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ORIGINAL ARTICLE/ARTICLE ORIGINAL

Automatic detection of rhythmic and periodic patterns in critical care EEG based on American Clinical Neurophysiology Society (ACNS) standardized terminology

Détection automatique de patterns rythmiques et périodiques dans l'EEG de soins intensifs basée sur la terminologie standardisée de l'American Clinical Neurophysiology Society (ACNS)

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Summary
Aims of the study. — Continuous EEG from critical care patients needs to be evaluated time efficiently to maximize the treatment effect. A computational method will be presented that detects rhythmic and periodic patterns according to the critical care EEG terminology (CCET) of the American Clinical Neurophysiology Society (ACNS). The aim is to show that these detected patterns support EEG experts in writing neurophysiological reports.
Materials and methods. — First of all, three case reports exemplify the evaluation procedure using graphically presented detections. Second, 187 hours of EEG from 10 critical care patients were used in a comparative trial study. For each patient the result of a review session using the EEG and the visualized pattern detections was compared to the original neurophysiology report.

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Results. — In three out of five patients with reported seizures, all seizures were reported correctly. In two patients, several subtle clinical seizures with unclear EEG correlation were missed. Lateralized periodic patterns (LPD) were correctly found in 2/2 patients and EEG slowing was correctly found in 7/9 patients. In 8/10 patients, additional EEG features were found including LPDs, EEG slowing, and seizures.
Conclusion. — The use of automatic pattern detection will assist in review of EEG and increase efficiency. The implementation of bedside surveillance devices using our detection algorithm appears to be feasible and remains to be confirmed in further multicenter studies.

MOTS CLÉS
Terminologie ACNS
USI ;
EEG ;
Détection automatique ;
Motifs rythmiques et périodiques ;
Soins intensifs

Résumé
Buts de l'étude. — L'EEG continu (cEEG) des patients en unité de soins intensifs doit être évalué plus efficacement pour optimiser le traitement. Nous présentons une méthode informatique de détection de patterns rythmiques et périodiques. Celle-ci est basée sur la terminologie de soins intensifs (CCET) de l'American Clinical Neurophysiology Society (ACNS). Le but est de montrer que la détection de ces patterns permet aux experts d'écrire plus facilement des rapports neurophysiologiques.
Méthodes et matériaux. — Dans un premier temps, trois études de cas illustrent la procédure d'évaluation en utilisant des détections présentées graphiquement. Ensuite, 187 heures d'EEG venant de dix patients d'unités de soins intensifs ont été introduites dans une étude comparative. Pour chaque patient, le résultat d'une session de révision utilisant l'EEG et la détection des patterns a été comparé avec le rapport neurophysiologique original.
Résultats. — Parmi les cinq patients ayant eu des crises épileptiques, les crises de trois patients ont été reconnues correctement. Les deux autres patients avaient des crises cliniques très subtiles et sans corrélation claire dans l'EEG. Les patterns périodiques latéralisés (LPD) ont été correctement reconnus chez les 2 patients concernés et un ralentissement du EEG a été correctement reconnu dans 7/9 cas. Pour 8/10 patients des caractéristiques additionnelles ont été identifiées, incluant des patterns périodiques latéralisés, un ralentissement de l'EEG et des crises.
Conclusion. — L'utilisation d'algorithmes de détection automatique basés sur la CCET assisteront dans la révision de l'EEG et augmenteront son efficacité. L'implémentation de dispositifs de surveillance utilisant notre algorithme sera possible et sera montré dans de futures études multicentriques.

Introduction

Over the past decade, a considerable amount of research effort has been expended to study the prevalence in EEG of nonconvulsive seizures (NCS) or nonconvulsive status epilepticus (NCSE) in acutely ill patients. In 1999, a publication by Kaplan [14,15] showed that the extended use of continuous EEG (cEEG) revealed many patients with NCS/NCSE that would have been undiagnosed without cEEG. Several years later, Claassen et al. reported that the percentage of patients in the intensive care unit (ICU) undergoing cEEG monitoring who were found to have seizures was 19% [4] with a very high percentage (92%) of these seizures being nonconvulsive. A recent cohort study at 11 North American sites showed that 30% of pediatric ICU patients had seizures and 11% of the patients had NCSE [1]. Continuous EEG remains the gold standard for diagnosis of NCS/NCSE. CEEG is beginning to be used in ICU seizure treatment studies [12] and has been shown to be favorably associated with good outcome [18]. Recently, it has also been reported that not only patients with primary neurological diseases but also medical/surgical ICU patients with secondary neurological complications benefit from cEEG monitoring [3,13].

There is significant cost associated with cEEG monitoring. EEG recording equipment, network connections, MRI and CT compatible electrodes [5], and 24-hour EEG technologist support for connecting and maintaining electrodes are needed. However, another significant source of cost is the physician effort needed to review the cEEG signal, which is recorded by approximately 20 sensors over a time period of hours to days. Optimal diagnosis would involve continuous analysis of this signal to detect seizures, but this is unfeasible for conventional ICU staffing models. In clinical practice, manual analysis of cEEG recordings is done by reviewing pages showing 10 to 20 seconds of EEG. In order to review this much data, the physician reviewer often has to view the cEEG recording very rapidly, which makes it easy to miss brief seizures. An automated detection system could evaluate the cEEG continuously and present results in real-time. Detailed analysis of EEG segments labeled by an automated detection system could replace continuous evaluation of the full EEG and avoid an error-prone accelerated review of long-term EEGs.

