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SUPPLEMENT ARTICLE

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Automated video-based detection of nocturnal convulsive seizures in a residential care setting

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Summary

People with epilepsy need assistance and are at risk of sudden death when having convulsive seizures (CS). Automated real-time seizure detection systems can help alert caregivers, but wearable sensors are not always tolerated. We determined algorithm settings and investigated detection performance of a video algorithm to detect CS in a residential care setting. The algorithm calculates power in the 2-6 Hz range relative to 0.5-12.5 Hz range in group velocity signals derived from video-sequence optical flow. A detection threshold was found using a training set consisting of video-electroencephalogaphy (EEG) recordings of 72 CS. A test set consisting of 24 full nights of 12 new subjects in residential care and additional recordings of 50 CS selected randomly was used to estimate performance. All data were analyzed retrospectively. The start and end of CS (generalized clonic and tonic–clonic seizures) and other seizures considered desirable to detect (long generalized tonic, hyperkinetic, and other major seizures) were annotated. The detection threshold was set to the value that obtained 97% sensitivity in the training set. Sensitivity, latency, and false detection rate (FDR) per night were calculated in the test set. A seizure was detected when the algorithm output exceeded the threshold continuously for 2 seconds. With the detection threshold determined in the training set, all CS were detected in the test set (100% sensitivity). Latency was ≤10 seconds in 78% of detections. Three/five hyperkinetic and 6/9 other major seizures were detected. Median FDR was 0.78 per night and no false detections occurred in 9/24 nights. Our algorithm could improve safety unobtrusively by automated real-time detection of CS in video registrations, with an acceptable latency and FDR. The algorithm can also detect some other motor seizures requiring assistance.

KEYWORDS
remote detection, seizure detection, SUDEP, video recordings

1 | INTRODUCTION

The importance of monitoring people who are at risk because of their seizures has often been stressed.[1–3] After convulsive seizures (CS), defined here as generalized clonic and tonic–clonic seizures, interventions such as repositioning, stimulation, or clearing of the airway may have a protective effect in preventing sudden unexpected death in epilepsy (SUDEP).[4] The person with seizures is often in need of assistance or first aid due to (non–life-threatening) injury, but is not able to alert

anyone. Alternative ways of alerting the caregiver are needed.

Several devices for automated seizure detection are on the market. Many seizure detection systems require sensors or complete devices to be attached to the individual.[5] Some patient groups such as children or people with intellectual disability may not tolerate wearable devices and may try to dislodge them. Unless properly concealed, such devices may also contribute to the social stigma associated with epilepsy. Alternatively, unobtrusive wireless sensors could be used, but these require regular charging and a reliable wireless connection to an alerting unit. Movement sensors that can be attached to the bed are widely used in nocturnal seizure monitoring and show fair detection performance for CS.[6,7] Such detectors, however, are only effective if the person is in bed. An alternative solution is remote detection.

Automated online analysis of video recordings can enable remote detection of the rhythmic vibratory or jerk-like body movements in CS. Such a system would be privacy-friendly as there is no need for video storage or for someone to monitor output. A number of studies have been performed on detecting CS using video recordings.[8–14] These studies were, however, proofs of principle, showing detection feasibility in small datasets recorded in controlled clinical settings. There is currently no working system available that has been shown to have good performance in real life settings.

Previously, we presented an algorithm aiming to discern CS from normal behavior in video recordings.[14] The algorithm quantifies the oscillatory movements seen as vibrations during the tonic phase, and clonic movements in the clonic phase.[15,16] The algorithm showed promising CS detection performance in a video-electroencephalography (EEG) training set and is suitable for real-time use. There is, however, currently no information on the behavior of our seizure detection algorithm in daily practice. A detection threshold is not yet established, and algorithm performance has not been validated in new test data. This is required to make the algorithm functional and to provide practical guidelines to enable its use.

We aimed to determine a detection threshold and to investigate the detection performance, and variables influencing performance, of our noncontact seizure detection algorithm. We pursued a realistic performance estimate by analyzing long-term nightly video recordings in a residential care setting.

