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Automated seizure detection in an EMU setting: Are software packages ready for implementation?

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ABSTRACT

Purpose: We assessed whether automated detection software, combined with live observation, enabled reliable seizure detection using three commercial software packages: Persyst, Encevis and BESA.
Methods: Two hundred and eighty-six prolonged EEG records of individuals aged 16–86 years, collected between August 2019 and January 2020, were retrospectively processed using all three packages. The reference standard included all seizures mentioned in the clinical report supplemented with true detections made by the software and not previously detected by clinical physiologists. Sensitivity was measured for offline review by clinical physiologists and software seizure detection, both in combination with live monitoring in an EMU setting, for all three software packages at record and seizure level.
Results: The database contained 249 seizures in 64 records. The sensitivity of seizure detection was 98% for Encevis and Persyst, and 95% for BESA, when a positive results was defined as detection at least one of the seizures occurring within an individual record. When positivity was defined as recognition of all seizures, sensitivity was 93% for Persyst, 88% for Encevis and 84% for BESA. Clinical physiologists' review had a sensitivity of 100% at record level and 98% at seizure level. The median false positive rate per record was 1.7 for Persyst, 2.4 for BESA and 5.5 for Encevis per 24 h.
Conclusion: Automated seizure detection software does not perform as well as technicians do. However, it can be used in an EMU setting when the user is aware of its weaknesses. This assessment gives future users helpful insight into these strengths and weaknesses. The Persyst software performs best.

1. Introduction

Seizure recording using video-EEG plays an essential role in diagnosing epilepsy, seizure classification and identification of candidates for epilepsy surgery [1,2]. Prolonged EEG recordings improve the chances of finding ictal activity [3]. Longer recordings, however, result in more review time and a cost increase.

The typical procedure of recording a prolonged EEG in an Epilepsy Monitoring Unit (EMU), involves continuous observation of individuals by trained nurses and staff, as well as alerts by patients who press an alarm at the onset of a perceived seizure [4]. This procedure detects around two-thirds of all seizures [5], and the remaining one third is detected by clinical physiologists who later review the entire EEG record offline. Automated detection software may serve as a screening tool to reduce the need for complete visual reviewing of the recording and save time, provided it is sufficiently reliable.

A pilot study showed that automated detection software in combination with sampled visual review could be used as a reliable substitute for a complete visual review of prolonged video-EEGs concerning IEDs (interictal epileptiform discharges) [6]. The number of seizures in that study was however too low to validate the performance of the automated seizure detection, not yet allowing its use as a substitute for visual review.

To approach the real life use of seizure detection software, we compared the seizure detection performance using online human observation (in live setting by trained nurses) in combination with both conventional review by clinical physiologists and software seizure detection using three commercially available software packages.

Abbreviations: EMU, Epilepsy Monitoring Unit; EEG, Electroencephalogram.

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2. Methods

2.1. EEG data

We retrospectively collected 286 anonymous prolonged video-EEG records (> 4 h) from 283 individuals aged at least 16 years between Augustus 2019 and January 2020. EEG data were recorded using the Micromed EEG system (Micromed, Mogliano Veneto, Italy), using the standard 10–20 international electrode recording and additional F9/F10 positions sampled at 256 Hz. We recorded EEGs exclusively in the context of clinical care, so, according to Dutch rules, individual informed consent was not required. The local medical ethics committee approved this study.

2.2. Automated detection software packages

We used three commercially available software packages: Persyst (Persyst Development Corporation, USA) version 14, Encevis (AIT Austrian Institute of Technology, Austria) detection), version 1.9.2. and BESA (BESA Epilepsy, Germany) version 2.0. Encevis is the only package that also uses the ECG channel for seizure detection. For all three packages, the output is a list of timed seizure detections. Additionally, BESA also presents lateralization information (i.e. left, right). We used only the seizure detection features of the software, ignoring other tools.

