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Multimodal detection of typical absence seizures in home environment with wearable electrodes

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Patients with absence epilepsy fail to report almost 90% of their seizures. The clinical gold standard to assess absence seizures is video-electroencephalography (vEEG) recorded in the hospital, an expensive and obtrusive procedure which requires also extended reviewing time. Wearable sensors, which allow the recording of electroencephalography (EEG), accelerometer and gyroscope have been used to monitor epileptic patients in their home environment for the first time. We developed a pipeline for accurate and robust absence seizure detection while reducing the review time of the long recordings. Our results show that multimodal analysis of absence seizures can improve the robustness to false alarms, while retaining a high sensitivity in seizure detection.

KEYWORDS

epilepsy, typical absence seizures, multimodal, EEG, wearables, home monitoring, accelerometer, gyroscope

1 Introduction

Absence seizures are the main seizure type in various idiopathic generalized epilepsy syndromes, among others, in juvenile absence epilepsy (JAE) (Hirsch et al., 2022). Typical absence seizures are characterized by motor arrest and impaired awareness. On the electroencephalogram (EEG), they are visualized by 3–4.5 Hz generalized spike-and-wave discharges. In patients with JAE, lifelong treatment with antiseizure medications may be required as relapse after withdrawal is high (83%) (Hirsch et al., 2022). Even patients who are considered to be seizure free under treatment, can still relapse (25%).

It is, therefore, paramount to accurately detect absence seizures in order to improve therapeutic decisions. However, the subtle clinical manifestation of absence seizures hampers the patient's and the caregiver's ability to correctly report the seizure in the seizure diary. In studies with patients with absence seizures, 86%–94% of the absences are not reported (Keilson et al., 1987; Akman et al., 2009; Swinnen et al., 2021). As such, the

seizure diary is an unreliable method, although commonly used in clinical practice as well as surrogate endpoint in trials for antiseizure medication (Fisher et al., 2012).

Current diagnostics are based on the clinical history and in-hospital monitoring of seizures with video-EEG (which is considered the gold-standard for seizure detection). Hence, devices that could record the seizures during normal everyday life conditions could facilitate a better logging of the seizure events, as the use of ambulatory EEG is limited due to the complexity of placement and the visibility and constraints in daily life.

An explosion in the capability of monitoring individuals *via* sensors built into smartphones or wearable devices has been taking place. Following the views of the patients, the devices need to be “as ‘normal’ as possible,” “non-stigmatizing” and “non-intrusive” (Bruno et al., 2018). Furthermore, the majority of the patients were willing to use a wearable device for long-term seizure tracking, envisaged by the possibility of understanding their condition better. The detection of absence seizures with wearable devices is a very suitable use-case, since the number and location of electrodes is likely to be less important than in focal epilepsies (Duun-Henriksen et al., 2012).

However, the clinical adoption of wearable EEG remains challenging, since no phase-4 clinical study, proving the feasibility and comfort of the device in a home environment, has yet been conducted. Furthermore, there are challenges regarding the signal quality and the time needed by the neurologists to annotate the data. Hence, research for automated seizure detection algorithms, tailored for wearable EEG, is still in its infancy, especially in wearable detection of absence seizures (Kjaer et al., 2017; Dan et al., 2020; Swinnen et al., 2021; Japaridze et al., 2022), (semi) automated seizure detection would facilitate the adoption of EEG wearables in clinical practice. Furthermore, even the annotation of wearable EEG data, compared to vEEG, is not trivial (Zhang et al., 2022).

In a previous paper (Swinnen et al., 2021), we reported the performance of an EEG-based wearable, CE marked device to detect absence seizures, the Sensor Dot (SD; Byteflies). SD is a discrete, user-friendly wearable that consists of four electrodes, creating two ipsilateral channels. This device was developed during SeizeIT1 (2016–2019). The initial results currently reported belong to an extension of SeizeIT1, SeizeIT2 which is a larger multicenter trial with focus on clinical validation of the SD in people with typical absence, focal impaired awareness, and generalized tonic-clonic seizures (EIT Health: SeizeIT2, [clinicaltrials.gov: NCT04284072](https://clinicaltrials.gov/ct2/show/study/NCT04284072)) (EIT Health, 2020).

In the same paper we proposed a novel automated absence detection algorithm which achieved a mean sensitivity of 0.983 in the detection of absence seizures, with mean False Alarm (FA) per hour equal to 0.9138. The use of the automated algorithm reduced the review time of a 24 h recording from 1 to 2 h to around 5–10 min for the neurologists.

Nevertheless, the reported results in (Swinnen et al., 2021) were obtained from data acquired within the hospital environment. We argued that the first phase of the recording of each patient will consist of routine monitoring in the EMU after which these data can be used to train the algorithm. The obtained classifier can be used to detect seizures from the data acquired when the patient wears the SD at home. Similar assumptions are being made by all of the aforementioned studies with wearable devices and absence seizure detection. Even in the phase-3 clinical trial of Epihunter (Japaridze et al., 2022), the data were not obtained in an actual home environment [as proposed in (Beniczky and Ryvlin, 2018)].

As observed from the data obtained from the patients in the home environment with SD, the performance of the automated seizure annotation was lower, compared to the performance of the algorithm trained and tested with data obtained in the hospital (Swinnen et al., 2021), especially in terms of FAs. In the current paper we will present a pipeline for the automated absence seizure detection for in-home monitoring, which will be tested and validated, for the first time, with data obtained from patients with absence seizures in their home environment. The focus of the current paper will only be the algorithmic pipeline, used to flag the possible seizures, the physiological findings of the home studies will be released in future publications. The goal of the pipeline is to be used by the neurologists in the rest of the subjects and reduce the time needed to annotate the data. The neurologists are requested instead of reviewing the whole recording to only review the provided alarms from the algorithm.

