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Seizure Detection Software Used to Complement the Visual Screening Process for Long-Term EEG Monitoring

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Abstract

It is widely recognized that visual screening of long-term EEG recordings can be time-consuming and labor-intensive due to the large volume of patient data produced daily in most Epilepsy Monitoring Units (EMUs). As a result, seizures, especially those with only electrographic changes, are sometimes overlooked, which for some patients could result in missed information for diagnosis, an unnecessarily prolonged hospital stay, and unavailable EMU beds for others. In this report, we propose that a better solution for identifying seizures in long-term EEG recording is to combine detection results from a reliable (high sensitivity and low false detection rate) automated detection system with EEG technologists' visual screening process. Using commercially available detection software, we present case studies that demonstrate potential benefits of this method that could help improve detection rates and bring greater efficiency to the seizure identification process in long-term EEG monitoring.

Keywords

EEG review; epilepsy monitoring unit; long-term; scalp EEG; seizure detection; visual screening

INTRODUCTION

Many seizures recorded in Epilepsy Monitoring Units (EMUs) can be recognized due to patients' behavioral manifestations; however, as many as 30% of seizures manifest purely electrographically (Ives and Woods 1980). Therefore, in order to identify as many seizures as possible for diagnostic purposes, visual screening of long-term EEG recordings is an

important task. Unfortunately, this process can be very time-consuming. Due to the high volume of patients monitored in many EMUs every day, in addition to other responsibilities. EEG technologists are asked to screen long-term EEG recordings at playback speeds far faster than real time. Consider that when reviewing at a common speed of 10 pages per second (given a page size of 10 seconds), brief seizures may be on the screen less time than that of an eye blink (approximately 300 to 400 milliseconds). As a result, seizures can be overlooked, which for some patients could result in missed information for diagnosis, an unnecessarily prolonged hospital stay, and unavailable EMU beds for others.

Since the first automatic seizure detection methods were introduced in the early 1980s (Gotman 1982, Gotman 1990, Wilson et al. 2004, Saab and Gotman 2005, Hopfengärtner et al. 2007, Meier et al. 2008), most EEG labs have access to available automated seizure detection software. However, automated seizure detection algorithms have not been used as much as anticipated. One of the reasons for this is the limited sensitivity automated algorithms have for detecting epileptic seizures. Most algorithms do not have a sensitivity better than 70 to 80% due to multiple factors such as variation of ictal EEG patterns, artifact-contaminated ictal EEGs, and abnormal background activities before seizures (Kelly et al. in press). If an EEG technologist expects an automated seizure detection algorithm to have the ability to detect all seizures, then she or he could soon be disappointed with its performance and stop using it. Another reason automatic seizure detection systems have limited clinical utility is their high false detection rate. For a clean (i.e., nearly artifact-free) recording, this is generally not a large problem. However, for recordings with lower-than-average signal qualities, which are not unusual in long-term EEG monitoring, detection systems can generate hundreds of false detections. For such cases, it is extremely time-consuming and labor-intensive for EEG technologists to distinguish true detections from false ones. As a result, such detection systems are not often used consistently in EEG labs.

Our multi-center research team has developed a reliable and clinically useful automatic seizure detection system, IdentEvent™ (Kelly et al. 2008, Kelly et al. in press, Halford et al. 2009, Shiau et al. in press). The primary design goal of IdentEvent™ was to provide clinical users working with long-term EEG monitoring, a seizure detection system that generates a low false detection rate (approximately two per 24 hours) while detecting 80% of seizure events with scalp EEG changes. Although this limited sensitivity prevents this and other automated algorithms from replacing human reviewers, we suggest combining human and automated detection approaches. Suppose that on average the seizure identification rate from EEG technologists' rapid (e.g., 100 times faster than real time, or 0.1 second per page) visual screening is 80%, and that also 80% detection sensitivity can be expected from a seizure detection system, the combined process could yield a seizure identification sensitivity as high as 96% (when the two processes are independent).

We will use the remainder of this report to: (1) present seizure events from sample EEGs that could be missed by a fast visual screening process, (2) discuss the detection performance of IdentEvent™ in a large clinical study, and (3) summarize this report and discuss future development directions.

CASE STUDIES

Case A

Patient A, with a history of intractable complex partial and secondarily generalized seizures, was admitted to an EMU for long-term video-EEG monitoring. After undergoing 160 hours (6 days and 16 hours) of recording, one seizure (complex partial and secondarily generalized) was identified at the 109th hour (i.e., on the 5th day from the beginning of the monitoring) and it was the only seizure noted in the video-EEG report after the completion of the monitoring.