2.3. Review

2.3.1. Reference standard

The EEG data of all seizures mentioned in the original EEG report were reviewed in a consensus procedure by at least one clinical physiologist and one epileptologist. Seizures were categorized according to when the seizure was first detected: in the live setting, i.e. through nurses' observations and individuals' alarm buttons, or offline through clinical physiologists' review. All detections were recorded into a sheet. EEG outside seizure selections was not reviewed.

The same records were analyzed with the three automated detection software, and all detections made by one or more software packages were compared with the seizures mentioned in the original EEG report. Detections were classified as congruent if the software detection fell within a time window of 30 s before the onset or after the end of the seizure, and incongruent otherwise.

All incongruent detections were reviewed by a trained human expert with more than five years' experience in reviewing EEGs. An actual seizure detection was defined as repetitive epileptiform EEG discharges of > 2 Hz or a characteristic pattern with a quasi-rhythmic spatio-temporal evolution (i.e. a gradual change in frequency, amplitude, morphology or location), usually lasting ten or more seconds [7]. A second human expert then double-checked this. Software detections that did not meet the criteria were considered false detections. Two or more false software detections within 60 s were counted as a single false detection.

The reference standard included all seizures mentioned in the clinical report supplemented with true detections made by the software and not previously detected by clinical physiologists. The durations of all ictal EEG patterns were identified, and seizure classification was determined using the latest ILAE seizure classification [8]. Only the first ten seizures per EEG record were included to reduce sampling bias. We regarded records in which any seizure was detected as positive for epilepsy, regardless of whether all seizures in that record had been identified.

2.3.2. Analysis

In an EMU setting most seizures are detected in the live setting, so our primary outcome measure was the sensitivity for live seizure detection in combination with both offline review by clinical physiologist and software seizure detection for all three software packages. Differences in performance between the clinical physiologists and all three software packages were analyzed using the McNemar test for non-parametric data using SPSS (IBM Corp. Released 2019. IBM SPSS Statistics for Windows, Version 26.0. Armonk, NY: IBM Corp.) We made a distinction between seizures with no or short (< 10 s) ictal pattern and seizures with a seizure pattern duration of at least 10 s. We also measured sensitivity using the software seizure detection alone, including the seizures detected online. Finally we estimated the false positive rate per 24 h.

3. Results

3.1. Seizure detection

3.1.1. Database characteristics

We included 286 prolonged EEG records from 283 people (135 male, 148 female) with a median age of 36 years (range 16 – 86 years) and a summed recording time of over 8771 h. The median duration was 20 h and 40 min (range 4 h and 3 min to 97 h and 56 min).

There were 336 seizures in 64 records (range 1 – 39 seizures per record). From the eight records with more than ten seizures we included the first ten, remaining 249 seizures for further analysis.

3.1.2. Performance per record

Of the 64 records containing seizures, 56 were recognized as containing seizures in the live setting. In the later offline review, clinical physiologists detected seizures in an additional eight records. The software packages did not identify one record which contained one generalized myoclonic event. BESA missed two further records, one having a focal seizure and one containing an electroencephalographic seizure. See Fig. 1. Hence, sensitivity for the combination of live observation and offline review by clinical physiologist was 100% (CI 93–100%). Sensitivity for the combination of live observation and automated detection using Persyst and Encevis was 98% (CI 90–100%) and 95% (CI 86–99%) when using BESA. There was no statistically significant difference in performance between the reference standard and either of the software packages (for all $P > 0.05$) nor between the reference standard and the clinical physiologist ($P > 0.05$).

3.1.3. Performance per seizure

Of the 249 seizures, 184 were recognized in the live setting. Table 1 shows the recorded seizure types, the duration of ictal patterns, and the clinical physiologists' performance. Sensitivity for the combination of live monitoring and offline review by a clinical physiologist was 98% (CI 95–99%). The five undetected seizures were all focal in nature.