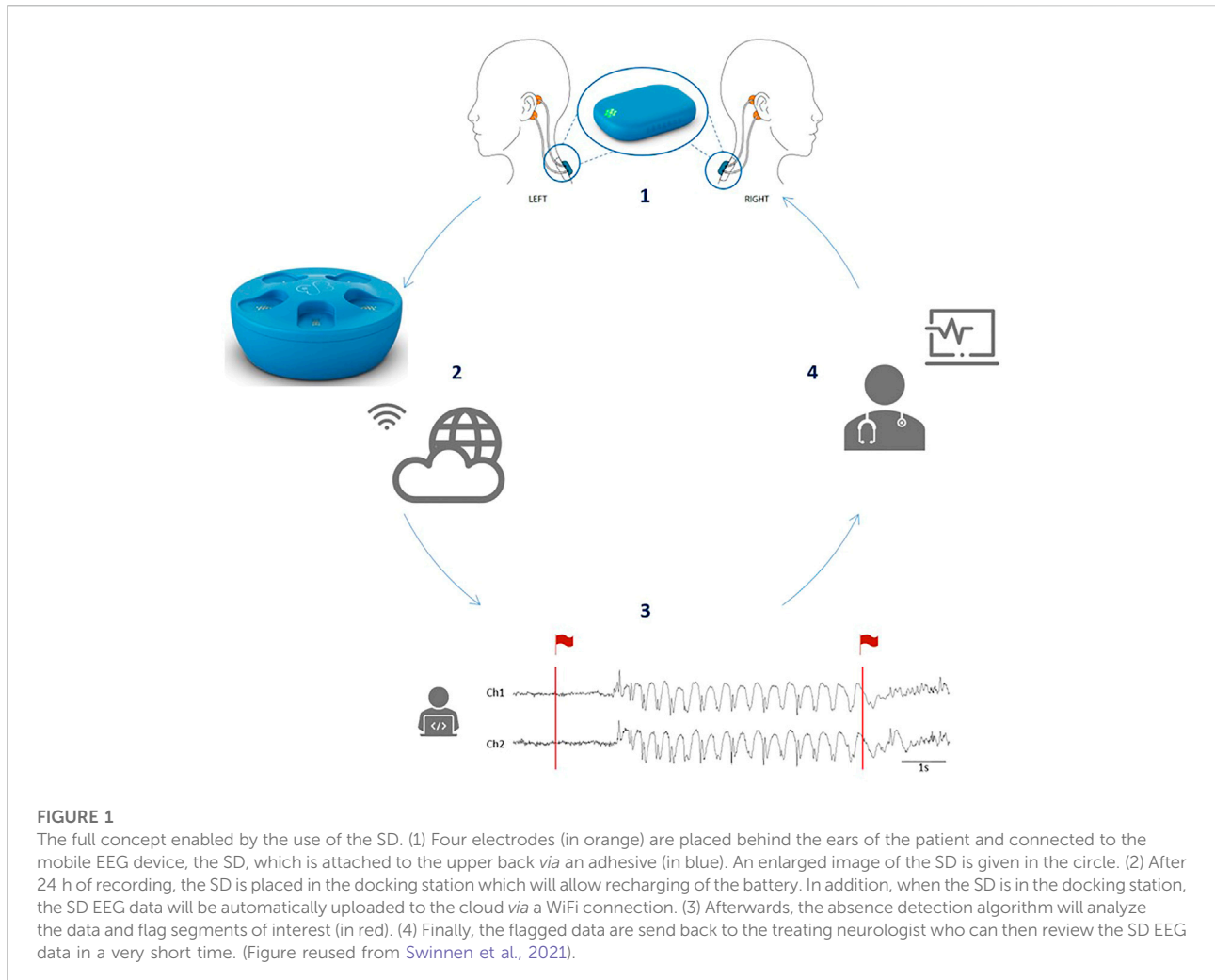
2 Materials and methods

2.1 Patients

The current home-based phase of the SeizeIT2 study, is a follow up of the phase-2 clinical study of SeizeIT2 presented in (Swinnen et al., 2021). In total 13 patients were enrolled in two epilepsy centers: University Hospital Leuven and University Hospital Freiburg. Patients with a confirmed electroclinical diagnosis of refractory Juvenile Absence Epilepsy were enrolled between 11 March and 15 June 2022 if they had previously participated in the in-hospital phase (Phase 2 study). Here, we used data of the first four patients (mean age = 21 years; 3 female, 1 male) that were enrolled, to explore the algorithmic pipeline.

In addition we included one patient with refractory absence epilepsy, which is part of a long term monitoring study in patients with different seizure types (Plug&Patch—PnP, [clinicaltrials.gov: NCT04642105](https://clinicaltrials.gov/ct2/show/study/NCT04642105)), who had only measured EEG at home with SD.

All patients from the trials gave written informed consent and the studies were approved by the ethics committee of UZ/KU Leuven.



2.2 Data collection

The patients had been initially admitted to UZ Leuven and were followed for a 24-h vEEG monitoring (Schwarzer EEG amplifier, O.S.G.) using the standardized 25-electrode array of the International Federation of Clinical Neurophysiology. Behind each ear, two additional Ag/AgCl cup electrodes (Ambu Neuroline cup, Ambu) were attached on the mastoid bone for concomitant recording with the SD. The SD, a small device of $24.5 \times 33.5 \times 7.73$ mm (mm) and 6.3 g, was attached on the upper back using a patch (Figure 1), and two bipolar channels were created by connecting the ipsilateral top and lower electrode. Impedance was $\leq 5k\Omega$ at the beginning and checked throughout. The sampling rate of the SD and video-EEG was 250 Hz. Battery life and memory storage of the SD were 24 h and 2 Gb, respectively.

