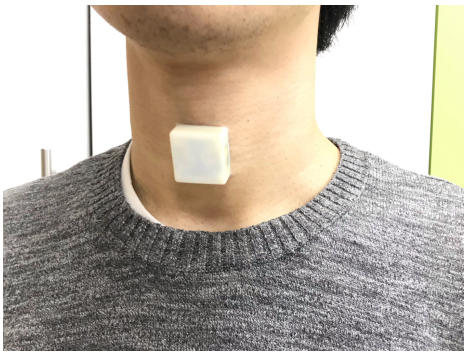

Fig. 1. Placement of the sensing device on the patient. Image shows one of the investigators wearing the device.

The VEEG recordings were reviewed by consultants at the hospital and were used to annotate seizures that occurred during the monitoring period only. The annotations and timestamps of seizure events extracted included the onset and offset of seizures, intervention of nurses, and post-seizure interviews.

Overall, the database used in this work had anonymized signals from 33 subjects (18 male, 15 female). Fifteen out of the 33 subjects in the database had seizures during monitoring and only these were used to develop and evaluate the algorithm presented in this paper. The median age of these 15 patients was 32 years (range: 20 – 53). Four of them were female and the remaining eleven were male. The total duration of the signals in the database was 667.3 hours. The median recording duration per patient was 47.6 hours (range: 4.4h – 76.6h). A total of 36 seizure events had been annotated in these patients. Thirty-one of these events were focal onset seizures, two generalized onset seizure, two focal-to-bilateral tonic-clonic seizures and one unclassified seizure. The median duration of all seizure events was 69s (range: 11s – 700s). Focal seizures had a median duration of 70s (range: 11s – 200s), generalized seizures were 22s and 24s each, focal-to-bilateral tonic-clonic seizures lasted 19s and 58s, and the unclassified seizure was

34s long. Table I shows the seizures' type, characteristics and duration in the database used.

TABLE I
DESCRIPTION OF SEIZURE TYPES AND THEIR DURATION.

Seizure number	Patient number	Seizure type	Motor	Duration (s)
1	8	Focal aware	N	71
2		Focal aware	N	71
3		Focal aware	N	71
4		Focal aware	N	27
5		Focal aware	N	103
6		Focal aware	N	71
7		Focal aware	N	40
8	9	Focal aware	N	51
9		Focal aware	N	41
10		Focal aware	N	23
11		Focal aware	N	42
12		Focal aware	N	37
13		Focal aware	N	45
14	10	Focal aware	N	78
15		Focal impaired awareness	N	700
16	12	Focal impaired awareness	Y	77
17	13	Focal aware	N	76
18		Focal aware	N	137
19		Focal aware	N	193
20		Focal aware	N	65
21	16	Focal aware	Y	68
22		Focal aware	Y	35
23	18	Focal aware	Y	83
24		Focal aware	Y	55
25		Focal aware	Y	36
26	20	Focal aware	N	71
27	21	Focal to bilateral tonic-clonic	Y	55
28	23	Generalized	Y	24
29		Generalized	Y	22
30	24	Focal aware	N	11
31		Focal to bilateral tonic-clonic	Y	183
32	26	Focal impaired awareness	Y	29
33	30	Focal impaired awareness	N	82
34	34	Unclassified	Y	34
35	35	Focal aware	N	56
36		Focal aware	N	79

For the purpose of this study, the signals recorded were labelled as ictal, preictal, postictal and interictal according to Fig. 2. Ictal periods were defined as the five minutes period before the annotated onset of the seizure and ending at the offset annotation. The EEG onsets which were marked by the epileptologists were used (offset = onset + duration); except for one seizure where this information was not available and the clinical onset and offset times were used instead.

The five minutes of signal segments preceding the seizure onset were labelled as 'ictal' to ensure that all seizure data were accounted for in the analysis due to the timing discrepancies in the acoustic and VEEG data acquisition systems.