Quantitative EEG (QEEG) was a first step towards an automatic and objective interpretation of the EEG signal to assist in evaluation and decision-making. QEEG allows

Table 1 Summary of the critical care EEG terminology (CCET).

Main term 1	Main term 2	Plus (+) modifier
G: generalized	PD: periodic discharges	No +
L: lateralized	RDA: rhythmic delta activity	+F: superimposed fast activity
BI: bilateral independent	SW: rhythmic spike-and-wave OR Rhythmic sharp and slow wave OR Rhythmic polyspike and wave	+R: superimposed rhythmic activity
Mf: multifocal		+S: superimposed sharp waves or spikes, or sharply contoured - applies to RDA only +FR: if both subtypes apply - applies to PD only +FS: if both subtypes apply - applies to RDA only

a time-compressed view at a scale of a few hours using measures like median amplitude or asymmetry that are supposed to capture clinical important information from the EEG. Numerous applications and assessments of QEEG have been reported in the literature [6—8,15,16,19,21]. A common problem is artifacts and physiological EEG patterns that contribute to the QEEG measure in the same way as pathological EEG patterns [20]. For example, the mean amplitude of the EEG cannot differentiate between high amplitude artifact and seizure activity, for which reason the interpretation of this single measure is highly ambiguous.

There is a need to standardized EEG patterns in order to avoid misinterpretation between staff members and different clinical sites. The standardized critical care EEG terminology (CCET) of the ACNS [11] lays a foundation for a common nomenclature for ICU EEG by defining clinically relevant EEG patterns. Table 1 summarizes the available codes to describe rhythmic and periodic EEG patterns. The codes for pattern localization (main term 1) and pattern type (main term 2) are concatenated to give a single pattern code, e.g. ''LRDA'' for lateralized rhythmic delta activity. These CCET codes showed a high interrater agreement [9,17]. In this work, we present a computational method for automatic detection of clinically significant EEG patterns in cEEG recordings from ICU patients based on the CCET criteria.

Materials and methods

We developed a computational method to detect rhythmic and periodic patterns according to ACNS CCET. Pattern locations and pattern types are defined for all detections in a time interval of a few seconds. In addition to EEG patterns defined in CCET, rhythmic patterns with frequencies of more than 4 Hertz are detected.

The automatic detection algorithm was developed by utilizing long-term EEG recordings from a neurological intermediate care unit and a neurological ICU as development dataset. This development dataset was recorded at the 2nd Neurological Department of the Neurological Center Rosenhuegel (NCR) and the Department of Neurosurgery at the Medical University of Vienna (MUV) using the international 10—20 electrode placement system at a sampling rate of 256 Hz.

The goal of this computational approach is to transcribe automatic detections to clinically established wording. This contrasts with conventional QEEG methodology, which evaluates the EEG to report technical measurements. The link between technical measurements and EEG patterns of interest is not always so clear. For example periodic patterns (PD) and spike wave activity (SW) at 1 Hertz have a similar rhythm in a time-frequency plot but they are very different clinical patterns and have different implications for the patient. Another advantage of a tool such a method is a strong data reduction property since it provides high-level data extraction. A periodic pattern (PD) can stretch over minutes or hours without changing frequency or amplitude. A computational method that recognizes PDs can define the start and the end of the pattern instead of reporting the same detection at short fixed intervals. This data compression property of the detection algorithm allows the graphical representation of several days of EEG on a few pages.

Implementation of automatic pattern detections based on CCET

The definitions of rhythmic and periodic EEG patterns in the CCET [11] are given using clinical wording that specifies only limited technical details in terms of signal morphology. Because of this, a detailed description of the way CCET was implemented by our detection algorithm will be given in this section.

Main term 1 of the CCET defines several categories for the localization of EEG patterns. First of all, rhythmic and periodic patterns can be generalized (G) or lateralized (L). In addition predominant areas can be specified. The implementation of recognition of the main term 1 in our detection algorithm supports generalized (G) and lateralized (L) pattern. A pattern qualifies as lateralized (L), if the maximum amplitude of the pattern in one hemisphere is at least 50% higher than in the contralateral hemisphere, based on bipolar transverse and longitudinal montages only. If not qualified as lateralized, the pattern is generalized. If a generalized pattern has 50% higher amplitude in the frontal, midline, or occipital area compared to a contralateral or bilateral reference area, the pattern is predominant. Frontally, midline, and occipital predominant patterns are therefore detected according to the CCET definition except that again only bipolar longitudinal and bipolar transverse montages are used.

The CCET defines various types of rhythmic and periodic patterns in main term 2 (see Table 1). These pattern types