For the home-based study, all five patients received *via* post the SD kit (Byteflies, Belgium), containing the two-channel EEG-based SDs, the EEG-holder, the docking station, and four Ambu BRS neonatal electrocardiography (ECG) adhesive electrodes, here used for behind-the-ear EEG. The Inertial Measurement Unit (IMU) is

embedded in the SD and are collected simultaneously with the EEG data. They received instructions on paper and *via* phone call on how to install the docking station and connect it to Wi-Fi in order to allow upload of SD data to the cloud. They were also instructed on how to place the electrodes behind the ears on the mastoid bone, two on each side of the head, with the upper and lower electrode being approximately 5 cm apart. Electrodes on the same side had to be connected to create two ipsilateral, left and right, EEG channels. Impedance was not checked in the home-environment. Four of the patients had one SD recording at home lasting 22, 23, 24, and 24 h, respectively. The fifth patient had SD recordings at home during 16–24 h per day, twice per week for several months¹.

¹ Following (Swinnen et al., 2021) the definition was selected for research purposes only, considering that we aimed to study whether these typical EEG patterns can be equally detected by the ML algorithm. A 3 s 3-Hz SWD might not always have a clinical correlation (Guo et al., 2016).

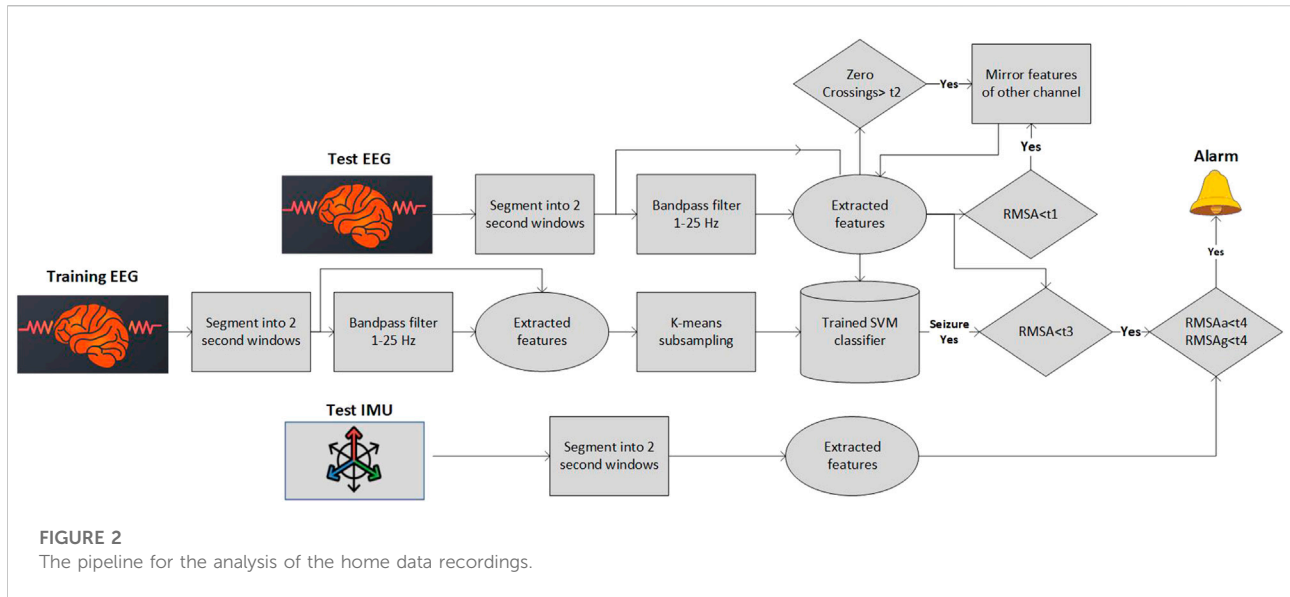


FIGURE 2 The pipeline for the analysis of the home data recordings.

2.3 Pipeline for the ML-based seizure detection

The pipeline that we have used for the analysis of the in-home recordings consists of several blocks (Figure 2). The main Machine Learning (ML) algorithm is similar to the one used in (Swinnen et al., 2021) with minor modifications (as will be described). Extra blocks have been added in order to detect movement artifacts, flat lines and disconnected electrodes which constitute a significant portion of the in-home recordings. All the pipeline blocks will be described in detail in the following subsections.

2.3.1 Preprocessing and segmentation

Each EEG SD channel was filtered with a bandpass filter (1–25 Hz). Subsequently, the data were segmented in 2-s windows with 50% overlap. The same segmentation process was performed for the signals of the IMU, the accelerometer and the gyroscope, which is embedded in SD.

2.3.2 Balancing the classes

The seizure detection task is a highly unbalanced problem. Limited number of seizure segments exist and the background (non-seizure) segments are dominant. As noted in (Swinnen et al., 2021) when a random subsampling of the background data is implemented the algorithm suffers from stability issues, with high standard deviation of the sensitivity and the false alarm rate. Therefore, different under-sampling approaches have been tested and we opted for the use of an adapted version of the cluster-based under-sampling approach (Yen and Lee, 2009). The number of background samples, N_k , selected from each cluster

k was set equal to $N_k = mS_s \frac{S_{b_k}}{S_b}$. Where m is the ratio between the background and seizure samples we aimed to obtain in our training set, K is the number of clusters on which we clustered all the background samples and S_s , S_b and S_{b_k} are the total number of seizure samples, the total number of background samples and the number of background samples in the k cluster, respectively. Similarly, to (Swinnen et al., 2021) m was set equal to 25 and $K = S_s$ (which varies per patient).