The preictal and postictal windows were both set at 15 minutes before the beginning and after the end of ictal period respectively. Signal times which did not fall into any of these categories were subsequently grouped as interictal. When

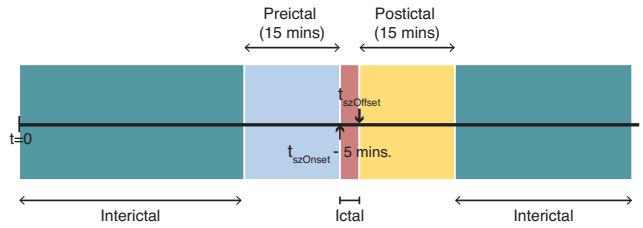

Fig. 2. Definition of stages in acoustic recordings containing seizure. $\mathbf{t_{szOnset}}$: time of seizure onset; $\mathbf{t_{szOffset}}$: time of seizure offset.

defining the ictal stage of the recordings, if a nurse attended to the patient before the seizure offset, the ictal period used in the training was shortened to this time, to exclude data segments from when the patient is in presence of the nurse. This is because when attending to a patient having seizure, the nurses would assess the patients' state of awareness by asking questions and requesting that they perform certain tasks. This would introduce systematic characteristics to the signals, which are unrelated to the physiological status. The risk of including such data was that the classifier could be unintentionally trained to detect these instead of physiological changes.

B. Seizure Detection Algorithm

An overview of the proposed seizure detection algorithm based on internal physiological body sounds is shown in Fig. 3. It consists of the following stages: preprocessing, features extraction, training and classification of seizure epochs using RUSBoost classifiers, followed by the post-processing of the classification results. These stages are explained in the following sections.

1) Data Preprocessing: The signals acquired by the acoustic sensor were sampled at 2000 Hz and filtered with an 8^{th} order Butterworth band-pass filter with corner frequencies of 100 Hz and 900 Hz. This was performed to remove DC components and higher-frequency external acoustic interference that may have been captured by the sensor. The filtered signals were then split into 20s segments, with a 15s overlap. All the extracted segments in the ictal period defined in Fig. 2 were given a label of "1" (seizure segments) and the rest of the segments were labelled "0" (non-seizure segments).

To reduce the risk of the classifier learning systematic features (*e.g.*, patient's speech that happen during and after seizures) over physiological features, some data in the dataset were removed from the classifier training. The removal of such systematic features accounted for approximately 9 hours (or 1.3% of all data segments). Partially overlapped segments (such as those between the preictal and ictal stages, post-ictal and inter-ictal stages, *etc.*), which accounted for approximately 45 minutes, were also excluded from the training of the classifier. In cases where the sensor wireless connection disconnected during data acquisition, segments without signals were also removed. The amount of signal segments removed for this reason was approximately 11 hours (or 1.6% of all data segments). There were no other attempts to remove noisy data or signal segments in the training stage. However, any

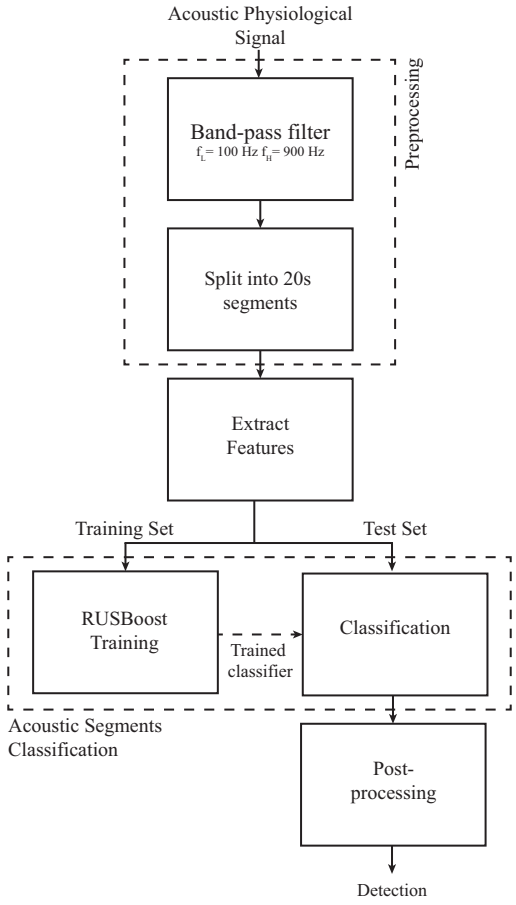

Fig. 3. A high level overview of the proposed algorithm.

