Automated video-based detection of nocturnal motor seizures in children

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SUPPLEMENT ARTICLE

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Automated video-based detection of nocturnal motor seizures in children

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Abstract

Seizure detection devices can improve epilepsy care, but wearables are not always tolerated. We previously demonstrated good performance of a real-time video-based algorithm for detection of nocturnal convulsive seizures in adults with learning disabilities. The algorithm calculates the relative frequency content based on the group velocity reconstruction from video-sequence optical flow. We aim to validate the video algorithm on nocturnal motor seizures in a pediatric population. We retrospectively analyzed the algorithm performance on a database including 1661 full recorded nights of 22 children (age = 3-17 years) with refractory epilepsy at home or in a residential care setting. The algorithm detected 118 of 125 convulsions (median sensitivity per participant = 100%, overall sensitivity = 94%, 95% confidence interval = 61%-100%) and identified all 135 hyperkinetic seizures. Most children had no false alarms; 81 false alarms occurred in six children (median false alarm rate [FAR] per participant per night = 0 [range = 0-0.47], overall FAR = 0.05 per night). Most false alarms (62%) were behavior-related (eg, awake and playing in bed). Our noncontact detection algorithm reliably detects nocturnal epileptic events with only a limited number of false alarms and is suitable for real-time use.

KEYWORDS

children, epilepsy, remote detection, seizure detection, sudden unexpected death in epilepsy (SUDEP)

1 | INTRODUCTION

Nocturnal convulsive seizures, particularly if unwitnessed, pose the highest risk of sudden unexpected death in epilepsy (SUDEP).[1,2] Nocturnal supervision seems to have a protective effect on SUDEP, likely by permitting an intervention, but the exact protective mechanism is unknown.[3,4] Seizure detection devices (SDDs) can be used to alert for nocturnal seizures and allow others to intervene. Wearable devices are not always tolerated, especially not by children or those with intellectual disabilities, and may require charging. We previously demonstrated good performance of a remote real-time video-based seizure detection in adults living in a residential care setting.[5] The algorithm was able to detect all 50 nocturnal convulsive seizures (sensitivity = 100%) with a median false alarm rate (FAR) of 0.78 per night and a latency of

≤10 seconds in 78% of detections. We aimed to validate the video detection algorithm in a pediatric population.

Key Points

- We previously demonstrated good performance of our real-time video-based algorithm for detection of nocturnal convulsions in adults
- We validated our algorithm with long-term nightly videos of children with refractory epilepsy at home or in a residential care setting
- The algorithm detected 118 of 125 nocturnal convulsions (median sensitivity per participant = 100%, overall sensitivity = 94%)
- All 135 nocturnal hyperkinetic seizures were detected
- False alarms occurred in only six of 22 children (overall false alarm rate = 0.05 per night) and were mostly behavior-related

2 | MATERIALS AND METHODS

2.1 | Algorithm adjustment

The methodology used was previously published.[6] Detection thresholds were recently determined in a training set and the detection performance was validated in a test set of nocturnal video recordings of adults with refractory epilepsy.[5] The algorithm is composed of different steps to identify specific movement patterns of convulsions in the video image sequence. The first step is to reconstruct spatial movements by creating a vector field of velocities from changes in luminance (optical flow). Second, these velocities are grouped into six rates of spatial transformation (translation [horizontal and vertical], rotation, dilatation, and shear rates [horizontal and vertical]). Subsequently, time-frequency spectra of these group velocities are calculated using Gabor aperture functions with central frequencies ranging from 0.5 to 12.5 Hz. The final step is to derive the power in the 2- to 6-Hz frequency range (which is assumed to be the spectrum of convulsive seizures) relative to the total Gabor power. The relative 2- to 6-Hz power is expressed as a value between zero and one, thus reflecting the probability of registering a convulsion. If the output signal exceeds the previously determined threshold of 0.51 for >4 seconds, an alarm is set.[5] We made the following adjustments to the original algorithm: (1) the optical flow calculation was extended to the multichannel (color) level to avoid potential information loss due to the image interpolation to the grayscale[7] and (2) a novel algorithm (Global Optical Flow Reconstruction Iterative Algorithm [GLORIA]) was applied to bypass the time-consuming task of first reconstructing the local vector field and subsequently fitting the group transformation templates.[8] The GLORIA algorithm improves calculation speed by directly reconstructing relevant global group transformation velocities from the image sequences.