2.3.3 Feature calculation

The feature set used in this study is similar to the one used in (Swinnen et al., 2021). The feature set was chosen among the features used in (Kjaer et al., 2017) and in (Vandecasteele et al., 2020) after performing Random Forest selection (Deviaene et al., 2019). Our final feature set is given in Table 1. The thirteen different features were extracted from each window and each channel separately. Due to the subject dependent differences in the amplitude of the EEG over time, normalization of the features was needed to achieve optimal detection of seizure events. We have used the median decaying memory as the optimal normalization method for line length features. The main difference between the feature set used in (Swinnen et al., 2021) is the fact that the zero crossings were computed from the raw signal and not the filtered one. Similarly to Swinnen et al. (2021) all the frequency domain features were derived using the raw signal.

2.3.4 Discarding of bad quality segments

We noticed that in home recordings there are some segments (not whole recordings) that one of the channels is either flat, or disconnected. In such cases, the original algorithm that was

TABLE 1 Feature set of EEG.

Time domain	<ul style="list-style-type: none"> • Zero crossings (raw signal) • Cross-correlation between two consecutive windows • Root mean square error amplitude
Frequency domain	<ul style="list-style-type: none"> • Power of the signal in frequency band 1–30 Hz • Relative power of the signal between bands 3–12Hz and 1–30 Hz • Log-Sum of Wavelet Transform: 32–64 Hz • Log-Sum of Wavelet Transform: 16–32 Hz • Log-Sum of Wavelet Transform: 8–16 Hz • Log-Sum of Wavelet Transform: 2–4 Hz • Cross-correlation of same window in two different bands 3–12 Hz and 1–30 Hz • Dominant phase • Mean phase variance • Mahalanobhis variance between each point of the 3–12 Hz band and 1–30 Hz

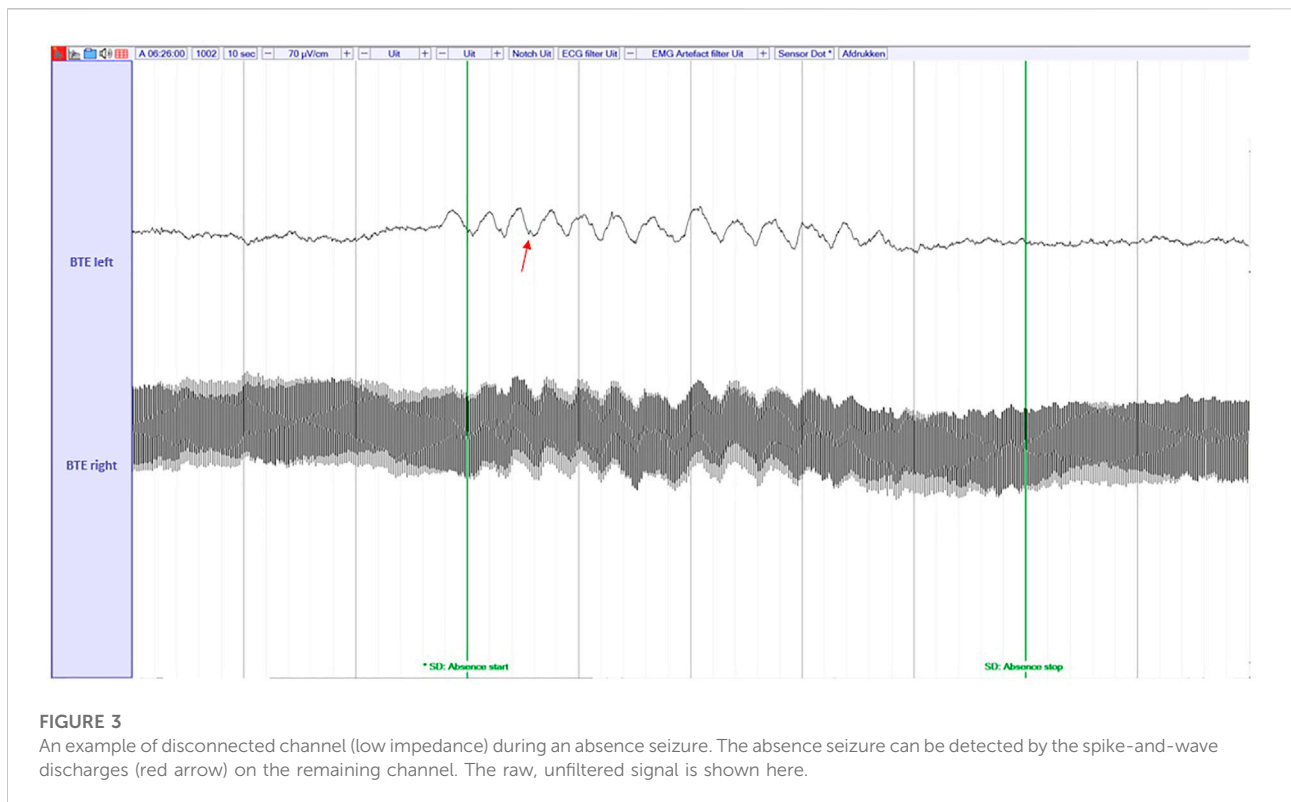
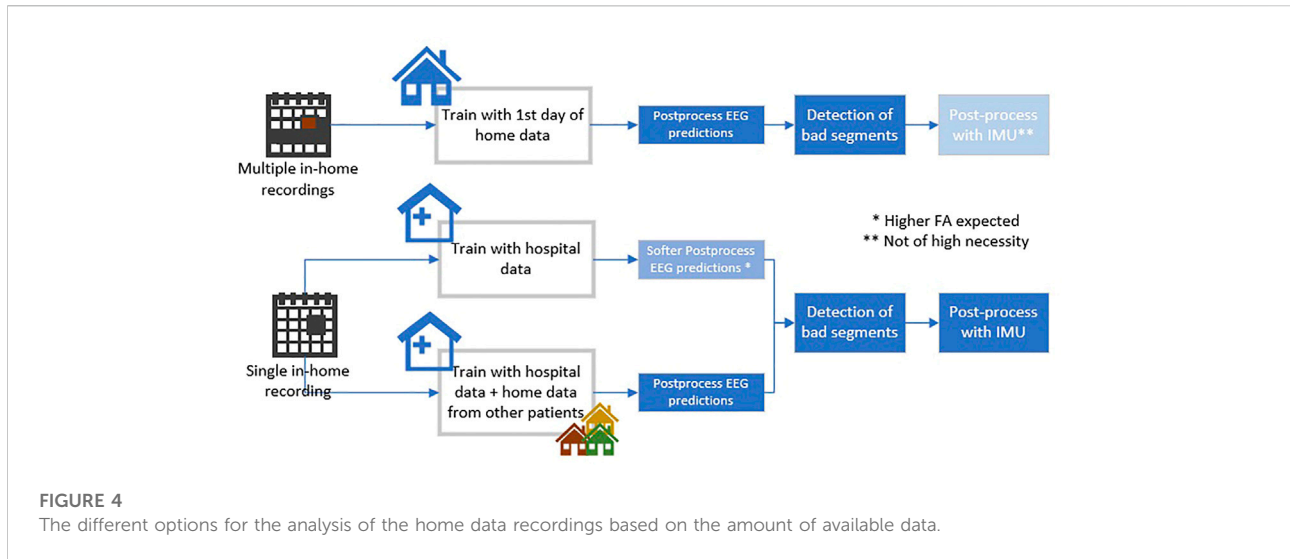