Table 2 and Fig. 2 show the performance of the three software packages. Sensitivity for the combination of live monitoring and seizure detection by Persyst was 93% (CI 89–96%), by Encevis 88% (CI 83–92%), and by BESA 84% (CI 78–88%). The differences in performance between the clinical physiologist and the software packages were significantly different (Persyst, $P = 0.02$; Encevis $P < 0.001$; BESA $P < 0.001$). The undetected seizures are shown in table 2; they mostly concerned generalized myoclonic, generalized tonic seizures. Whether focal seizures remained undetected depended on the software package (Table 2). Closer inspection of the focal seizures showed subtle events, with slowly evolving ictal patterns with low amplitudes and frequencies (See Supplementary data). The generalized myoclonic seizures had short (one to two seconds) ictal patterns and occurred in people with a (suspected) generalized myoclonic epilepsy. The missed tonic seizures had somewhat longer (two to five seconds) ictal patterns and occurred only in individuals with mental impairment and a history of tonic seizures.

Sensitivity regarding all 249 seizures was 56% (CI 49–62%) for Persyst, 52% (CI 45–58%) for Encevis and 43% (CI 37 – 49%) for BESA. Sensitivity regarding seizures with an EEG pattern lasting 10 s or longer was 91% (CI 87–94%) for Persyst, 83% (CI 77–87%) for Encevis detected and 69% (CI 63–75%) for BESA detected (Table 3).

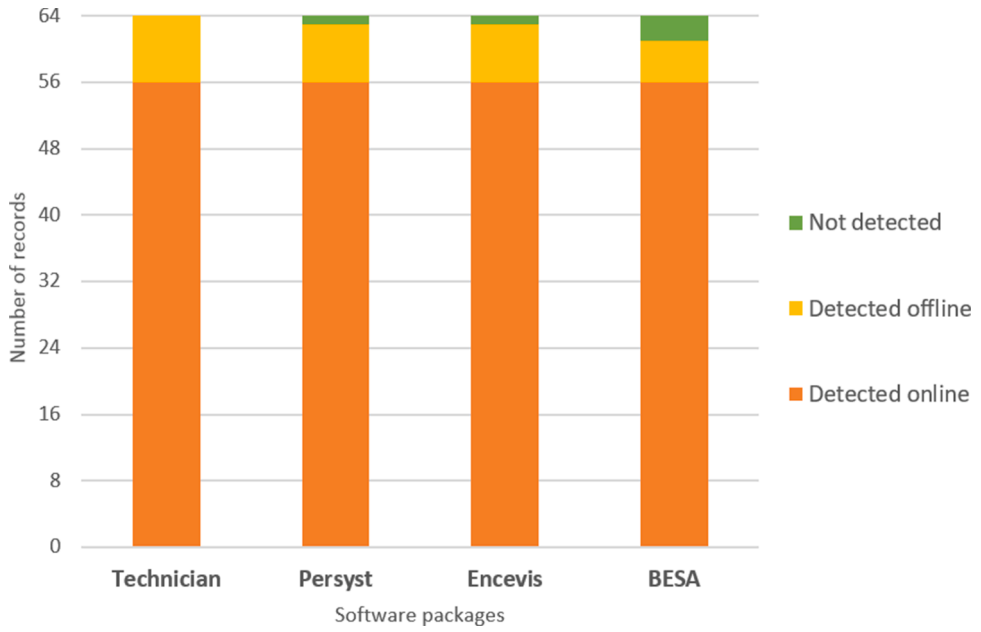

Fig. 1. Performance software packages on record level.

Table 1
Seizures detected in live setting or by clinical physiologists.