are periodic discharges (PD), rhythmic delta activity (RDA), and repetitive spike-and-wave or sharp-and-wave (SW) patterns. PDs are defined as uniform discharges repeating in regular intervals with a clear inter-discharge interval (IDI). Only discharges with waveforms having less than 4 crossings of the baseline are allowed in order to distinguish periodic from burst suppression patterns. The average frequency allowed for PDs ranges from 0.2 to 3 Hz. The so-called ''relative amplitude'' is defined as the average discharge amplitude divided by the average amplitude between the discharges. The value of the relative amplitude of a periodic pattern has to be above 1.6 to be detected. Rhythmic delta activity (RDA) is defined as repeating discharges with uniform morphology without an inter-discharge interval. The computational detection of RDA conforms to this definition. Several modifiers to the main term 2 pattern types are defined in the standardized terminology that describes variants in the morphology. The modifier ''+S'' is defined as a pattern with frequent intermixed sharp waves/spikes or a sharply contoured pattern and is only applicable to patterns of type RDA. These ''RDA + S'' patterns are detected if at least one unequivocal spike is included in a RDA pattern or the pattern has a sharply contoured morphology. Spike-and-wave or sharp-and-wave (SW) patterns are defined as polyspike, spike or sharp wave consistently followed by a slow wave in a regularly repeating and alternating pattern. The automatic detection of SW is based on detected RDA + S patterns and requires in addition that 20% of the discharges in the RDA + S pattern coincide with unequivocal spike-and-waves or sharp-and-waves. This is a more relaxed condition compared to the CCET and increases the robustness of the automatic detection. Finally, a frequency up to 4 Hertz is allowed to qualify for SW in our method. The detection of rhythmic theta and rhythmic alpha patterns (RTA, RAA) is logically equivalent to the RDA detection but requires more than 6 successive discharges and frequencies between 4—7.5 or 7.5—12 Hertz, respectively. The modifier ''amplitude'' is defined as the average amplitude of all discharges in the pattern. The discharge amplitude is defined as the minimum of the two peak-to-peak voltages measured from the start of the discharge to the maximum and from the maximum to the end of the discharge. The modifier ''frequency'' is determined as the average distance between consecutive discharges in a pattern.

Our automatic detection method does not capture the full depth of the CCET. The main term 1 types bilateral independent (BI) and multifocal (Mf) are not implemented. This means that patterns of this main term 1 type are assigned to generalized or lateralized patterns, depending on the exact amplitude distribution over channels. The modifiers amplitude and frequency are implemented but other modifiers and EEG background are not evaluated in this version.

Calculation procedure

The following is a description of how the detection algorithm processes EEG data. At the beginning, EEG artifacts are removed using the PureEEG algorithm [10]. The PureEEG algorithm is based on a neurophysiological model and utilizes an iterative Bayesian estimation scheme to remove typical scalp EEG artifacts like movement, muscle, line noise, and loose electrode artifacts. The output of the PureEEG algorithm is a clean EEG signal that is solely used for further analysis. This approach assumes that all following pattern detections are of cerebral origin. Frequencies below 0.4 Hertz and above 70 Hertz are then removed by a finite impulse response filter. Bipolar longitudinal and transverse montages are created according to ACNS' proposal for clinical EEG montages [2]. The signal in each bipolar channel is divided into segments that represent spikes, waves, or any other discharge item with durations between 40 milliseconds and 1.5 seconds and amplitudes above 20 microvolts. The wave segmentation procedure scans the EEG signal in the time domain for arbitrary peaks with more than 20 mV. Each peak is then extended on both sides as long as the waveform lies above two projection lines that start at the borders of the starting peak and have 20% reduced slope value. All resulting wave segments below 40 milliseconds and above 1.5 seconds are dropped. These single-channel segments are then combined over several channels to build multi-channel segments. The spatial distribution of potentials within multi-channel segments is checked and segments with non-cerebral origin are discarded. All multi-channel segments are then marked as spike, sharp wave, or non-spike segment by a spike-detection algorithm. The multi-channel segments are also used to build groups of representing RDA, RDA + S, SW, RTA, RAA, and PD segments as described above. Whether a pattern meets minimal requirements for duration and the number of discharges is checked and patterns that do not meet criteria are discarded. The spatial location of all detected patterns is analyzed and a main term 1 definition is assigned. Finally, segments of equal pattern type are concatenated to groups with a maximal duration of 30 seconds. Fig. 1 summarizes the major calculation steps of the algorithm. These groups are displayed in the main term 1 and 2 plot of the graphical user interface.

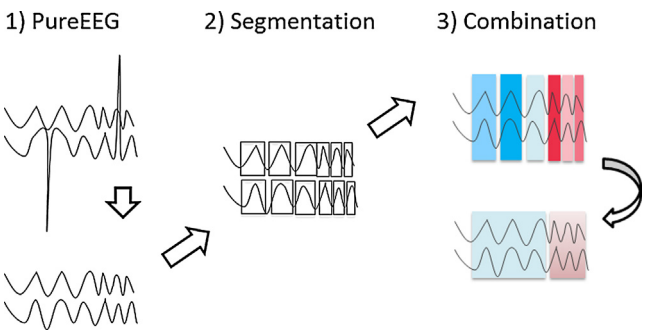

Figure 1 The three major steps of the detection algorithm: 1) Artifact removal using the PureEEG algorithm. 2) Channel wise discharge segmentation. 3) Combination of discharge segments over several channels followed by grouping in time. The final pattern groups represent EEG patterns with multiple discharges in a certain spatial area.

Graphical detection user interface

A graphical user interface (GUI) was created to present information of the detected patterns to a reviewer. This detection user interface simplifies review session by allowing visual recognition of clusters with similar information.