FIGURE 3 An example of disconnected channel (low impedance) during an absence seizure. The absence seizure can be detected by the spike-and-wave discharges (red arrow) on the remaining channel. The raw, unfiltered signal is shown here.

developed to detect seizures based on two channels is not able to capture the seizure solely from the remaining, non-artifacted channel (e.g., such a case can be seen in Figure 3). We do not want to discard the complete recording or the whole channel for

the entire recording in order to maximize the data utility. In every segment (window of 2 s) we check the zero-crossings of the raw signal and the Root Mean Squared Amplitude (RMSA) of the filtered signal. RMSA equal (or very close) to zero indicates a flat



line, a very big number of zero-crossings per segment indicates a possible misplacement of the electrode (high impedance). Hence, we have set two different thresholds $t_1 = 0.01$ and $t_2 = \frac{2F_s}{5}$ (Figure 2), with F_s being the sampling frequency. In the case that the RMSA of the specific segment of one channel is lower than t_1 , or the zero crossings are above t_2 the segment of the specific channel is considered bad and only the features of the other channel are used (the features of the non-bad channel are mirrored in the bad channel).

2.3.5 Training and classification

A weighted Support Vector Machine (SVM) with a radial basis function kernel was used as classifier. Even though a cluster-sized sub-sampling method was used for balancing the clusters, still the ratio m was not set to one but equal to $m = 25$, which is why the weighted version of the classifier was used. The weights given to each non-seizure and seizure data point were $\frac{N+S_s}{2N}$ and $\frac{N+S_s}{2S_s}$, respectively, with N being the number of background samples selected during the sub-sampling and S_s the total number of seizure points.

Three different approaches are being used for the training of the SVM model, based on the availability of the data (Figure 4). We opted for different alternatives for the detection pipeline since the amount of data collected per patient in the home environment fluctuates among different studies (e.g., SeizeIt2 and PnP). The available in-home data determines the best training scheme for the ML models.

- Train with data of the test patient obtained during first day of in-home recording. The first day shall be annotated by the neurologists. This approach shall be used when multiple days exist (PnP study).
- Train with the hospital data of the patient. In this case the post-processing (explained in next subsection) must be

softer in order to capture all the seizures. A bigger number of FAs is expected

- Train with annotated home data from other patients (if available) and “personalize” with the hospital data of the test patient.

The values of the hyperparameters, which resulted in the maximum sensitivity in the training set, were selected for the test set (in our use-case we were looking for maximum sensitivity to mark all possible events after which they were reviewed by an epileptologist). Hence, the hyperparameter search is not likely to overfit the dataset as it is only exposed to the training set.

2.3.6 Multimodal postprocessing

In (Swinnen et al., 2021) (where our models were trained and validated only with in-hospital data) we had a single EEG-based postprocessing rule. As mentioned before with the data obtained from the home of the patients we noticed high FAs rates. Most of the FAs were arising from the movement of the patients within their home environment, which was not present in hospital. In order to minimize the FAs we employed the accelerometer and gyroscope data obtained from IMU. The use of IMU and Electromyography (EMG) data in a multimodal framework is common for the detection of tonic-clonic seizures (Milošević et al., 2016) but has never been employed in the context of absence seizure detection.

Four different postprocessing rules were set:

- If the (normalized) RMSA of the segment is above $t_3 = 200 \mu V$ the segment is considered as artifact and no alarm is provided
- An alarm for seizure detection is given only when three consecutive windows were noted as seizures

TABLE 2 Results of the PNP patient trained with the first day of in-home recording. In the first column in parenthesis the total number of seizures per subject. In the last column the number of seizures missed by the neurologists and detected by the algorithm can be viewed (in the metrics they are counted as FAs though).