Key Points

- Our algorithm calculates relative frequency content in the optical flow signal to detect convulsive seizures (CS) in video recordings
- Objective performance results were obtained by automated processing of long-term nightly videos and 50 CS in a residential care setting
- All CS in the test set were detected, with 78% of latencies being ≤10 seconds, and the median false detection rate was 0.78 per night
- The algorithm can also detect some other motor seizures that may require assistance

2 | METHODS

2.1 | Video data

We retrospectively analyzed 2 separate video databases; a training set to find a suitable detection threshold and a test set to study detection performance. The training set is an existing video database that was described previously.[14,17] The detection algorithm was developed in 2012 using this database,[14] and in the present study we reused the database to find suitable detection settings. The test set is a novel video database consisting entirely of new subjects. Test set data were collected under the LICSENSE trial (NTR4115), by the Dutch TeleEpilepsy consortium, a collaboration between University Medical Center Utrecht, Stichting Epilepsie Instellingen Nederland, and Kempenhaeghe.[18] The study protocol was approved by a regional ethics committee and written informed consent was given by all participants or their guardians. All data were handled anonymously.

2.2 | Training set

The training set consisted of 50 video-EEG recordings selected randomly from an epilepsy monitoring unit (EMU) database, recorded between 2003 and 2011. The training set contained 72 CS from 50 individuals. Videos were recorded with Bosch (Bosch Security Systems, B.V.) Dinion-LTC 0610, and Ikegami (Tsushinki Co., Ltd., Ohtaku, Tokyo, Japan) B/W CCD ICD-47 E-type cameras. All digitized recorded images were in mpeg2 format with a resolution of 352(H)×288(V) pixels and a fixed frame rate of 25 frames per second.

2.3 | Test set

The test set comprises a selection from the video data collected in the LICSENSE trial, conducted in 2015 and 2016. In this observational study, performance of the Nightwatch (LivAssured BV), a wearable seizure detection system, was tested in residential care settings, where most residents have mild to severe intellectual disability. Those residents with at least one monthly nocturnal CS were included and

monitored at night for a period of 3 months. Caregivers kept a seizure diary. In a random 10% sample of all nights, the full video recording was reviewed by an experienced epilepsy nurse (off-line analysis), and seizures were annotated. Seizure annotations are limited to symptoms visible on the video.

In this study, 2 nights were selected from the 10% screening samples of 12 individuals—one night with one or more annotated CS, and another night without. If no CS were present, a night with CS was selected based on diary entries, or a second night without CS was selected. These nights were screened in the same way and by the same observers as the 10% screening sample. Additional CS recordings were included in the test set to enable accurate estimation of the sensitivity and latency of the algorithm, accounting for the low number of CS in the selected nights. In total, 50 recordings with CS were selected randomly from LICSENSE trial subjects. Overrepresentation of data from a particular subject in the performance estimates was prevented by incrementing the number of seizures selected per subject, until 50 seizures were included.

Videos were recorded with FOSCAM (Shenzhen Foscam Intelligent Technology Co., Ltd., Shenzhen, China) FI9805E Outdoor 960P PoE IP cameras, with infrared illuminator for night-time recordings. Recordings were in mp4 format, with a resolution of 640(H)×480(V) pixels. Frame rate was variable, but had a minimum of 25, and a stable mean of ~30 frames per second over the 4-second windows used in algorithm calculations. Each half hour the recording system recorded a new video, resulting in video epochs of up to 30 minutes.

2.4 | Seizure annotations

Two neurologists (RT, GV, or JA), blinded to the results, independently determined seizure category to establish the detection desirability of the seizures found. Any incongruence was solved by consensus. Detection desirability of specific seizure types was determined as (see Table 1): *essential*—for CS (category I), as they are an important SUDEP risk factor[1,19,20]; *desirable*—for long generalized tonic, hyperkinetic, and other major seizures such as series of short myoclonic/tonic seizures (categories IIa, b, and c, respectively), as these seizures may be harmful or require assistance; and *nonclinically vital*—for minor seizures (category III). In the training set, only annotations of CS are used, which were based on the video-EEG report.