data that were removed from the training stage were instead included in the testing and evaluation stage.

The intensity and amplitude of the acquired physiological sounds change throughout the day and could be a characteristic at different stages of seizures. Hence, the recordings were not range normalized because the maximum and minimum values for the full recording were *post-hoc* knowledge and will not be available in real-time monitoring systems. Similarly, data in the 20s segments were also not normalized before features were extracted.

2) Features Extraction: In this stage, the dimensions of the raw acoustic data were reduced by using a set of features to represent the original acoustic segments. Features based on the Mel-frequency cepstrum coefficients (MFCCs) were used in this paper. MFCCs are defined as *"the real cepstrum of a windowed short-time signal derived from the FFT (fast Fourier transform) of that signal"* [63]. These features were chosen because they are motivated by perceptual factors. Their ability to model the human auditory system, in terms of the non-linear perception of loudness and frequency is advantageous [64], and are hence widely used in domains such as automatic speech recognition and speaker identification. Since changes in physiological functions, including respiration do happen during seizures, MFCC features were thought to be ideal for representing the acoustic signals collected by the sensor.

The process of calculating the MFCCs involves the following steps:

i. Windowing the signal
ii. Calculating the FFT of the windowed signal
iii. Calculating the power spectrum from the FFT
iv. Applying a Mel filter bank to the power spectrum
v. Summing and logging the energy in each frequency band
vi. Finally, applying the discrete cosine transform (DCT) to the logged summed energy results in the MFCCs.

In this work, MFCC features were extracted from each 20s sound segments using the *"rastamat"* library [65]. The first 13 coefficients returned by the function were retained. These correspond to an energy coefficient and 12 cepstral coefficients. This number of coefficients is commonly used in audio recognition and classification tasks, as it represents the lower frequency components that are related to the timbre of the signal [66]. A sample segment from the interictal period as well as the ictal period are shown in Fig. 4.

3) Classification of Acoustic Seizure Segments: The random under sampling and boosting (RUSBoost) classification algorithm [67] was selected for the task of classifying seizure acoustic segments from the ictal stage, and non-seizure acoustic segments from the interictal and preictal stages. Since the data collected were from long-term monitoring, the amount of data samples corresponding to seizure events were much smaller when compared to those in the non-seizure periods. To illustrate the class imbalance in this work, data segments from ictal periods only formed 0.5% of the entire dataset. Regular classifiers generally do not work well in datasets with such class imbalance, and this results in strong bias towards the class with more samples. Therefore, to effectively learn from the dataset, a classification algorithm that is equipped to handle the class imbalance, the RUSBoost, was used.

The training of classification models was carried out in a workstation using the Statistics and Machine Learning Toolbox in MATLAB 2018a. The base classifier used in MATLAB for RUSBoost was a Classification and Regression Tree (CART). Acoustic segments in the dataset were randomly split into training and test sets in each iteration, with 70% of all segments making up the training set, and the remaining 30% forming the test set. In each iteration, the RUSBoost model was trained using only data segments from the training set. For every learning cycle of the RUSBoost base classifier, a subset of the training data was selected at random (the random undersampling part of RUSBoost) until an equal number of samples per class was obtained to train the base classifier (*i.e.*, a minority class ratio of 50%). The number of learning cycles used in this work was 50 to maximize the chance of different data points being used in the training, stage while keeping the time it takes to train the models reasonable. Fifty iterations of the RUSBoost model training were performed, and the results of samples from the test set were aggregated by majority voting.