Patient A's EEG recording was then independently processed by IdentEvent™, which reported seven events in the entire recording:

1st detection: during the first day of the recording, and it was verified as a false detection.

2nd and 3rd detections: during the third day of the recordings, and they were both verified (with video-EEG saved at the recording EMU) as true seizure events. These two events were not noted in the original video-EEG report.

4th and 5th detections: during the fourth day of the recording, and were both verified as false detections.

6th detection: during the sixth day of the recording, and it was verified as a false detection.

7th detection: during the seventh day of the recording, and it was verified as a false detection.

A possible reason why the two seizure events that occurred during the third day of the recording were overlooked was their brevity (the first event lasted about 12 seconds and the second lasted about 16 seconds). A second potential reason could be due to the subtlety (both events were very localized at right temporal and frontal regions with subtle EEG changes) of their EEG changes. Brief and subtle electro-graphic seizures provide relatively small visual changes on the screen and therefore can be easily missed by fast playback visual screening. Figure 1 shows the EEG traces (A, B, and C) of the first event (in longitudinal bipolar montage).

However, the complex partial seizure with secondary generalization was rejected by IdentEvent™ detection due to its fast generalization (approximately eight seconds after the onset). The EEG signals were quickly dominated by large movement and muscle artifacts. This type of seizure is unlikely to be missed by a human EEG reviewer. Therefore, if IdentEvent™ detection had been combined with the fast visual EEG screen in a timely fashion, with three seizures recorded and identified, then Patient A might be discharged after five days of recording with two more seizure events identified for diagnosis or presurgical evaluation. It is also worth noting that IdentEvent™ generated only five false detections during the entire 6.7 days of recording (less than one false detection per day on average).

Case B

Patient B, with a history of intractable complex partial and secondarily generalized seizures, was admitted to an EMU for long-term video-EEG monitoring. After undergoing 91 hours (3 days and 19 hours) of recording, two seizures were identified and noted in the clinical video-EEG report. Both seizures were classified as complex partial (without secondary generalization). A typical seizure from Patient B, consisting of seconds of muscle activity followed by clear ictal discharges, is shown in Figure 2.

Patient B's EEG recording was independently processed by IdentEvent™, which reported a total of five events in the entire recording, including both events noted in the video-EEG report. The other three detected events (all occurred ahead of the two reported events) were all verified and confirmed as true seizure events. Again, the combination of the EEG technologist's visual screening and IdentEvent™ detection would provide more seizure events (five versus two) for diagnosis, and the patient could have been discharged after two days of EEG monitoring.

Case C

Patient C, with a history of intractable complex partial and secondarily generalized seizures, was admitted to an EMU for long-term video-EEG monitoring. After undergoing 23 hours of recording, six seizures were identified and noted in the clinical video-EEG report. All six seizures were classified as complex partial without secondary generalization and had clear EEG onsets starting from the **right temporal region** (Figure 3).

Patient C's EEG recording was independently processed by IdentEvent™, which reported a total of seven events in the entire recording, including all six seizure events noted in the video-EEG report. The additional event detected by IdentEvent™ was confirmed as a complex partial seizure (relatively more subtle than the other seizures) (Figure 4) starting from the **left temporal region**. No false detection was generated by IdentEvent™ from this patient's recording.

The use of IdentEvent™ for this patient resulted in a different clinical benefit compared to the previous two cases. Here it provided a complete and more accurate capture of seizure onsets that impacted the patient's presurgical evaluation.

PERFORMANCE STATISTICS OF IDENTEVENT™

IdentEvent™ utilizes an algorithm that analyzes 5-second epochs of the scalp EEG recording sequentially over time and generates seizure detections when sufficient criteria are met. The algorithm begins by calculating a number of quantitative measures from the raw signal. After these mathematical descriptors are calculated, the EEG epoch must pass a set of artifact rejection criteria (ARC) designed to eliminate false detections arising from common sources in scalp EEG recordings (muscle contraction, movement, sleep patterns, etc.). If the ARC are passed, then the EEG epoch is further examined to determine whether its signal characteristics match with the criteria designed for detection of unilateral onset (left- or right-sided) or bilateral onset seizure activity. When all signal characteristics pass these criteria, the time of the EEG epoch is then stored in a list of seizure detection events.