The start and end times of category I and II (a, b, and c) seizures in the test set were annotated by a trained technical physician (EG) who was blinded to detection algorithm results. The moment when the first behavioral change is observed, signifying clinical seizure onset, is annotated as the seizure start. Timing was based on the video and audio recording only. It is therefore possible that seizure activity started before the onset of a seizure is observable in the video. The end-of-seizure annotation is placed where the last observable seizure symptom ends and signifies the start of the postictal period. The start of the oscillatory period of CS was also annotated. The first visible oscillatory movements may either be vibratory movements during a tonic phase or the first clonic jerks of the clonic phase. Five-second annotation margins were applied before the seizure and oscillatory period start points to allow for slightly earlier detections.

TABLE 1 Seizure categories and the need for detection of these seizures

Category	Description	Detection need
I	Convulsive seizures (CS): Tonic–clonic seizures (may start with a clonic phase) or generalized clonic seizures	Essential
IIa	Tonic seizures that last longer than 30 s	Desirable
IIb	Hyperkinetic seizures	Desirable
IIc	Other major seizures: These seizures cannot be classified as tonic–clonic, tonic, or hyperkinetic seizures and may include a cluster of short tonic or myoclonic seizures	Desirable
III	Minor seizures: All other seizures	Nonclinically vital

2.5 | Convulsive seizure detection algorithm

The detection algorithm used in this study was described previously.[14] The algorithm consists of 4 steps: (1) optical flow calculation,[21] reconstructing the vector field of velocities from luminance changes, presumably resulting from movements recorded by the camera; (2) reconstruction of group velocity parameters, obtaining 6 time series representing the rates of spatial transformations; the translation (horizontal and vertical), rotation, dilatation, and shear rates (horizontal and vertical); (3) extraction of the "seizureness spectrum," representing the dominant component of the time-frequency spectra of the 6 spatial group velocities. Spectra are calculated using Gabor aperture functions with central frequencies ranging from 0.5-12.5 Hz, in 1-s windows; (4) calculation of the spectral contrast quantity, defined as the power in the 2-6 Hz band relative to the total Gabor power (0.5-12.5 Hz), in 4-s moving windows with 75% overlap. The 2-6 Hz frequency range was identified as the "spectral footprint" of CS. In some seizures the motion oscillations extend beyond this frequency range, but the range was considered optimal to minimize overlap with normal behavior. After the first 4 s of a registration,

each second the algorithm generates a dimensionless output value between 0 and 1. These values correspond to very low (close to 0) to very high (close to 1) proportion of oscillatory movement in the 2-6 Hz frequency range, and with that the likelihood of registering a CS.

2.6 | Determination of algorithm settings

To construct a functioning detector from the algorithm output, we implemented a detection threshold using the training set. A suitable threshold promotes detection sensitivity for CS as high as possible while keeping the number of false positives low. The detection threshold was set at the third percentile of detection output maxima during all oscillatory phases, obtaining 97% sensitivity in the training set. This was done to account for the possibility that not all CS had good quality recording; for example, caregivers may obstruct the view. A threshold resulting in 100% training set sensitivity would produce significantly more false positives.

After finding the detection threshold, a delay parameter was set to diminish the number of false positives caused by short oscillatory movements in the video. Suprathreshold algorithm output is ignored when the output does not stay above threshold for a duration equal to or longer than the delay parameter. The delay parameter was incrementally increased and set to the highest value where detection sensitivity was maintained, and latency did not increase more than the delay itself.

2.7 | Performance analysis

Detection performance was measured in terms of sensitivity and latency for CS (category I) and false detection rate (FDR) per night (8 hours). Detection performance for category II seizures is not a goal but considered a helpful sideline and is measured secondarily. Detection of category III seizures implies a false detection.

The algorithm detects a seizure when its output exceeds the threshold equal to or longer than the delay parameter during the seizure event. The seizure event is defined as the period between start and end annotations of the seizure. Detection latency is defined as the time between the start of the seizure and the detection. For CS, latency is also calculated from the start of the oscillatory phase, as detection of the seizure before the start of this period is not expected due to the algorithm's sensitivity to rhythmic movements. Factors possibly influencing detection latency were investigated visually.