Date	EEG		EEG + post		EEG + post + bad		EEG + post + bad + IMU		
	Sens	Fas/h	Sens	Fas/h	Sens	Fas/h	Sens	Fas/h	Extra Seiz
D2-10-21 (2)	0,50	5,60	0,50	0,00	0,50	0,10	0,50	0,10	1,00
D3-11-21 (5)	1,00	5,66	0,80	0,14	1,00	0,14	1,00	0,14	1,00
D4-11-21 (4)	0,75	8,62	0,50	0,12	1,00	0,73	1,00	0,69	3,00
D5-11-21 (2)	1,00	2,61	0,50	0,21	1,00	0,10	1,00	0,10	1,00
D6-11-21 (4)	1,00	11,79	1,00	0,34	1,00	1,29	1,00	1,22	2,00

- Whenever two seizures (of three windows each) were separated only by one non-seizure window, they were merged
- If the standard deviation either of the accelerometer or of the gyroscope is above a specific threshold $t_4 = 0.05$ then the specific EEG segment is considered a movement artifact and no alarm is provided. The multimodal postprocessing based on the IMU data has significantly decreased the FAs in some patients.

3 Results

In this section we will provide some initial results from the two home studies. The selection of the recordings of the patients that were analyzed was based on the number of seizures. We selected the first four patients of SeizeIt2 recorded in 2022 that had at least one absence seizure and the first 6 days of the first absence patient of PnP study for which at least one seizure was recorded. In both datasets, the onset and end of all 3-Hz generalized spike- and- wave discharges (SWD), lasting 3 s or more¹, were marked by neurologists. We will refer to these annotations as “absences,” these annotations were used as the ground truth for the performance metrics that will be presented.

In this section we will try to justify and explain the usability of the different blocks of our pipeline. We will compare the results with the three different training options and to the

algorithm presented in (Swinnen et al., 2021) that was tested only with in-hospital recordings. We must note that for the PnP patient no in-hospital recording exists, hence only the first training option will be used. For the SeizeIt2 patients since we have a single day of in-home recordings we will use options two and three for training.

The following metrics were applied to determine the performance of the seizure detection algorithm [following the definitions in Vandecasteele et al. (2020)]:

- Sensitivity: $\frac{TP}{TP+FN}$. A seizure was detected correctly (TP) if the detection occurred between the EEG onset and end of the seizure. A seizure was not detected (FN) if no overlap between the alarm and the seizure existed.
- FAs/h. FAs within 3 s of each other were counted as one FA.

We will not report specificity measures since for all cases the specificity was above 99%, due to the highly imbalanced classes.

As can be noted from Table 2 in the PnP patient, the postprocessing decreases significantly the Fas/h, with a slight decrease of the sensitivity in most of the recordings. The removal of the bad segments (column 4) retains the low FA rate but increases the Sensitivity, reaching 1 in almost all of the days. There is minor influence from the postprocessing with the IMU data.

For the SeizeIt2 data (Table 3) we can see that the postprocessing has similar effect as in the PnP patient. We shall note the tremendous decrease in the FAs/h for Subj-3. Furthermore, the IMU postprocessing results in a slight decrease in the sensitivity in Subj-3. The decrease is due to the activity noticed in accelerometer and gyroscope during two seizures (Figure 5). We note the very low performance of all the versions of the algorithm in the last Subject.

¹ Following (Swinnen et al., 2021) the definition was selected for research purposes only, considering that we aimed to study whether these typical EEG patterns can be equally detected by the ML algorithm. A 3 s 3-Hz SWD might not always have a clinical correlation (Guo et al., 2016).

TABLE 3 Results of the Seizelt2 patients trained with the hospital recordings. In the first column in parenthesis the total number of seizures per subject.

Subject	EEG		EEG + post		EEG + post + bad		EEG + post + bad + IMU	
	Sensitivity	Fas/h	Sensitivity	Fas/h	Sensitivity	Fas/h	Sensitivity	Fas/h
Subj-1 (23)	0,96	15,60	0,91	2,64	1,00	2,76	1,00	2,60
Subj-2 (72)	0,92	9,66	0,88	0,74	0,99	0,76	0,93	0,63
Subj-3 (4)	0,75	42,34	0,75	38,43	1,00	41,40	1,00	1,22
Subj-4 (55)	0,13	20,32	0,11	12,59	0,13	19,49	0,13	9,72