See the Appendix for further details on how the algorithm works. The points in the EEG recording when these seizure detection events occurred can be easily reviewed by the EEG interpreter to confirm or reject detected seizure occurrences.

A clinical validation study for IdentEvent's™ seizure detection performance was conducted in a test dataset (completely independent from the algorithm's training dataset) of 32 long-term scalp EEG recordings (from 32 patients) collected from two EMUs. The test dataset contains a total of 75 epileptic seizure events in 2,388 hours of EEG recordings. Each video-EEG recording was reviewed (by experienced EEG technologists with typical clinical post hoc EEG review procedures) for seizure identification and classification at the clinical sites. EEG recordings were further independently reviewed by DSS. When potential additional seizure events or false positives were identified, they were verified with the clinical investigator (JJH and KMK) with video-EEG recordings. For each patient, the *entire* long-term EEG recording was included in the analysis for performance evaluation so that the test data can be considered as representative of typical clinical EEG recordings, which contain many patients' normal physiological conditions as well as many types of recording artifacts.

All detection thresholds in the current version of IdentEvent™ are preset (i.e., no user adjustment is necessary). Over the entire test dataset, IdentEvent™ performed with a seizure detection sensitivity of 83% with approximately 1.6 false detections per 24 hours of EEG recording.

DISCUSSION

In this report, we have introduced a recently FDA-approved seizure detection system, IdentEvent™. IdentEvent™ has a low false-detection rate and can identify brief (as short as 10 seconds) and subtle seizure events that could be easily over-looked by fast-playback EEG visual review. We have also discussed the clinical significance of timely identification of as many seizure events as possible in long-term EEG recordings in EMUs, and how an automatic seizure detection system can assist EEG technologists to achieve this goal. We propose that a better solution for identifying seizures in long-term EEG recording is to combine detection results from a reliable (high sensitivity and low false detection rate) automated detection system with EEG technologists' visual screening process. Case C above illustrates how a subtle seizure detected by IdentEvent™, and not detected by visual EEG screening, can have considerable clinical significance.

IdentEvent™ can also potentially alleviate the need for an EEG technologist's visual review of the entire recording by providing timely identification of a sufficient number of seizure events in long-term EEG recordings, although additional human review would improve sensitivity. For example, suppose that a patient has three seizures recorded in the first day of EEG monitoring. Instead of waiting for the completion of three to four days of monitoring, the EEG technologist can have IdentEvent™ process the EEG recording the next morning. In this circumstance, if IdentEvent™ reports all three recorded seizures and those three seizures are sufficient for the epileptologist or neurologist to make an accurate diagnosis, then it is possible that the patient may not need to stay in the EMU for more than that one day. However, it is important that the detected events are verified by a human EEG reviewer

and it is important to remember that additional human review of the entire EEG dataset will reveal additional seizures in certain patients.

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APPENDIX

This section details each of the 10 steps in the algorithm process.

Step 1	The algorithm begins analyzing the EEG at the beginning of a continuous EEG recording. The algorithm imports one calculation epoch at a time. The algorithm uses non-overlapping, 5.12-second epochs of 16-channel scalp EEG referential montage data for analysis (19 standard EEG channels excluding Fz, Cz, and Pz).
Step 2	The algorithm filters the EEG signals into two desired frequency ranges: filter-A with a range of 25 to 70 Hz and filter-B with a range of 1 to 20 Hz. The rationale for this filtering process is to reduce the possibility of false detections caused by the signal artifacts from patients' normal activities (e.g., muscle contractions, movements such as blinking, chewing, etc.) as well as from EEG recording systems (e.g., 60 Hz artifact). Within these frequency ranges, the information relevant to seizure activity is preserved.
Step 3	After generating filtered EEG signals for each raw signal, the algorithm calculates an EEG descriptor MaxW from filter-A signals. This descriptor identifies the maximum signal amplitude of the filter-A signal within

the calculation window. Simultaneously, using the filter-B EHG signals, the algorithm calculates the following EEG descriptors: 1) pattern match regularity statistic (PMRS); 2) signal deviation (STDv); 3) local maximum and minimum signal deviation (STDn_max and STDn_min); and 4) maximum zero crossing frequency (FMXv), for each of the 16 channels.