When the algorithm output exceeds the threshold equal to or longer than the delay parameter at times other than during seizure events that were considered essential or desirable for detection, a false detection is generated. If a second false detection occurs within a 10-s blackout period after the first detection, this second false detection is disregarded. After the blackout period, new false detections are again taken into account. False detections were categorized as the following: detections of category III seizures, detections during the postictal phase after a seizure, detections with caregivers present (not during a postictal phase), and other false alarms.

3 | RESULTS

An example of the detection algorithm output is shown in Figure 1. The algorithm output threshold that detected 97% of seizures in the training set (threshold: 0.51) and a 2-s detection delay was applied to the algorithm for use in the test set. The test set consisted of recordings from 24 full nights (total duration ~253 hours) of 12 subjects, with 5 hyperkinetic and 9 major seizures recorded in 7

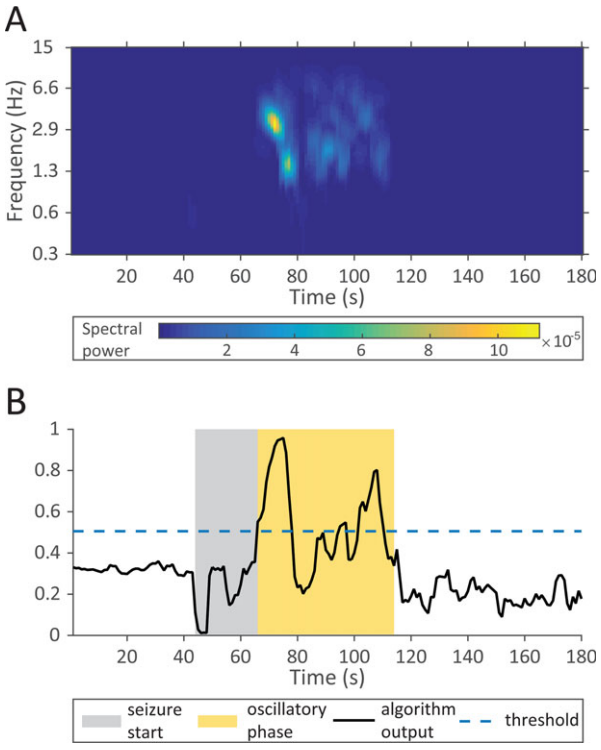


FIGURE 1 Example of the algorithm output around the time of a convulsive seizure. A, Gabor time frequency "seizureness spectrum," representing the dominant component of the time-frequency spectra of the 6 spatial transformations of the optical flow output. B, Convulsive seizure detection algorithm output (black solid line), defined as the power in the 2-6 Hz spectrum relative to the 0.5-12.5 Hz spectrum. The colored boxes together represent the timeframe of the seizure, where the gray box shows the start of the seizure before the oscillatory phase, which is indicated with the yellow box. In this case, the seizure detection threshold (dashed blue line, at 0.51) is exceeded by the algorithm output just when the oscillatory phase of the seizure starts

different subjects. Fifty CS were included from 9 different subjects (mean 5.5 seizures per subject, range 1-8). Six of the included seizures occurred within the 24 full-night recordings.

All CS were detected in the test set (100% sensitivity), with latencies shown in Figure 2. Seventy-eight percent of CS were detected within 10 seconds from the start of the oscillatory period. Detection latencies for seizures in subjects covered completely by a blanket (n = 19) were not significantly different from latencies in those who were uncovered (n = 7) or partly covered (n = 24) (2-sample Kolmogorov-Smirnov test, $P > .05$). In cases where detection latency was longer than 20 seconds, either a fluctuating oscillation amplitude was seen in the tonic phase, or caregivers were present, creating low-frequency "noise" in the video with their movements. Category II seizures were detected with a sensitivity of 57%. Detection latencies varied between 7 and 35 seconds. No tonic seizures longer than 30 seconds (category IIa) were registered in the test set. Three of five hyperkinetic seizures were detected (category IIb), and 5 of 9 other major seizures (category IIc).