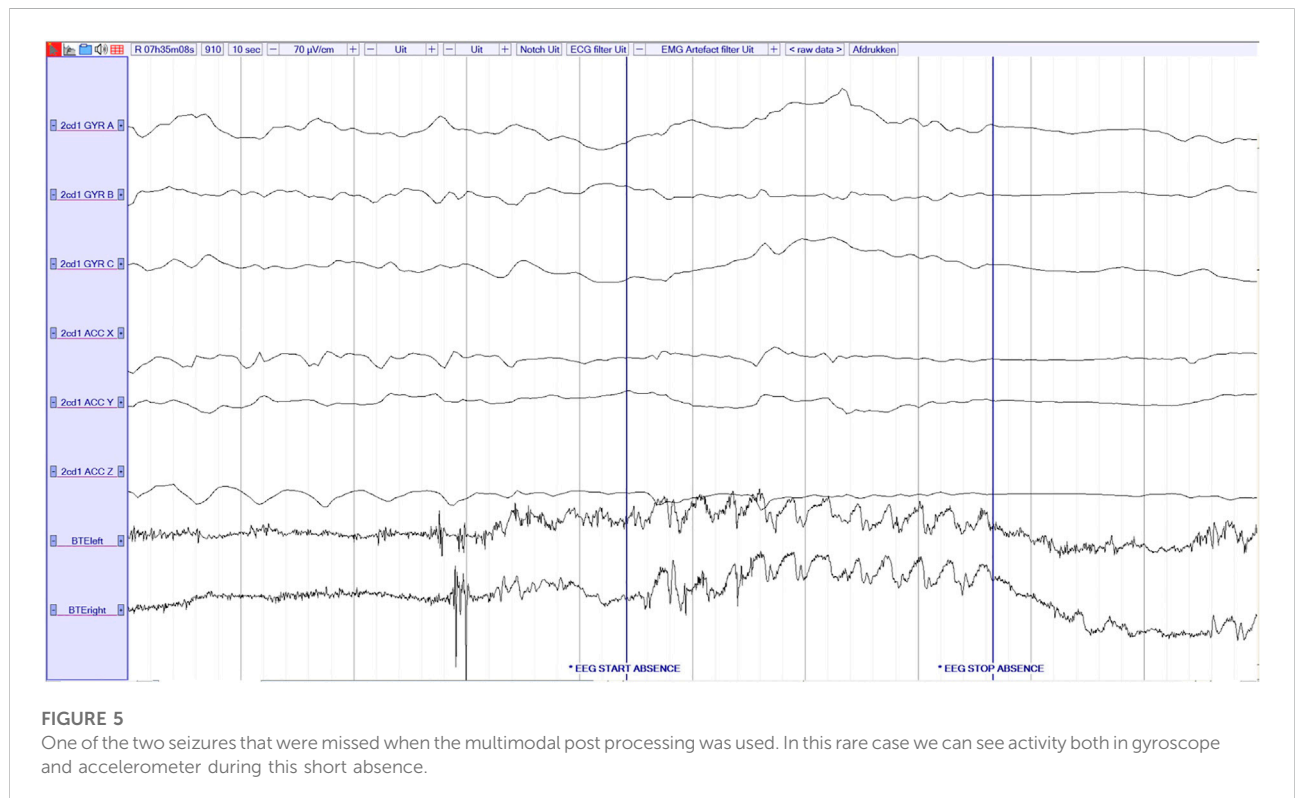
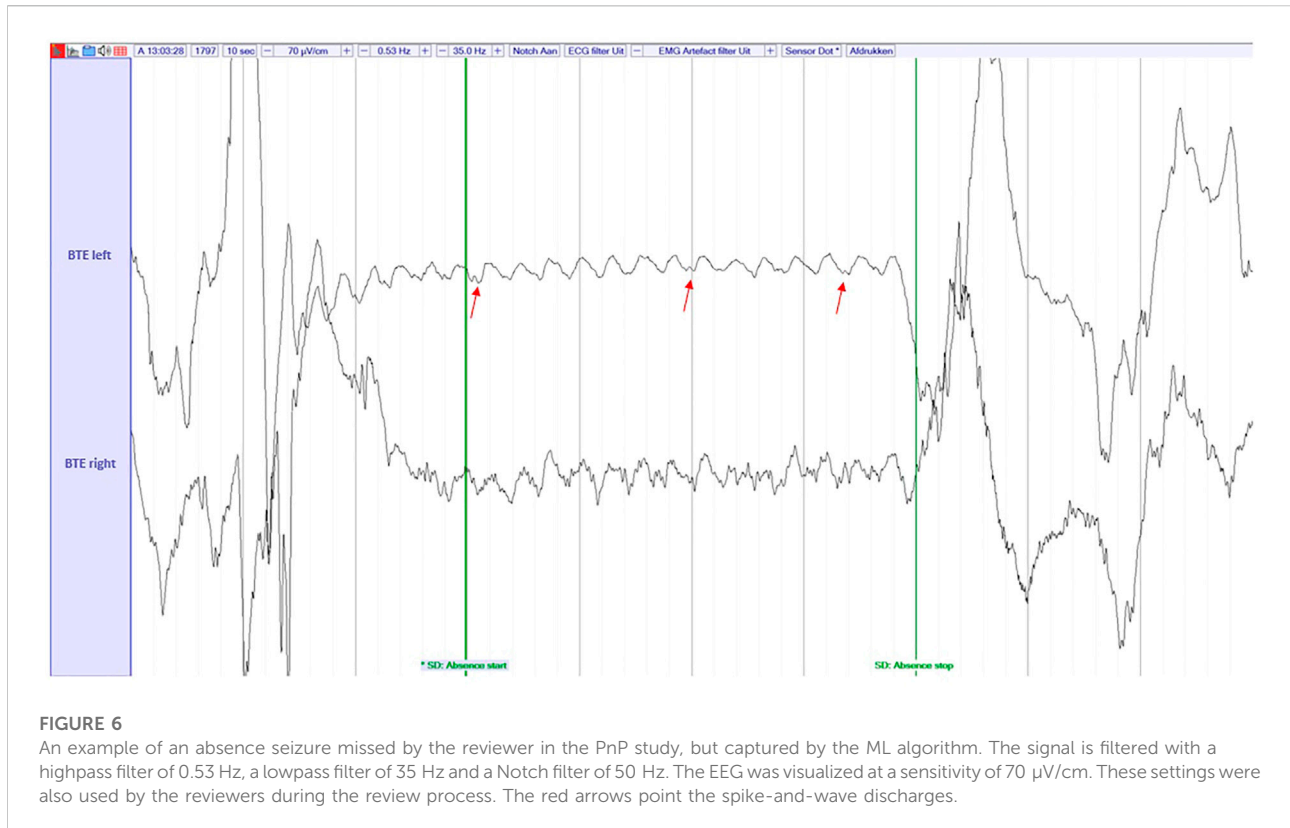


TABLE 4 Results of the Seizelt2 patients trained with the hospital recordings + in-home recordings of other patients. In the first column in parenthesis the total number of seizures per subject.