- Step 4** PMRS quantifies the regularity of an EEG signal based on the repeatability of the signal patterns. Typically, we have observed that the PMRS values drop to the lowest point during the seizure and move back to higher values immediately after the seizure ends. These observations suggest that the EEG signal during the ictal period is less complex than other periods and that the signal during the postictal period is more complex. Although PMRS is very sensitive to EEG seizure patterns, there are other patterns that may exhibit similar values due to rhythmic activities, and therefore could cause false detections. In order to reduce these false detections, the system also calculates Max., STDv, STDn_max, STDn_min, and FMXv descriptors based primarily on frequency and amplitude variation. STDv is simply the sample standard deviation of the signal amplitude within the calculation window; STDn calculates the minimum and maximum 1-second standard deviation within the calculation window; and FMXv estimates the maximum 1-second frequency of one-directional zero crossing within the calculation window. STDv can reject the false detections caused by muscle activity, significant movement activity, electrode artifacts, and recording system artifacts. The difference between STDn maximum and minimum can reduce false detections caused by certain sleep patterns. MaxW is also used for rejecting sleep patterns. FMXv serves as an additional rule for rejecting detections caused by signal patterns with high frequency and high rhythmicity.
- Step 5** Based on the above EEG descriptors (calculated above), a set of artifact rejection criteria (ARC) is applied to reject EEG segments that are dominated by (1) recording artifact (e.g., electrode failure, recording system artifact), (2) muscle and chewing “artifacts,” and (3) sleep EEG pattern “artifacts.”
- Step 6** A critical criterion for this seizure detection algorithm includes PMRS values decreasing significantly for the selected EEG channels at the seizure onset. The detection of these PMRS decreases is controlled by a statistical threshold (baseline) comparison. The algorithm uses a combination of sample mean and sample standard deviation of the previous values (preceding approximately five minutes). To reduce the effects from signal artifacts to the baseline values, the PMRS values are automatically adjusted to a preset “seizure-free” value (≈ 0.6) when the corresponding FMX or STD values exceed the preset thresholds.
- Step 7** After determining the detection threshold, the algorithm compares the current EEG descriptors with three sets of criteria for detecting a seizure event. These three sets of criteria were designed based on the EEG signal characteristics of (1) left-unilateral EEG seizure onset, (2) right-unilateral EEG seizure onset, and (3) bilateral EEG seizure onset.
- Step 8** After a seizure is detected, the system will save the detection time. This allows the software to call the user's attention to that segment to review for possible seizure activity.
- Step 9** After the detection process is completed for the current segment, the system checks whether the end of the recording was reached.
- Step 10** If the end of the recording was reached, then the algorithm stops processing. The software then allows the user to review the entire EEG record, calling attention to the seizure detection times stored in step 8, for possible seizure activity. If the end of the record has not been reached, then the system goes back to step 1 and reads and analyzes the next segment of EEG.
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FIG. 1.

Thirty seconds of continuous longitudinal bipolar EEG traces including one seizure event:

(A) Ten-second EEG starting at about 15 seconds before the seizure onset. (B) Ten-second EEG starting at about five seconds before the seizure onset.

(C) Ten-second EEG starting at about five seconds after the seizure onset. Seizure ended at about the eighth second.

FIG. 2. Thirty seconds of continuous longitudinal bipolar EEG traces including one seizure event: (A) Ten second EEG starting at about 15 seconds before the clear seizure onset. (B) Ten-second EEG starting at about five seconds before the clear seizure onset. (C) Ten-second EEG starting at about five seconds after the clear seizure onset. (D) Ten-second EEG starting at about 15 seconds after the clear seizure onset. The seizure ended after trace D.

FIG. 3.

Thirty seconds of continuous longitudinal bipolar EEG traces including one seizure event in Patient C: **(A)** Ten-second EEG starting at about 4 seconds before the seizure onset. **(B)** Ten-second EEG starting at about six seconds after the seizure onset. **(C)** Ten-second EEG starting at about 16 seconds after the seizure onset. It is clear that the EEG onset of this seizure started from the **right** temporal region.

FIG. 4.

Thirty seconds of continuous longitudinal bipolar EEG traces including one seizure event in Patient C: **(A)** Ten-second EEG starting at about five seconds before the seizure onset. **(B)** Ten-second EEG starting at about five seconds after the seizure onset. **(C)** Ten-second EEG starting at about 15 seconds after the seizure onset. Although the seizure onset is more subtle, it is clear that the EEG onset of this seizure started from the **left** temporal region.