2.2 | Validation in a pediatric population

For validation, we used a dataset of all children in the LICSENSE trial (NTR4115). This prospective multicenter study validated a wearable multimodal SDD (NightWatch) combining heart rate and accelerometry. Children with refractory epilepsy were included if they were ≥3 years of age and had at least one monthly nocturnal motor seizure (ie, tonic-clonic [TC], generalized tonic lasting >30 seconds, focal hyperkinetic, and a "remaining" category, consisting of TC-like seizures with atypical semiology and clusters of minor seizures lasting >30 minutes). Exclusion criteria comprised frequent nonepileptic movement patterns (eg, choreatiform movements, sleep walking) and only minor motor seizures. They were monitored for a period of 2 to 3 months in their home or in a residential care setting. All recorded sequences of digital images had an H.264 (MPEG-4) format with a resolution of 640(H) × 480(V) pixels, 24-bit RGB color encoding, and a constant frame rate of 32 frames per second. Experienced epilepsy nurses analyzed all alarms generated by the wearable device together with caregivers' seizure diaries and screened 10% of all recorded nights for possibly missed seizures. Events were annotated as "seizure" or "no seizure," and seizure type was specified (eg, convulsive, hyperkinetic). Isolated minor seizures were annotated as "no seizure" and classified as false alarms. In case of doubt, annotations were discussed with a neurologist.

We retrospectively analyzed the detection performance of the algorithm on the annotated LICSENSE video database. All timestamps of the video alarms were compared with the annotations of the LICSENSE database. If the algorithm detected a clinical event also reported by the caregiver or coincided with a NightWatch alarm, the video detection was labeled with the same annotation. All other video alarms were designated as "new alarms" and annotated by experienced epilepsy nurses, and in case of doubt discussed with a neurologist.

Detection performance was evaluated as sensitivity for the detection of convulsive seizures per participant and FAR per participant and as overall sensitivity for the detection of all seizures of a specific seizure type (ie, TC, generalized tonic lasting >30 seconds, focal hyperkinetic, and "remaining") and overall FAR (ie, total number of false alarms divided by total number of recorded nights). We restricted sensitivity analysis to those who had motor seizures during the

trial period; FAR was calculated for the entire dataset. False alarms were categorized as (1) awake and playing or moving in bed, (2) rhythmic movement disorder (eg, body rocking), (3) rhythmically moving object in the room, and (4) another person in the room. For the generalizability of the results, we also calculated the F_1 score for the detection of convulsive seizures.[9]

The study protocol of LICSENSE was approved by a regional ethics committee, and written consent was provided by participants or their guardians provided assent was applicable. Data were handled anonymously.

3 | RESULTS

The dataset included 1661 full recorded nights of 22 children (13 male) with a median age of 9 years (range = 3-17 years). Sixteen children were monitored in a residential care setting, three at home, and three between home and in a residential care setting. We analyzed 125 convulsive seizures in eight children, including 45 previously unreported seizures ("new alarms"). The video detection algorithm was able to detect 118 of 125 convulsive seizures (median sensitivity per participant = 100% [range = 0%-100%], overall sensitivity = 94% [95% confidence interval = 61.1%-100%], F_1 score = 0.70; Figure 1A). The algorithm also detected all 135 hyperkinetic seizures (median sensitivity per participant = 100%, overall sensitivity = 100%) occurring in three children. The overall sensitivity of the algorithm for the detection of generalized tonic seizures lasting >30 seconds was 3.3%, and it was 1.3% for the detection of the "remaining" major seizures. Median FAR was 0 per participant per night (range = 0-0.47; overall FAR = 0.05/night). All 81 false alarms were clustered in six children (Figure 1A). Most false alarms (62%) were behavior-related (awake and playing in bed; Figure 1B).

The calculation speed of the algorithm was improved; a video epoch of 366 seconds took 263 seconds to analyze using the old algorithm and 194 seconds with the new GLORIA algorithm (with MATLAB 2019b [MathWorks], Windows 10pro [Microsoft], Intel I Core i7 7700 processor, 3.5 GHz, 32 Gb RAM).

4 | DISCUSSION

This phase 2 study (according to the recent SDD guidelines)[10] validated our seizure detection algorithm in children, and it showed good performance for the detection of nocturnal convulsions and hyperkinetic seizures. False alarms were mostly behavior-related during wakefulness. Our adjustments in the processing speed make the algorithm more suitable for real-time use and ready for clinical implementation.

A limitation of this study is the evaluation of possibly missed seizures, as we did not screen all recorded nights. This is almost inevitable for such a long-term follow-up study, but may have induced an overestimation of the sensitivity.