Seizure type	Total #	# first detected in live setting (online)	# first detected by clinical physiologist (off line)	# not detected (live or by clinical physiologist)
Generalized tonic clonic	1	1	0	0
Focal to bilateral tonic clonic	13	13	0	0
Focal impaired awareness	80	69	11	0
Focal aware/unknown - motor	59	49	8	2
Focal aware – non motor	26	26	0	0
Absence	11	4	7	0
Generalized myoclonic	21	15	6	0
Generalized tonic	14	3	11	0
Focal electro-encephalographic	24	4	17	3
Total #	***249***	***184***	***60***	***5***
Duration ictal EEG $\geq$ 10 s	146	95	46	5
Duration ictal EEG $<$ 10 s	103	89	14	0

= number of seizures.

3.1.3. *False positive detections*

False positive rate for Persyst is 1.7 per 24 h, for Encevis 5.5 per 24 h and for BESA 2.4 per 24 h. Most of the false positives were chewing artifacts, non-seizure related tachycardia (Encevis), muscle artifacts, movement artifacts or interictal activity.

4. Discussion

Seizure detection by a combination of live monitoring and automated software had a sensitivity of 95% (BESA) and 98% (Encevis, Persyst) when aiming to detect at least one of the seizures occurring within an individual record and sensitivity of 84% (BESA), 88% (Encevis) and 93% (Persyst) when aiming to detect all seizures. Clinical physiologists' review had a sensitivity of 100% on record level and 98% on seizure level. Hence, Persyst detected the highest number of seizures, and BESA the lowest. The software packages performed better on seizures with 10 s or longer duration. We found a false positive rate of 1.7 and 2.4 per 24 h when using Persyst and BESA, which we considered acceptable. This false positive rate is lower than reported in previous literature, using an older version of Persyst [9]. A validation study of the currently used version (P14) reported false positive rate comparable to present study [10]. Encevis showed a considerably higher false positive rate.

Earlier studies found that detection algorithms had a sensitivity for epileptic seizures between 73% and 96% [11,12]. A recent study comparing the same three software packages reported a sensitivity of 76.6% for BESA, 77.8% for Encevis and 81.6% for Persyst on a database containing largely focal seizures [9]. In our study we approach how the software would really be used in an EMU setting, by reviewing the combination of live human observation and offline review, comparing the performance of the clinical physiologists versus the software. Furthermore our database also contains generalized seizures, such as myoclonia and tonic seizures. Sensitivities for these seizure types, and for focal aware seizure, are low. This is due to the fact that they usually have no or short EEG correlates [13]. The highest sensitivities are reported for (focal to) generalized tonic-clonic seizures and focal seizures with impaired awareness [13].

Both the present study and previous reports suggest that detection software does not perform as well as clinical physiologists. We believe, however, that detection software can be of use provided the user is aware of its weaknesses. Patients can usually detect myoclonus and focal aware seizures themselves, and report them via the push button [14,15]. This does not apply to generalized tonic seizures; our data show a large proportion of those were undetected in the live setting. This seizure type usually occurs in people with mental impairment with a history of tonic seizures. We suggest EEGs of this population should be thoroughly

Table 2
Seizures not detected online.

Seizure type	Total # not detected online	# detected by Persyst	# detected by Encevis	# detected by BESA
Generalized tonic clonic	0	0	0	0
Focal to bilateral tonic clonic	0	0	0	0
Focal impaired awareness	11	11	10	7
Focal aware/ unknown - motor	10	8	7	5
Focal aware – non motor	0	0	0	0
Absence	7	6	6	5
Generalized myoclonic	6	0	0	0
Generalized tonic	11	5	2	1
Focal electro-encephalographic	20	18	10	6
Total #	***65***	***48***	***35***	***24***
Duration ictal EEG ≥ 10 s	51	48	34	24
Duration ictal EEG < 10 s	16	0	1	0

= number of seizures.

visually reviewed to avoid missing significant events. Our previously proposed method with a targeted sampled review, including a period after waking in people with suspected JME, can also increase seizure detection [6]. Thus, the ictal patterns seen in myoclonic seizures, which are usually are too short to be detected by a seizure detector, will be detected by a spike detector. To a lesser extent, slowly evolving seizures with low amplitudes and frequencies can also be missed by the software. Previous literature shows that the use of quantitative EEG spectrograms can increase the detection of these seizures [16]. Automated detection software, however, also detected five additional seizures, which were initially missed in the offline review by the clinical physiologist. Finally, in the design of this study we used automated seizure detection as a screening tool. Detections made by the software must always be checked and verified by experts.