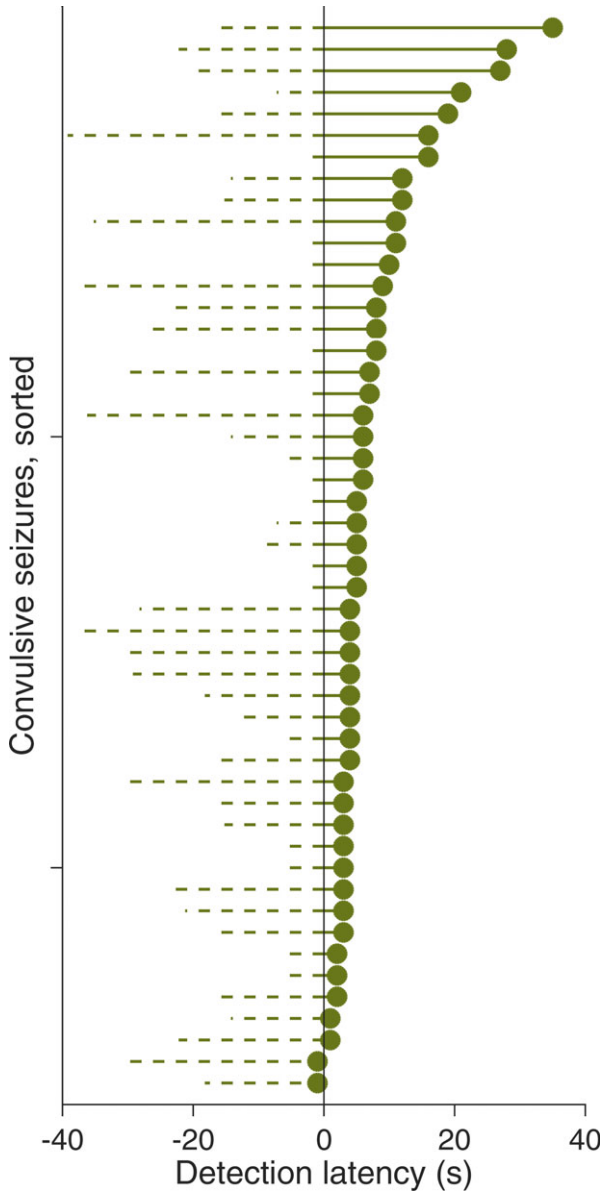


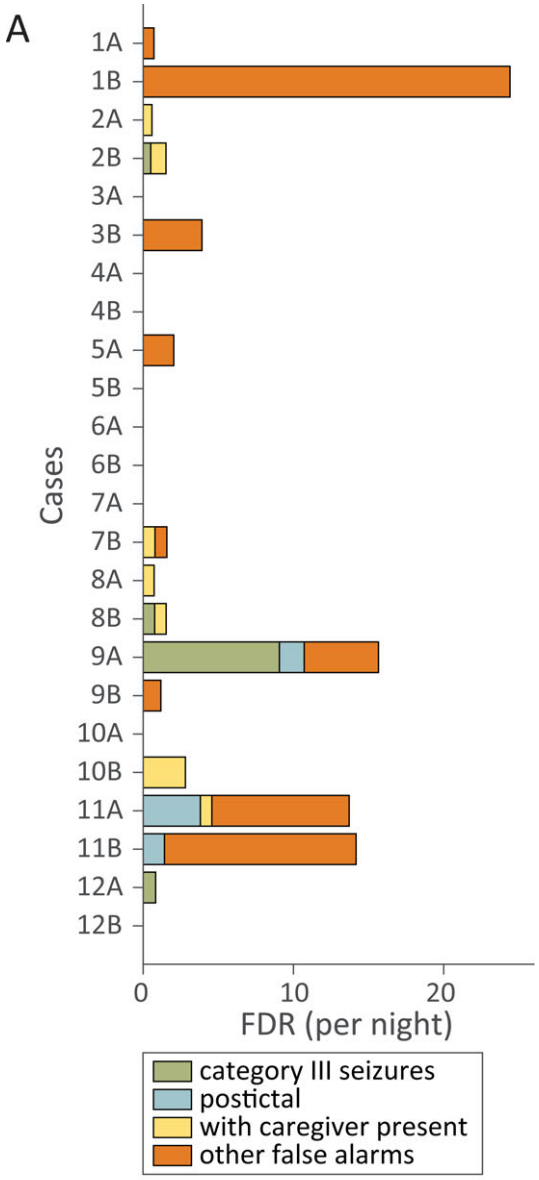
FIGURE 2 Detection latencies for the 50 convulsive seizures in the test set, sorted according to detection latency. The circles indicate the moment in time when the detection was made, calculated from the start of the oscillatory phase (at time = 0 seconds). The dotted lines indicate the duration of the convulsive seizures before the oscillatory phase. This duration may include symptoms of a focal onset of the seizure