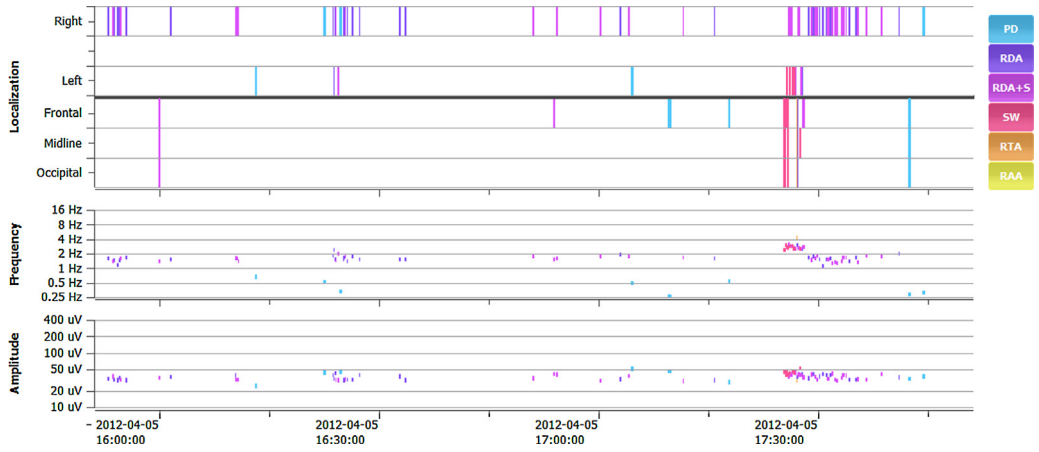

Figure 2 The detection user interface showing of 2 hours of EEG recording. The graphical interface displays rhythmic and periodic pattern detections with colors corresponding to main term 2 (PD, rhythmic delta activity [RDA], RDA + S, SW) or faster rhythmic activity (rhythmic theta activity [RTA], rhythmic alpha activity [RAA]). The ''localisation'' plot shows the predominant areas of the activity. Lateralized patterns are displayed using a box with small height on the correspondig lateralization line (right, left). Generalized patterns may have a predominance in a specific area (frontal, midline, occipital) and will be displayed using a box with small height. A generalized pattern without anterior-posterior predominance is shown as rectangle spanning over the positions of ''frontal'', ''midline'', and ''occipital''. The frequency and amplitude of all patterns are shown on the second and third plots, respectively. This zoomed detection plot of case 1 shows right lateralized rhythmic activity (LRDA, LRDA + S) at the beginning and near the 16:30 timepoint. An electrographic seizure with a spike-and-wave morphology (GSW and LSW, red colored markers) can be observed at 17:30. Post-ictal slowing is marked by LRDA and LRDA + S (violet and magenta markers).

Fig. 2 shows an example of the GUI from a 2-hour EEG recording. It displays periodic discharges (PD), rhythmic delta activity (RDA), and spike-and-wave patterns (SW), rhythmic theta activity (RTA), and rhythmic alpha activity (RAA) as color-coded bars. All detected patterns are presented on separated but time aligned plots showing localization, frequency, and amplitude.

The localization of the pattern (main term 1) can be observed on the upmost plot. Predominant patterns are plotted as rectangle in one of the five possible vertical positions, which are labeled as ''right'', ''left'', ''frontal'', ''midline'', and ''occipital''. A generalized pattern without predominance is shown as rectangle spanning over the positions of ''frontal'', ''midline'', and ''occipital''. This kind of visualization enables the observation of trends in the spatial distribution of pattern potentials.

Frequency and amplitude of all patterns are shown on the second and third plots, respectively. The vertical position indicates the frequency and amplitude of the patterns on logarithmic scales, respectively. Trends in frequency or amplitude might reveal additional information that can be uncovered on these plots. The underlying EEG can be viewed in an EEG viewer by clicking on a time position in the GUI.

Assessment methodology

We assessed the performance of our detection method in two parts. In the first part, three cases from neurological ICUs are presented that were retrospectively analyzed with our computer algorithm. We summarized the original EEG reports and compared them with the detections shown on the detection user interface, to exemplify the evaluation procedure and to show differences and additions between the neurophysiological report and automatic calculated detections.

In the second part, we present the results of a preliminary evaluation of the ability of our detection algorithm to capture ACNS-defined features of the cEEG from ICU patients. For this study, we randomly selected 10 ICU patients including 187 hours of EEG with an associated clinical EEG report from the Comprehensive Epilepsy Center, Medical University of South Carolina (MUSC) recorded between October 2011 and April 2012. All EEGs were recorded using the international 10—20 electrode placement system at a sampling rate of 256 Hz. The average age of the patients was 57 years (min. 25, max. 74) and the average recording duration was 19 hours (min. 11 h, max. 30 h). The clinical indication for long-term EEG recording included altered mental status, intercerebral hemorrhage, history of status epilepticus with new onset seizures, and stroke. The neurophysiology reports from MUSC included general EEG annotations and statements but no ratings according to CCET terminology. We asked a clinical neurophysiologist from the Neurological Center Rosenhuegel (NCR) blinded to the original EEG report and naive to these EEGs to write reports using our detection user interface (and the raw EEG, if needed) using only 10 minutes of time per patient. These detection-guided reports (DGR) were then compared to the original clinical reports (CR) from MUSC. All of the reports from MUSC were generated by academic clinical neurophysiologists board certified by the American Board of Clinical Neurophysiology. A comparison of the reports was done manually by matching keywords like ''slowing'', ''seizure'', and ''periodic discharge''. Interictal patterns with less than 6 cycles [like temporal intermittent rhythmic delta activity (TIRDA)] were excluded because they are not covered by the CCET nomenclature. If older terms were used, which predated the ACNS