Our study has some limitations. It is a single center study and results may differ in other settings. We also only used EEG recordings from teenagers and adults, so our results do not apply to pediatric EEGs. We only focused on seizure detection. In an additional, yet unpublished, study we also compare the performance of the spike detection features of these software packages [17]. We used a pragmatic approach for the reference standard. However, ideally the EEG records should be reviewed in their totality and by two epileptologists. Furthermore, the online usability of these detection software packages should be investigated, as they might possibly be beneficial for patient safety and ictal testing. Lastly, it would be insightful to look at experts' confidence of this software.

5. Conclusions

Automated seizure detection software does not perform as well as clinical physiologists do. However, it can be used in an EMU setting when the user is aware of its weaknesses. The software is most sensitive to focal seizures with impaired awareness and tonic clonic seizures and least sensitive to generalized tonic and generalized myoclonic seizures.

The use of such detection software can potentially save time. This assessment may give future users helpful insight into the strengths and weaknesses of this software and help prospective users choose a software package. The Persyst software has the best performance.

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Table 3
Total number of seizures.

Total #	Total # ***249***	# detected by Persyst ***139***	# detected by Encevis ***129***	# detected by BESA ***107***
Duration ictal EEG ≥ 10 s	146	133	121	101
Duration ictal EEG < 10 s	103	6	8	6

= number of seizures.

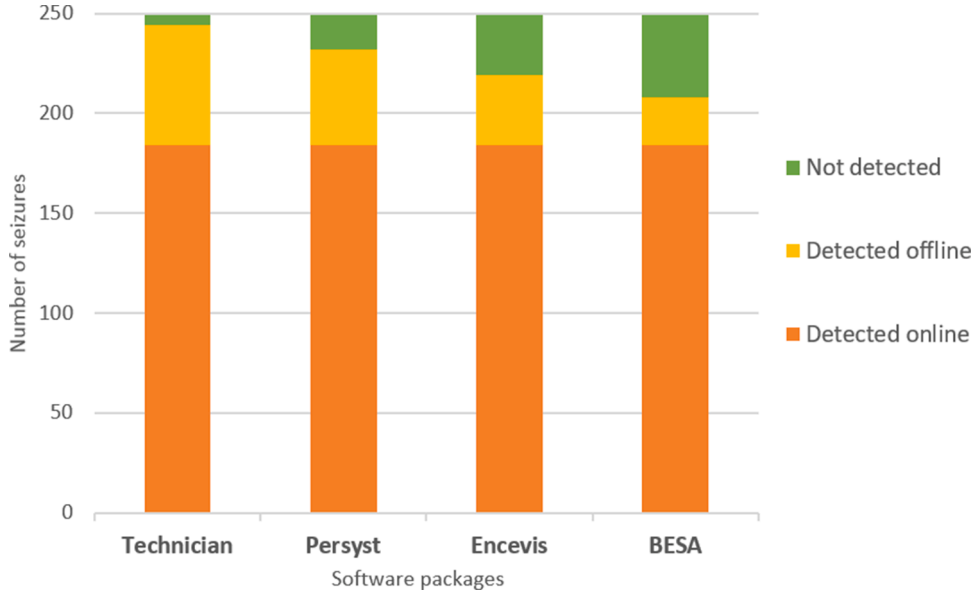

Fig. 2. Performance software packages on seizure level.

Declaration of competing Interest

None of the authors has any conflict of interest to disclose.

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