False detection rates (FDRs) for all nights are shown in Figure 3. Median FDR was 0.78 per night (95% confidence interval [CI] 0-2.0 per night). No false detections occurred in 9/24 nights, which applied to both nights for 2 patients. In more than half of the cases, an FDR of one or less per night occurred. FDR was high (>5 per night) in 4 cases, corresponding to 3 subjects. Detection of category III seizures caused 12% of false detections, which were all myoclonic jerks (frequent in case 9A). Eight percent of false detections occurred during the postictal period, due to physical restlessness (all after category I or II seizures). In 8% of false detections, the detection occurred when a caregiver was in the room (not during a postictal period). Examples of false detection causes in these cases were movement of a flash light beam or patient manipulation. Other false alarms (72%) were caused by patient behavior (45%), such as scratching and fidgeting (frequently in case 1B), and video disturbances (27%), such as objects (eg, cobwebs, curtain cord) moving due to airflow fluctuations.

4 | DISCUSSION

This study shows that our noncontact seizure detection algorithm can perform well in a test set of new cases, when applying detection settings that were optimized using a training set. The algorithm detected all CS with an acceptable latency in a test set of nightly video recordings in a residential care setting. Seizures with a 2-6 Hz oscillatory movement pattern, observed for 2 seconds or longer, are detected, even when the subject is covered by a blanket. Detection latency is minimally 2 seconds, plus the time it takes for the seizure activity to manifest in a clear oscillatory movement pattern. Hyperkinetic seizures and other major seizures with a 2-6 Hz movement pattern can also be detected. The algorithm's calculations are computationally light and use only the last registered 4 s of data, making it suitable for real-time use.

In more than half of cases, an FDR of one or less per night was observed. In a small number of cases, however, a high FDR was observed. False detections were most



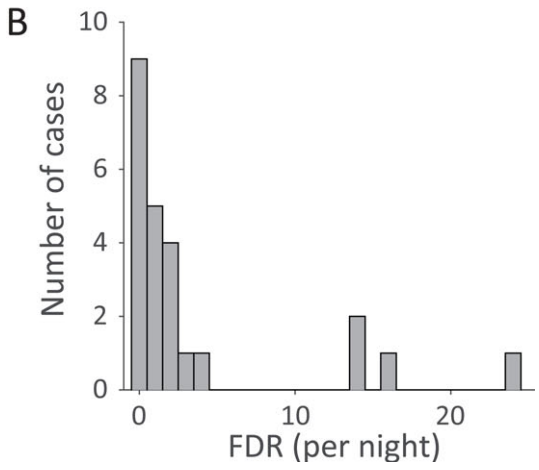


FIGURE 3 A, Test set false detection rates (FDRs) per night (8 hours) for each case. The colors in the stacked bars indicate the situation in which the false detection occurred. Green bars indicate detections of nonclinically vital seizures (category III, see Table 1), blue bars indicate detections during the postictal phase after a seizure, yellow bars indicate detections when a caregiver was present (not during a seizure or postictal phase), and orange bars indicate other false alarms. B cases 2-6, 8, and 11 included a category I seizure. B, Histogram of FDR results per night, where each case is an observation