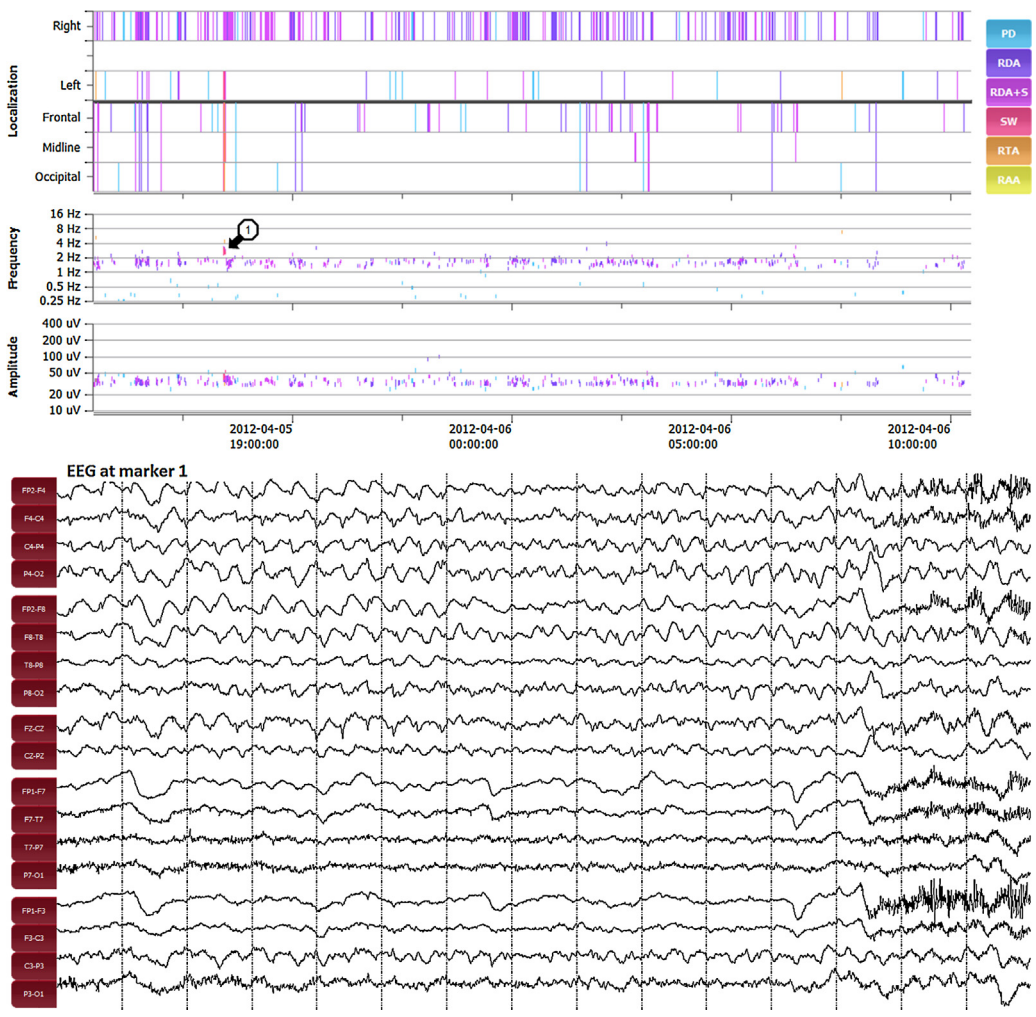

Figure 3 The detection user interface of case 1 shows the result of 20 hours of EEG from a 49-year-old female patient with a brain abscess. Marker 1 shows the time point of an electrographic seizure with repetitive spike-and-wave (SW) activity. The short-term seizure event stays clearly visible on a large time scale because of the color-coded pattern morphology.

terminology [such as ''periodic lateralized epileptiform discharges'' for lateralized periodic discharges (LPDs)], these were considered equivalent. The localization information in both reports was matched based on lateralization or generalization. More precise localization terms referring to a region (i.e. frontal-temporal) were excluded from comparison.

Results

Case reports

Case 1: patient with brain abscess

The patient is a 49-year-old female with history of a brain abscess. The video-EEG monitoring procedure revealed focal, right hemispheric delta slowing and a single electrographic seizure at 17:25:57. The screenshot on Fig. 3 shows detections of RDA and RDA + S from the beginning of the recording by displaying violet and magenta colored bars, respectively. The location of these patterns is mostly on the right hemisphere indicated by most boxes drawn at the label ''right''. The corresponding EEG segments show interictal delta waves at approximately 2c/s with amplitudes of 50 uV. The most prominent group of spike-and-wave detections (in red at marker 1) corresponds to the electrographic seizure mentioned in the original EEG report. The segments without detected patterns did not show any clinically relevant abnormal EEG activity. This case shows that the detection algorithm is able to pinpointing to clinically interesting EEG segments.

Case 2: patient with stroke and abnormal movements

The patient is a 59-year-old female with a history of stroke and repetitive movements of the right forearm. During video-EEG monitoring, left hemispheric slowing together with LPDs on the left parasagittal region were reported. No seizures occurred. The detection result on Fig. 4 confirms a continuous LPD in the left hemisphere (PD colored in light blue) for the first 4 hours of recording with a sudden decay in frequency in the evening at 20:10 (marker 1). In addition, occasional rhythmic delta activity with sharp morphology (RDA + S, colored in magenta) was found in the same time span on the same hemisphere. After a pause of two hours,