4) Classification Post-processing: A post-processing stage is added to help reduce the dependency on individual segment classification results to detect seizures, which may cause isolated false positives.

The post-processing stage works as follow. It looks at the classification outputs, C, for the previous M acoustic segments

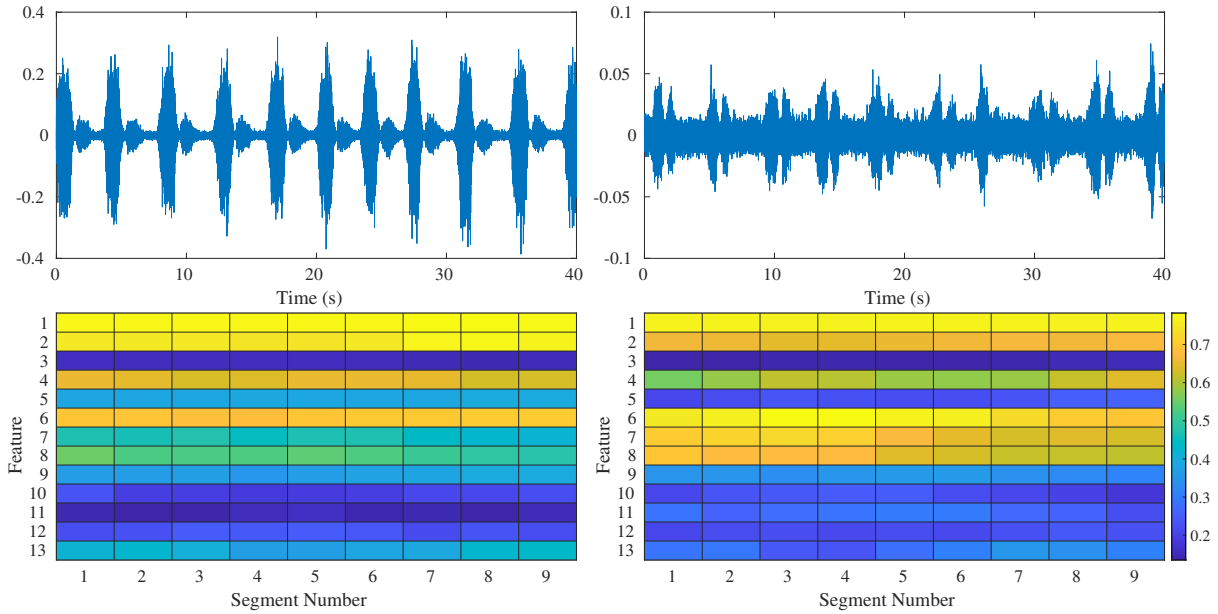

Fig. 4. Raw acoustic signals and the extracted features from one of the patients recording in the dataset. **Upper left**: The filtered acoustic signals taken during the interictal period. **Lower left**: The features extracted for signals from the same interictal period. **Upper right**: The filtered acoustic signals taken during the ictal period. **Lower right**: The features extracted for signals from the same ictal period.

and calculates the ratio according to (1).

$$p = \frac{1}{M}\sum_{i}^{M} C(i) \tag{1}$$

Then, the ratio, p, is compared to a predetermined threshold, thr. If the ratio is greater than the threshold, the algorithm then indicates that a seizure has occurred. Mathematically this is represented by (2), where a 0 at the output (H) indicates that no seizure is happening and 1 that a seizure is happening.

$$H = \begin{cases} 0 & p < thr \\ 1 & p \geq thr \end{cases} \tag{2}$$

A refractory period of 1 minute was also assumed and hence any subsequent seizure detected within this window was considered part of the same event.

5) Performance Evaluation: The entire recordings for the patients were used in the evaluation analysis. The metrics commonly reported to measure the performance of seizure detection algorithms [12], were also used in this work, these are the:

- Event sensitivity,
- False positive rate (FPR), and
- Detection latency.