frequently caused by active behavior of an awake or postictal patient, that is, scratching or fidgeting. Myoclonic jerks were in some cases also detected despite their short duration, as oscillatory movements occurred when limbs bounced on the bed after an event. In some cases, video disturbances by objects moving in airflow caused false alarms. Combining detection output from video with other noncontact inputs (eg, sound) might diminish the chance of false positives, but possibly at the cost of sensitivity and latency. In light of the favorable sensitivity and latency findings with the current algorithm, such a tradeoff to improve the FDR could be considered. Alternatively, awake users could be empowered to disable false detections manually, although giving a user time to disable a false alarm will inevitably lengthen detection latency. Which FDR is acceptable may depend on the individuals involved and their living conditions. If the subject can be observed from a distance via video connection in case of an alarm, like in a residential care setting, a higher FDR could be acceptable compared to a home setting where caregivers are awakened by alarms.

In this phase 2 study (according to the standards for seizure detection studies proposed in the current issue[22]) an extensive dataset with randomly selected long-term recordings was used, where data was not clipped, edited, or filtered before automated processing. Bias was prevented by concealing the algorithm output from the experts annotating seizures. Prior to this, only feasibility of detection has been demonstrated, and the generalizability of detection results, particularly to real-life situations, remained unclear.[8,10,12–14] Performance was often calculated on the same data that was used to select appropriate detector settings, with short video fragments recorded in a controlled clinical environment and only the subject in view.

Most remote CS detection methods reported in literature are, like ours, targeted on movement periodicity (the exception being methods targeted on seizure sounds[23,24] and muscle activity[25–27]). CS have been detected in video recordings by calculating periodicity in the luminance signal[10–12] and with neural networks trained on optical flow motion tracking output.[8,9] In another study, colored pyjamas were used to facilitate movement quantification for CS detection.[13] Compared to other algorithms targeted on periodicity, the detection delay we used (2 seconds) is shorter than generally applied (10 seconds),[6,10–12] while maintaining a low false detection rate. This

can be attributed to the application of spectral contrast (opposed to power) and the output-smoothening effect of the 4-second calculation window.

We used an extensive test set, but all recordings were made during the night and all events of interest derived from a small number of subjects. Detector settings were, however, based on a much larger sample in the training set, which contains 72 CS from 50 individuals in day- and nighttime recordings. It is likely, therefore, that detector sensitivity and latency in practice will be close to the sensitivity and latency in the training set (97% and <10 seconds in 81% of detected seizures, respectively). Realistic FDR results during daytime could not be derived from the fragmented video registrations in the training set. We expect false detections to be more frequent during the day in individuals with a tendency for false detection–causing behavior. False detection rates might be different in other target groups that were not in the test set, such as children or adults outside of residential care.

The detection settings of our algorithm are presumably generic, as they were chosen using a data set from different subjects and video data from different hardware than the data used for validation. Although personalized detection settings would possibly have improved detection performance, this requires long (supervised) training sessions, making it less practical for direct deployment. Lengthening the detection delay could, for example, prevent false detections caused by short rhythmic movement patterns, while retaining sensitivity for CS if they have rhythmic movement patterns with a longer duration. If needed, personalization should be attempted only by professionals in a controlled setting, where video and EEG recordings enable checking and analysis of missed seizures and false detections.

Our detection algorithm could be used in a real-time automated noncontact monitoring system to increase the safety of people with epilepsy at home, without intruding on privacy, as no video storage or monitoring is necessary. The algorithm is highly sensitive to CS and false detection rates are low in most cases. For some subjects, application of our algorithm could be unsuitable in practice; that is, subjects with many false detections, who are unable to disable false alarms themselves. Future work should focus on prospectively evaluating real-time detection performance of the algorithm in a broad target group of users.

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DISCLOSURE OF CONFLICT OF INTEREST

SEIN has granted LivAssured an exclusive license for the commercial use of the video-detection algorithms. RDT has received fees for lectures from Medtronic, UCB, and GlaxoSmithKline. FSL holds shares in ProLira. The remaining authors have no conflicts 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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