Subject	EEG		EEG + post		EEG + post + bad		EEG + post + bad + IMU	
	Sensitivity	Fas/h	Sensitivity	Fas/h	Sensitivity	Fas/h	Sensitivity	Fas/h
Subj-1 (23)	0,96	15,60	0,91	2,64	1,00	2,76	1,00	2,60
Subj-2 (72)	0,92	9,66	0,88	0,74	0,99	0,76	0,93	0,63
Subj-3 (4)	0,75	42,34	0,75	38,43	1,00	41,4	1,00	1,22
Subj-4 (54)	0,91	2,43	1,21	12,59	0,95	1,71	0,91	1,12



When we train the SVM with data obtained from home recordings of other patients and “personalize” it with the hospital recording of the test patient (Option 3- Figure 4), we note that the performance in Subj-4 increases significantly and is comparable to the other Subjects (Table 4). There is a minor effect to the rest of the Subjects.

We must note that both for the PnP subject and the SeizeIt2 subjects, the algorithm found some seizures that were missed by the neurologists (and are currently counted as FAs, since they were not included in the gold standard). More specifically for the PnP subject eight seizures were found that were initially missed by the neurologist (the extra seizures per recording can be viewed in the last column of Table 2), while for the SeizeIt2 subjects 1 seizure was found (examples of missed seizures can be viewed in Figure 6).

4 Discussion

According to the standards for testing and clinical validation of seizure detection devices (Beniczky and Ryvlin, 2018), our studies can be classified as a phase-4 study, since the accuracy and usability of the SD in a home environment is investigated in a multicenter trial (EIT Health: SeizeIT2, [clinicaltrials.gov: NCT04284072](https://clinicaltrials.gov/ct2/show/study/NCT04284072)). To the best of our knowledge, these are the

first (preliminary) results of a phase-4 trial of an automated detection of absence seizures with a wearable device. As mentioned in the introduction the full analysis and report for the findings of the study will follow in another publication and the main focus of this paper is to investigate design choices in the pipeline used for the automatic detection of the seizure events.

The current state-of-the-art have failed to provide accurate detection of the absence seizures with the home data mainly due to the high FA rate obtained. We have exhibited that our pipeline provides accurate detection of the absence seizures with very high sensitivity and low FAs/h. Furthermore, it managed to detect seizures that were initially missed by the neurologists. We shall note the difference in the amount of seizures missed by the two neurologists in the different studies which is probably due to the multiple recordings in the span of several months for the PnP study. The large amount of EEG data requires extended time for annotation of the seizures, hence, lower performance might be expected by the annotators. The need of automated seizure detection pipelines is evident when large amount of data are acquired. The lower signal quality of the in-home recordings and the presence of artifacts that did not exist in the hospital recordings, dictate the use of alternative blocks in our pipeline.

Furthermore, we have exhibited for the first time the added value of multimodality in the context of absence seizure detection. Multimodal seizure detection has been widely used

for the detection of motor seizures (Leijten, 2017) and focal seizures (Vandecasteele et al., 2021). However, multimodal approaches have not been employed for the detection of absence seizures, mainly due to lack of movement or heart rate variability during typical absence seizures. We have shown that detection of movement with SD can help into distinguishing seizure events from movement and dramatically decrease FAs (Subj-3, SeizeIt2).

The thresholding based on the standard deviation of the IMU signals was adopted in order to decrease the significant amount of FAs that were caused by the movement of everyday life. The hospital data do not include such movement segments, hence, the classifier, when trained only with hospital data do not recognize those segments as background but as seizure segments. “Turning off” the IMU postprocessing can result in a detection of a very limited number of seizures, similar to the one presented in Figure 5, for which the standard deviation (std) of the IMU data is above the threshold.

The current pipeline uses IMU modality only for postprocessing, an initial attempt to use an hierarchical clustering for detection of walking and running artifacts had inferior performance to the simple threshold-based postprocessing. However, different “true” fusion approaches (Chatzichristos et al., 2022) either early or late ones will be further explored.

Concerning the different training approaches that we have proposed we can note that it seems that in some cases (Subj-4, SeizeIt2) the in-hospital data differ a lot from the in-home data. In such cases the addition to the training set of data from in-home recordings of other patients can be beneficial. When multiple days of in-home recordings exist the training of the model with labelled data from one of the days provides the best performance. We recommend the use of the first option of the pipeline if there are multiple day recordings per subjects and the third pipeline when a single day of recording exist per subject.

Further work will aim to independently replicate those results with the data collected from the different centers that participate in SeizeIt2 and with the rest of the patients from UZ Leuven. Correct interpretation of artifacts in SD recordings will also be helpful in the detection of other seizure types and reduction of FA in the home setting.

Furthermore, when the amount of the data collected allows, we will study approaches based on Neural Networks which have shown significant success in several seizure detection applications (Chatzichristos et al., 2020; Japaridze et al., 2022), very recently even with the detection of absence seizures with two-channel EEG (Hartmann et al., 2022).

Data availability statement

The datasets presented in this article are not readily available because The dataset will be available after communication with the coauthor WV and after the results of the full study will be

released. Requests to access the datasets should be directed to wim.vanpaesschen@uzleuven.be.

Ethics statement

The studies involving human participants were reviewed and approved by Ethics comitee of UZ/KU Leuven. The patients/ participants provided their written informed consent to participate in this study.

Author contributions

CC wrote the main part of the paper and developed the pipeline for the analysis of absence seizures, LS and JM annotated the seizures, wrote part of the manuscript, and helped in the collection of the data. MB helped into the design of the multimodal fusion and tested alternative versions. WV and MD contributed to conception and design of the study as well as the analysis approach followed. All authors contributed to manuscript revision, read, and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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