The event sensitivity was defined as the ratio of detected seizures to the total number of seizures in the database. A seizure was considered detected if there was at least one detection output by the algorithm around a predetermined time window of a marked seizure onset. This time window is defined as the true positive window in this paper. Two window lengths were evaluated in this paper, 90s and 5 minutes. A window length of 5 minutes was used due to the ictal period timing that was previously defined in Fig. 2. The event sensitivity is mathematically defined in (3).

$$Event\ \ Sensitivity = \frac{Number\ of\ seizures\ detected}{Total\ number\ of\ seizures} \tag{3}$$

Likewise, if any detection fell outside of this window, it would automatically be considered as a false positive. The FPR metric was calculated by summing the number of false positives and normalizing it to the length of the recording in hours, as shown in (4).

$$FPR = \frac{Number\ of\ false\ positive}{Recording\ duration} \tag{4}$$

Detection latency was calculated as the time difference between the first detection in the true positive window of a seizure to the onset of that seizure, shown in (5).

$$Detection\ \ Latency = t_{detection} - t_{seizureOnset} \tag{5}$$

Some of the patients in the dataset had more than one seizure during their monitoring period, resulting in clusters forming in the data. The corrected event sensitivity was therefore calculated to account for the presence of such data clusters, using the method described in [61]. The intraclass correlation for a single proportion was first calculated [68], then the corrected event sensitivity and its 95% confidence intervals were found using the Wilson score modified for clustered binary data [69], utilizing the intraclass correlation that was calculated in the previous step.

In addition to the evaluation of the seizure detection algorithm's performance, the performance of the classifiers in identifying seizure breath segments was also evaluated. The following metrics were used:

- Classification sensitivity
- Classification specificity

Classification Sensitivity (SENS), measured the number of seizure acoustic segments correctly identified by the classifier, namely:

$$SENS = \frac{TP}{TP + FN} \tag{6}$$

Classification Specificity (SPEC), measured the number of non-seizure acoustic segments correctly identified by the classifier, namely:

$$SPEC = \frac{TN}{TN + FP} \tag{7}$$

In the equations above,

- TP was the number of seizure segments correctly classified
- FP was the number of misclassified non-seizure segments
- TN was the number of non-seizure segments correctly classified
- FN was the number of misclassified seizure segments.

IV. Results

The performance of the algorithm for detecting seizures was assessed using the performance metrics defined in the previous section. Through a majority voting process, if more than half of the classification outputs from the trained classification models were positive, the sample would be labelled as a seizure segment. The post-processing step was then applied to the newly labelled segments, using $M = 10$ and $thr = 1$, which were found as part of the algorithm development using the data from patients with seizures corresponding to the training dataset. The value for M represented just over one minute of data, corresponding to the median duration of seizures in the database. The threshold, thr of 1 was used as the classifiers trained had achieved good performance in identifying acoustic segments belonging to seizure and non-seizure parts of the recordings.

Two different true positive window lengths of 90s and 5 minutes, and the performance for each patient using the two window lengths are shown in Table II. The detection latencies for each seizure in the database evaluated using two window lengths of 90s and 5 minutes can also be found in Table III. A true positive window length of 90s effectively meant that all the positive outputs (or detections) by the algorithm around 90s of the marked seizure onsets would be considered as true positives and the seizure event considered as detected. Using this window length, the algorithm detected 33 out of the 36 seizure events, equivalent to an event sensitivity of 91.7%. The corrected event sensitivity was 88.1% (95% CI: 79% – 97%). The FPR was found to be 0.83/h (551 false detections in 667.3 hours of recording). The median FPR per patient was 0.53/h (range: 0.13/h – 3.36/h) and the median detection latency was -42s (range: -90s – 58s). Using the longer true positive window of 5 minutes, all seizure events in the dataset were successfully detected, resulting in an event sensitivity of 100%. After adjusting for clusters in the data, the corrected event sensitivity was 95.1% (95% CI: 90% – 100%). The FPR was also lower, at 0.70/h (469 false detections in 667.3 hours of recording), and the median detection latency was -243s (range: -295s – -117s). The median FPR per patient was 0.40/h (range: 0.05/h – 3.16/h).