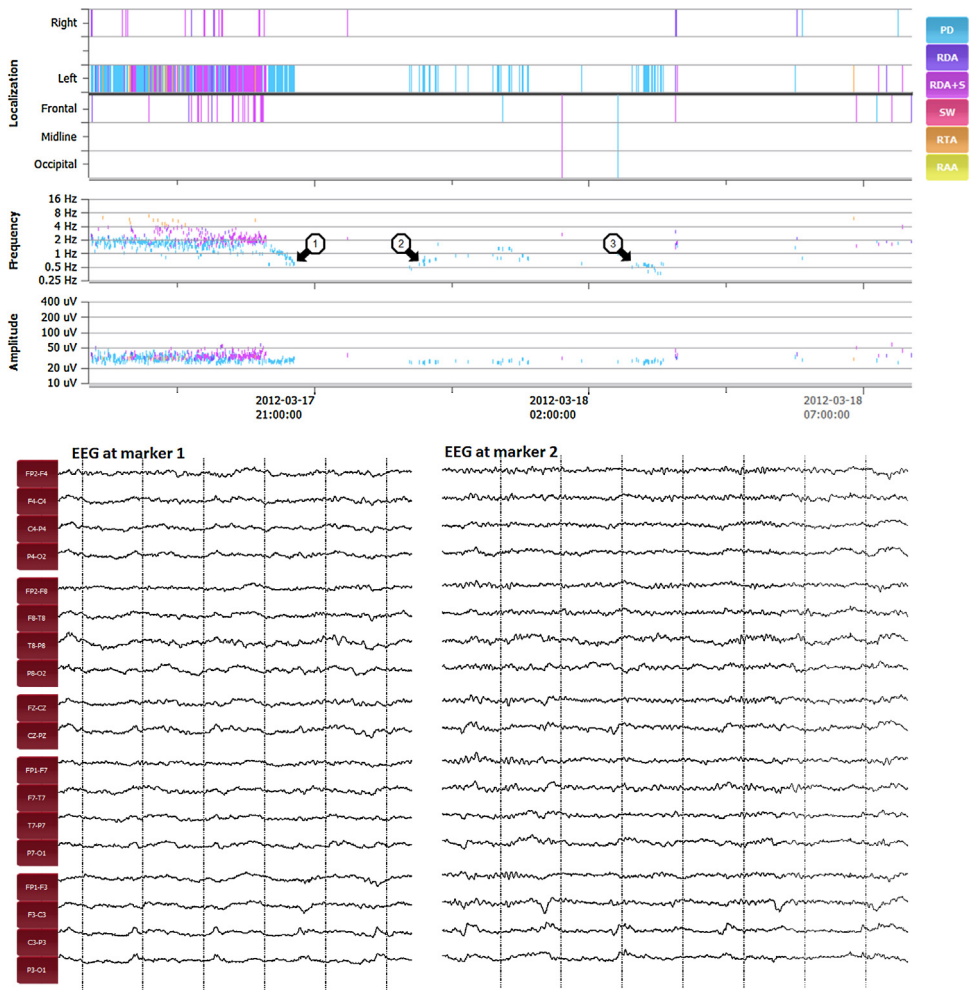

Figure 4 Case 2 is a 59-year-old female with a history of stroke and repetitive movements of right forearm. Left hemispheric lateralized periodic patterns with decaying frequency can be observed (marker 1). During the same time, rhythmic delta activity with sharp morphology (rhythmic delta activity + S, magenta color) can be seen. Periodic activity reappears after pauses of several hours (marker 2 and marker 3).

occasional LPD can be seen at 23:00 (marker 2) and at 03:00 in the morning of the next day (marker 3). It is interestingly to note the trend of the LPD frequency over time and the clusters of PD patterns shown in the GUI.

Case 3: patient with NCSE after ICH

The patient is a 74-year-old female with history of intracranial hemorrhage (ICH) and nonconvulsive status epilepticus (NCSE). The report from video-EEG monitoring at MUSC described diffuse arrhythmic delta slowing and frequent spikes from the left temporal region. At least nine seizures were identified from 21:22 to 22:23. The screenshot of the detection GUI on Fig. 5 shows an initial period with abundant spike-and-wave patterns in the left temporal region (LSW, shown in red) together with rhythmic theta activity (RTA, in orange). The time position of these very brief subclinical seizures can be observed by the SW markings (example marker 1). All seizure events are lateralized to the left side. In addition to the findings reported at MUSC a segment of LPD from the left hemisphere can be seen in the detection GUI analysis (marker 2). An interesting point is that a basic change in the EEG patterns can be observed on a large time scale.

Comparison between manual and detection-guided EEG review

The evaluation of the trial study comparing the detection-guided report (DGR) using 10-minute review time and the clinical report (CR) is summarized in Table 2. The CR was written using the evaluation of video, which allows a more reliable decision between seizure and artifact given an ambiguous EEG segment. Some patterns in the DGR were therefore described as ''episode of rhythmic theta activity at 6c/s'' instead of ''seizure with 6c/s'' but were considered to be equivalent.