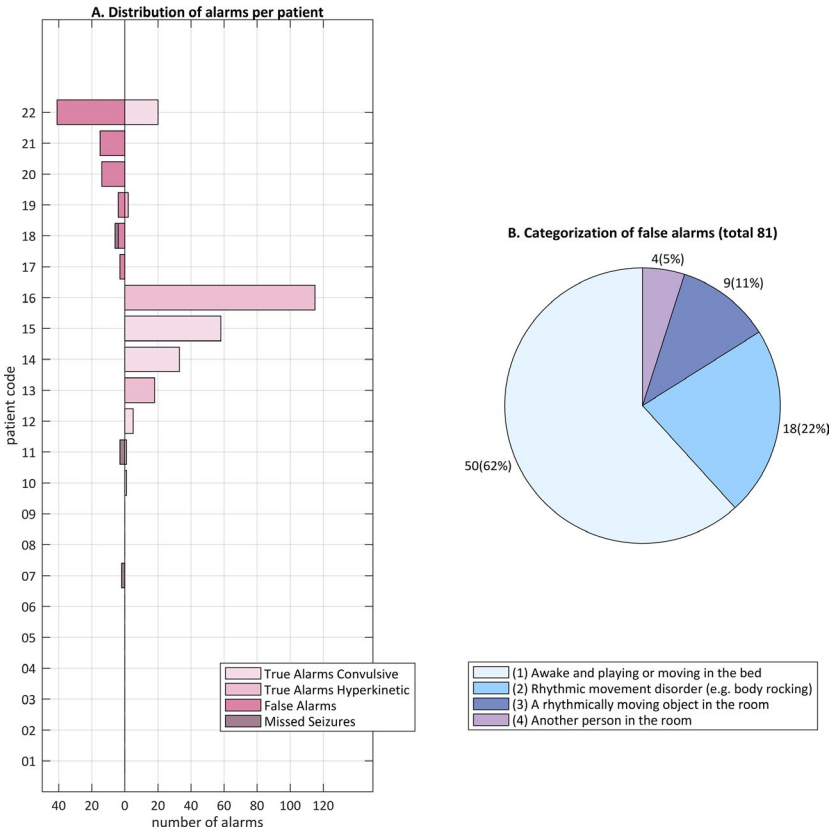

FIGURE 1 A, Distribution of video alarms (true and false) and missed seizures among all 22 participants. True alarms are defined as convulsive and hyperkinetic seizures. B, Categorization of false alarms

Previous results of our algorithm for the detection of nocturnal convulsive seizures in adults demonstrated a detection latency of ≤10 seconds in 78% of detections.[5] We do not expect that the algorithm adjustments described in this study influenced these results. Because the seizure onset could only be measured subjectively in this study and our detection algorithm already objectively identifies this first start of movement, we decided not to calculate detection latency in this study.

Several small phase 1 and phase 2 studies have been performed with various methods for automated video-based seizure detection, including motion tracking, periodicity estimation, and optical flow[11,12] All had acceptable detection rates (overall sensitivity = 75%-100%), but algorithms were tested and trained using the same dataset, thus posing a risk of overfitting.[13–16] All studies used retrospectively collected video epochs of infants and children with various motor seizure types and short selections of other nonepileptic movements, but lacked prospective or continuous data. These studies thus demonstrated the feasibility of these techniques, but overall performance is uncertain, as reliable FARs could not be derived.

Multiple phase 2, 3, and 4 studies on non–electroencephalography-based wearable SDDs have demonstrated good performance for the detection of convulsive seizures, with overall sensitivities of >90% and overall FARs ranging from 0.2/d to 1.44/d.[12] Best performance was achieved by multimodal devices combining various sensors including accelerometry, electrodermal activity, surface electromyography, and heart rate. Most devices were validated in an epilepsy monitoring unit with relatively short monitoring periods. Our dataset includes long-term (2-3 months) home-based video recordings, which not only resulted in a large number of seizures, but also allowed for a reliable estimate of the FAR. The absence of false alarms in the majority of children despite the long-term follow-up makes our detection algorithm an attractive alternative to wearable SDDs. Most false alarms occurred during wakefulness in the early evening or morning, thus minimizing false alarm impact. Our algorithm detected all hyperkinetic seizures. Other modalities (electromyography, accelerometry combined with heart rate) are likely more sensitive to detect a broader range of motor seizures.[17,18] A further advantage of our method is that it operates remotely, without sensors attached to the individual. A survey on first-hand experiences of people with epilepsy using wearable devices during a clinical stay indicated that most participants found the devices convenient.[19] The presence of wires, bulky size, discomfort, and need for support did, however, moderate experience. Visibility and accuracy were important determinants for wearing them in everyday life. Video systems may raise privacy concerns, but our system generates real-time alarms without requiring video storage or monitoring. Our analysis was restricted to the bedtime period. Daytime monitoring is possible but requires multiple cameras or portable video technology (drones, robots) likely to increase FAR due to the more diverse movement patterns and thus require other algorithms. Compared to other remote SDDs using bed sensors, our video algorithm had a higher sensitivity for the detection of convulsive seizures (overall sensitivity = 94% vs 89%) and fewer false alarms (overall FAR = 0.05/night vs 0.13/24 hours).[12]

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CONFLICT OF INTEREST

SEIN has granted LivAssured an exclusive license for the commercial use of the video detection algorithms. R.D.T. receives research support from Medtronic, and has received consultancy fees from Theravance Biopharma and fees for lectures from Medtronic, UCB, and Novartis. None of the other authors has any conflict of interest to disclose. We confirm that we have read the Journal's position on issues involved in ethical publication and affirm that this report is consistent with those guidelines.

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