Additionally, the algorithm was also tested on the set of patients that did not have recorded seizures during their monitoring or were not used in the training due to missing seizure recordings. In these patients, the median FPR per patient was 0.27/h (range: 0.00/h – 1.13/h). The results for each patient are shown in Table IV.

The classification stage of the seizure detection algorithm achieved a specificity of 90.64% and a sensitivity of 87.94% for seizures in the dataset. Table V shows the performance for different seizure types. Patient-specific metrics of the classification are also shown in Table VI. The median classification sensitivity attained across 15 patients was 88.82% (range: 72.86% – 96.09%), and the median specificity was 91.95% (range: 76.17% – 97.06%).

V. Discussion

In this work the feasibility of using physiological body sounds using a neck-worn wearable acoustic monitor, to automatically identify epileptic seizures has been investigated. An algorithm has been presented that was able to successfully detect 33 out of 36 seizures using a 90s true positive window around seizure events, and a FPR of 0.83/h. When using the 5 minute window, all seizures in the dataset were detected, with a FPR of 0.70/h. In recordings from patients with no seizure events, the algorithm resulted in a FPR of 0.37/h (246 false positives in 670.6 hours) and a median FPR per patient of 0.27/h (range: 0.00/h – 1.13/h), showing its ability to discriminate between seizure and non-seizure activity in acoustic signals.

The three seizures missed by the algorithm were seizures 9, 21 and 32 (in Table I), which belonged to different patients. The seizures missed all had a focal onset, but the secondary characteristics such as the presence of motor elements and awareness were different. It was noted though that using the longer true positive window, the algorithm appears to be able to detect them, indicating that there could be features in the lead up to the ictal periods that were detectable by the algorithm. Further analysis of the results revealed that the false positives reported by the algorithm were present around times when the recorded signals of interest were of lower quality, typically close to the noise floor of the sensor, and occasionally due to speech. Hence, optimizing the electronic design of the system, and introducing an artefact rejection preprocessing stage, potentially having a night/day mode, will likely improve the algorithm performance. While source separation techniques such as the empirical mode decomposition (EMD) or wavelet-based methods were not used in this preliminary work, it would be worth exploring separately in future works the effect these might have in enhancing the quality of the sensed signals and whether they could further improve the performance of the algorithm itself, with respect to just using a filter like the one used in this work. Moreover, false positive detections in some patients were also found to occur close to each other. Thus, increasing

TABLE II
SEIZURE DETECTION RESULTS FOR PATIENTS WITH SEIZURES DURING MONITORING, EVALUATED USING TRUE POSITIVE WINDOWS OF 5 MINS AND 90S.

Pat. Num.	Total Duration (h)	Num. Events	5 mins Event SENS	5 mins FPR (/h)	90s Event SENS	90s FPR (/h)
8	45.20	7	1	1.79	1	2.28
9	74.02	6	1	1.05	0.83	1.24
10	47.58	2	1	0.46	1	0.57
12	64.53	1	1	0.23	1	0.28
13	39.25	4	1	3.16	1	3.36
16	55.16	2	1	0.05	0.50	0.13
18	68.04	3	1	0.40	1	0.53
20	14.76	1	1	0.20	1	0.34
21	4.42	1	1	0.23	1	0.90
23	22.13	2	1	0.77	1	0.95
24	73.87	2	1	0.41	1	0.49
26	12.80	1	1	0.78	0	0.94
30	19.23	1	1	0.10	0	0.26
34	49.77	1	1	0.36	1	0.42
35	76.56	2	1	0.37	1	0.42

*Pat. Num.: Patient number; FPR: False positive rate; SENS: Sensitivity

TABLE III
DETECTION LATENCIES (IN SECONDS) FOR EACH SEIZURE, EVALUATED USING TWO DIFFERENT TRUE POSITIVE WINDOW LENGTHS.