The major items in both reports are described and additional findings in the DGR and detections missed in the DGR are outlined for each patient. A comparison between the DGR and the CR shows that in three out of five patients with reported seizures (patients P1, P3, and P6) all seizures from the original report were found. In patients P5 and P6,

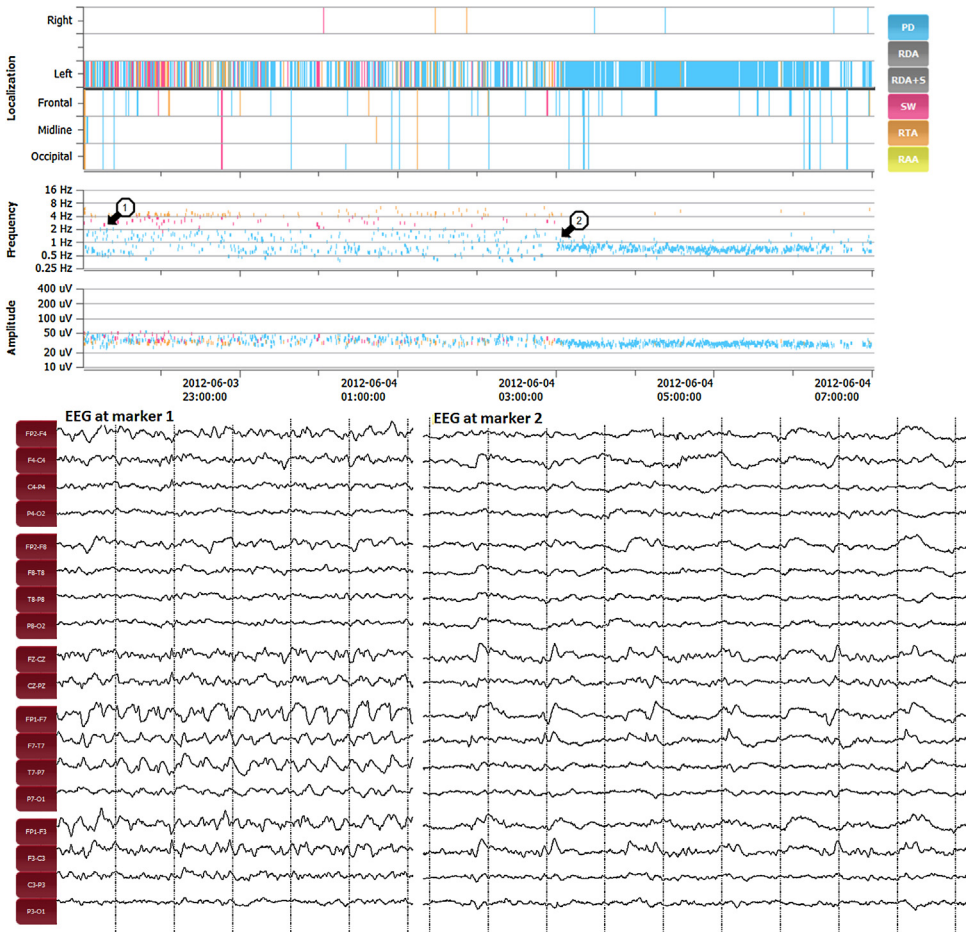

Figure 5 Case 3 is a 74-year-old female patient with history of intracranial hemorrhage and now with nonconvulsive status epilepticus. The detection user interface shows an initial period with many repetitive spike-and-wave patterns on the left temporal region (LSW shown in red, i.e. at marker 1) together with sharply contoured rhythmic delta activity (rhythmic delta activity + S, magenta). A period of lateralized periodic patterns (marker 2, light blue) can be observed over the same hemisphere, which continues for more than 3 hours.

additional seizures were found during the guided review. In one patient (P4), all 14 clinical seizures were missed because 12 seizures showed no clear EEG correlation and two showed only minor electrographic correlations. The seizures could only be picked up with extensive video monitoring showing a slight head movement and a movement of the right arm. The events were then annotated as complex partial seizures. Another patient (P7) had one seizure with poor electrographic correlation, which was missing in the DGR. LPDs were coincided in the reports of 2/2 patients (P1, P2). In three patients (P4, P5, and P10), LPDs were additionally found in the DGR. In patient P7, LPD was reported by the MUSC reviewer but GPD was reported in the DGR. The reports of EEG slowing by MUSC interpreters were in agreement in 7/9 patients (missing in DGR of P2 and P10). In two patients (P6 and P8), episodes of generalized rhythmic theta activity were reported in the DGR, which had not been mentioned in the MUSC clinical report. In one patient (P2), a focal slowing was not detected and reported in the DGR review because of the missing background evaluation capability in the detection method.

Discussion

In this article, we presented an automated computer algorithm that detects rhythmic and periodic patterns in ICU EEG recordings based on ACNS standardized critical care EEG terminology (CCET) [11]. This terminology was defined by a group of experienced neurologists using standardized clinical wording. Detection results are displayed on a graphical detection user interface to simplify review sessions. The interpretation of the detections on the user interface is then based on these clinically defined terms, therefore avoiding mathematical or technical nomenclature. A clinical application of such a detection user interface will allow a quick overview of several hours of EEG without overwhelming medical staff with technical information.

Due to the complexity of the EEG signal, in current clinical practice EEG can only by analyzed by highly trained EEG experts. These experts have limited time for EEG review and, due to the recent expansion in ICU EEG monitoring, they are currently be overwhelmed by the amount of EEG that needs to be reviewed at medical centers which are able to implement ICU EEG monitoring. Pre-analysis of EEG

Table 2 Comparison between 10 EEG reports written after time unlimited clinical video-EEG review (CR) and after a 10-minute EEG review using automatic detections of rhythmic and periodic patterns (DGR).