Seizure	5 mins	90s	Seizure	5 mins	90s
1	-180	-65	19	-214	-84
2	-282	-87	20	-152	-87
3	-275	-35	21	-120	–
4	-269	21	22	-238	-48
5	-240	-75	23	-279	-44
6	-288	-28	24	-261	-61
7	-254	-34	25	-237	23
8	-247	-42	26	-244	-4
9	-168	–	27	-272	-27
10	-208	-48	28	-216	-86
11	-224	-29	29	-235	-90
12	-241	-76	30	-226	-31
13	-160	-30	31	-272	-27
14	-117	58	32	-254	–
15	-295	-35	33	-237	-62
16	-237	-42	34	-274	-39
17	-187	-57	35	-259	-14
18	-244	-39	36	-260	-65

TABLE IV
FALSE POSITIVE RATES (FPRS) FOR PATIENTS IN THE DATABASE THAT DID NOT HAVE SEIZURES DURING MONITORING.

Patient Number	Total Duration (h)	FPR (/h)
2	1.06	0.00
3	38.70	0.03
4	10.07	0.30
5	34.67	0.09
7	25.07	0.16
11	14.91	0.27
14	64.36	0.08
15	47.58	0.42
19	96.77	0.39
22	56.40	0.89
25	6.17	0.81
27	85.19	0.22
28	47.66	1.13
29	22.95	0.30
31	56.13	0.27
32	32.29	0.06
33	1.29	0.00
37	29.31	0.55

*FPR: False positive rate

TABLE V
CLASSIFICATION METRICS FOR DIFFERENT TYPES OF SEIZURES SEGMENTS.

	Num. Events	SENS (%)	SPEC (%)
All Seizure	36	87.94	
Focal Seizure	31	87.96	
Generalized Seizure	2	80.94	90.64
Focal to Bilateral Seizure	2	90.52	
Unclassified Seizure	1	96.09	

*SENS: Sensitivity; SPEC: Specificity

TABLE VI
PATIENT SPECIFIC METRICS FOR SEIZURE ACOUSTIC SEGMENTS CLASSIFICATION.

Patient Num.	Num. events	SENS (%)	SPEC (%)
8	7	90.47	83.09
9	6	88.82	84.56
10	2	85.69	92.02
12	1	95.22	91.95
13	4	89.30	76.17
16	2	81.36	97.06
18	3	92.17	92.61
20	1	72.86	90.08
21	1	87.85	88.96
23	2	80.94	87.69
24	2	94.24	94.40
26	1	75.16	91.93
30	1	89.43	96.14
34	1	96.09	94.05
35	2	84.98	93.81

*SENS: Sensitivity; SPEC: Specificity

the duration of the refractory period, in which consecutive detections are grouped, might be able to reduce the number of false detections of this type. Tuning the algorithm, based on known patient specific disease characteristics might also be a way to optimize its performance. Long-term monitoring could help in the collection of enough information from the same patient so that the process of personalizing those parameters could take place automatically and be updated periodically. And depending on the final intended use of any device created

based on this methodology, adapting the post-processing stages could lead to better overall performance within the context of its application. Aside from the introduction of an additional step in the pre- and post-processing stages, the performance of the algorithm might potentially be also optimizable by using a larger database of signals for training.

Compared to other wearable systems described in Section II, the FPR achieved in this work is indeed noticeably higher. The range of FPR reported for studies using wearable systems were under 0.11/h [21], [22], [32], [34], [38], [43], [46], [59]. Nevertheless, it is important to note that this comparison is against algorithms developed and assessed on other seizure types, namely tonic, clonic and/or tonic-clonic. On the other hand, comparing the results of this paper with studies that were evaluated on mostly non-convulsive seizures, only two, [43] and [46] reported lower FPRs, at 0.9/24h and 1/24h respectively. The remaining two studies reported higher FPR, at 1.9/h [45]; and in the other, [42], it was between 1.8/h and 2.1/h, depending on the modality and system (ECG or PPG) examined. Whilst the FPR is below one (*i.e.*, the threshold under which a device is considered to be usable), it is still on a higher side. There could be the opportunity to tune the algorithm parameters so that the FPR is reduced, but this will come at a cost, and may result in a decrease in sensitivity. However, it is worth mentioning that the work presented here represents the first attempt to use acoustic physiological signals in this context and as a result, it is reasonable to assume that more research could lead to significant improvements.