ID	Clinical video-EEG report (CR)	Detection-guided report (DGR)	Additional in DGR	Missed in DGR	Rating
P1	Right side PLEDS which improve over time; brief electrographic seizures. Slowing	Frequent 0.5—1/s right LPD, slowing, and many brief electrographic seizures	—	—	=
P2	Left hemisphere slowing, PLEDS in the left parasagittal region, epileptiform discharges occurring at 2 Hz, twitching of the right hand	Left fronto-temporal LPDs until 9 pm disappearing for 4 h, and reappearing at 1 am with increasing frequency. No seizures	Time course of LPD, frequency changes	Slowing	±
P3	Focal right frontal-temporal hemispheric delta slowing. One electrographic seizure at 5:25 pm on 4/5/12	Slowing on the right, seizure with 3/s GRDA/GSW at 05:25 pm on 4/5/12	—	—	=
P4	Right parasagittal delta. Multiple subtle seizures	Occasional right LPD starting at 00:00 h, intermittent slowing on the right	LPD right (matching right parasagittal delta)	14 clinical seizures, only 2 with EEG correlate	±
P5	Diffuse arrhythmic delta slowing, TIRDA, no seizures	Intermittent slowing, abundant 1/s left LPD until approx. 11:00 pm, one brief electrographic seizure	One brief electrographic seizure, LPD	TIRDA (too short)	+
P6	Independent left and right temporal spike waves, one electrographic seizures	Intermittent slowing, 3 electrographic seizures	1 additional electrographic seizure, slowing, increasing theta activity at the end	Spikes left temporal	±
P7	Intermittent right frontal-central bursts of 2—3 Hz delta slowing, PLEDS, intermittent right frontal sharp wave discharges, one electrographic seizure	Occasional GPD, rhythmic theta at 7:00 pm, generalized slowing, no seizures	—	1 focal right seizure	—
P8	Continuous bilateral, frontally predominant generalized sharp waves, 5—6 Hz theta slowing of the background bilaterally	Slowing, GPD 11:30 pm to 4:15 am, 3—4/s GSW from 09:20 pm to 10:30 pm	Theta pattern from beginning to 1:00 am. GPD, GSW	—	++
P9	Diffuse arrhythmic delta slowing, triphasic waves	Slowing, continuous 1—2/s GRDA/GRDA + S/GSW of 1—10 s duration with fluctuating morphology starting from 11:00 pm, which matches NCSE criteria	Time course, more detailed pattern description	—	++
P10	Periods of intermittent generalized delta slowing	Very few episodes of low amplitude left LPD at 0.5/s or less, no background activity	LPD	Intermittent slowing	±

LPD: lateralized periodic patterns; PLEDS: periodic lateralized epileptiform discharges; TIRDA: temporal intermittent rhythmic delta activity.

performed by computer algorithms may speed the process of this EEG review and perhaps allow personnel with less EEG training to accomplish thorough EEG review.

The results of the trial study provide some evidence that review of long EEG recordings using our computer algorithm is possible in a short time period. In the limited series of cases presented, most of the important elements in the EEG were automatically detected in a short review time. The detection-guided reviewer had only 10 minutes time to evaluate 11 to 28 hours of EEG. Given this substantial time restriction, we think that the high detection accuracy we found is promising. The detection accuracy for PD and RDA was almost 100% compared to the extensive video analysis of the EEG, in fact, additional PD patterns were detected in many patients. In addition, generalized rhythmic theta was detected in two patients that were missed by the MUSC reviewer. The detection-guided reviewer missed several subtle seizures in one patient that did not show clear EEG correlation. These seizures could only be picked up using video-EEG and could not be detected by an automated system that only examined EEG. On the other hand, the detection-guided reviewer found additional information about pattern trends over a long time period. Manual analysis of highly complex EEG tends to pick out sporadic events to describe the patient status. The results show that systematic digital analysis of patterns additionally enables to capture trends hidden in complex EEG data. This information is emphasized in the reports of the detection-guided review of patients P2, P6, P8, and P9.

We envision the use of our automatic detection system for monitoring of intensive care patients, where EEG recording equipment would send the digitized EEG data in real-time during the recording. Sudden changes in the EEG could then be observed through periodic checks of the detection user interface by the ICU staff. The visual combination of detection representing rhythmic and periodic patterns in combination with other neuromonitoring parameters such as intracerebral pressure (ICP) on the same time scale could potentially reveal additional information.

Our computer algorithm detects patterns according to CCET nomenclature only. Information about normal patterns present in the EEG is not reported. In the future, we would like to add additional features that would evaluate and report features of the normal background EEG such as continuity, dominant frequency, and background amplitude. In such an approach, every EEG segment would be evaluated without exception.

We are aware that the study design has several significant weaknesses. First, there were only a limited number of cEEG recordings studied and these recordings were not collected prospectively. Second, the standard EEG reports to which the detection-guided report was compared, were based on only one MUSC reviewer and this MUSC reviewer was different for many of the EEG recordings. Third, only a single expert reviewer performed the detection-guided review. However, the high agreement between MUSC and the detection-guided reports and the high percentage of detection-guided reports with additional information encourage the initiation of a comprehensive prospective study.

Conclusion

A computational method to detect rhythmic and periodic patterns based on the ACNS' standardized critical care EEG terminology was presented. The results of three patient cases showed the potential of this system to review EEGs of critical care patients. An objective comparison in a preliminary trial study of 10 long-term EEG recordings showed that the utilization of a detection-guided review system could possibly assist with clinical EEG analysis. Further multicenter studies including larger prospectively acquired EEG recordings and validation using multiple expert EEG reviewers are needed to validate our computational method.

Disclosure of interest

The authors declare that they have no conflicts of interest concerning this article.

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