A practical advantage to wearable sensing at the neck lies in the vast amount of information that could be captured, using just a single, small wearable sensor. Compared to the limited number of physiological channels (typically two, PPG and movements) that can be acquired from other sensing sites, the neck can give access to airflow, photoplethysmography (PPG), movement and cardiac sounds [70], [71]. One limitation, however, of a wearable neck sensor is that it might only be widely acceptable for all patients to wear during the night.

In terms of the limitations of this work, it is worth noting that the data contained in this database was from patients with focal epilepsy. It would be useful to also evaluate the hypothesis, methodology, and potentially efficacy of the algorithm using signals from other types of epilepsy patients. The decision to include data from the five minutes preceding a seizures onset as 'ictal' also had a knock-on effect, and is reflected in the detection latency of the algorithm. For this reason, the algorithm had negative detection latencies in most of the detected seizures, which makes it appear to be predicting them ahead of the actual seizure onset.

To the best of the authors' knowledge, the algorithm presented in this paper is the first demonstration of seizure detection using acoustic internal body signals sensed on the neck. As a result, there are no existing studies that could be referred to for a direct comparison of the results. However, if these were compared with the results obtained in studies focused on other non-EEG based methods, the performance is found to be comparable to the best ones reported. And although some methods reported slightly better sensitivity, these generally either: did not report specificity/false positive rate (FPR) [20], [25], [27], [39], [41]; and/or relied on cumbersome approaches [29], [36], [39], [41], [47]; and/or had been tested on a very small database (less than 15 subjects/15 subjects with seizures: [16], [19], [20], [25], [26], [29], [32], [39], [56], less than 36 seizures: [16], [19], [22], [26], [29], [37], [52], [59]); and/or the performance massively degraded (or had not been tested) when seizures were not of generalized tonic clonic nature (GTCS) and/or involved minor motor seizures [21], [46], [47]; and/or were privacy intrusive [56], [57].

When used as a standalone seizure detection system, the algorithm showed specially promising results in the detection of non-convulsive seizures, which was the main type of seizure in this dataset. This would be particularly useful for patients whose primary seizure type may not be convulsive, and for whom existing systems based on the detection of convulsive movements would be known *a priori* not to work. It is worth noting though, that the approach presented in this paper does not invalidate the others. If used in conjunction with existing algorithms and sensing modalities, it could provide additional seizure detection input and might help to significantly improve the overall seizure detection performance. These improvements could be not only in terms of the reduction in the FPR, but also the sensitivity towards non-convulsive seizure, for which other conventionally used sensing modalities systems aiming to detect the seizure movements fail to work.

VI. Conclusion

Having a non-intrusive and easy to use monitoring system capable of providing a quantitative measure of seizure occurrence from long-term monitoring, even if the detection is not perfect, could allow doctors to better understand the progression of epilepsy patients, potentially leading to personalized optimizations in the management of the condition. This paper investigated the feasibility of extracting useful seizure related information from a physiological sensing modality that has not been investigated before: acoustic sensing from the neck. A novel machine learning algorithm for automatic detection of seizures was developed, that achieved a detection sensitivity of 88.1% (95% CI: 79% – 97%) after correcting for cluster effect, and a FPR of 0.83/h. This demonstrates the potential of acoustic sensing from the neck as an alternative method to EEG, and potentially complementary to other surrogate physiological modalities, particularly in the context of home-based long-term monitoring and management of epilepsy.

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