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Spectrograms for Seizure Detection in Critically Ill Children

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Summary: Electrographic seizures are common in critically ill children and a significant proportion of these seizures are nonconvulsive. There is an association between electrographic seizures and neurophysiological disturbances, worse short- and long-term neurologic outcomes, and mortality in critically ill patients. In this context, timely diagnosis and treatment of electrographic seizures in critically ill children becomes important. However, most institutions lack the resources to support round-the-clock or frequent review of continuous EEG recordings causing significant delays in seizure diagnosis. Given the current gaps in review of continuous EEG across institutions globally, use of visually simplified, time-compressed quantitative EEG trends such as spectrograms has the potential to enhance timeliness of seizure diagnosis and treatment in critically ill children.

Key Words: Spectrograms, Quantitative EEG, Critical care, Paediatric intensive care unit, Nonconvulsive seizures, Non-EEG experts, Neurophysiologists, Automated seizure detection.

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In this review, we describe quantitative EEG (qEEG) trends and spectrograms, outline spectrograms types and common patterns, and summarize studies in critically ill children evaluating spectrogram-based seizure diagnosis by EEG experts as well as nonexperts. This will allow readers to evaluate both retrospective and real-time performance data of spectrograms for seizure identification in critically ill children. In addition, we present some recent advances related to spectrogram-based seizure detection. Finally, we focus on gaps in existing literature and important considerations relevant to the implementation of a spectrogram-based seizure screening program for critically ill children.

ELECTROGRAPHIC SEIZURES IN CRITICALLY ILL CHILDREN

Electrographic seizures (ESs) are common and difficult to diagnose at the bedside in the pediatric intensive care unit. Around 30% to 40% of critically ill children with acute neurologic problems develop ES during their intensive care stay, and roughly, 10% to 20% of critically ill children have a significant burden of seizures that would meet criteria for electrographic status epilepticus (Fig. 1).[1–3] More importantly, critically ill children can have seizures that are either completely subclinical without any motor manifestations or only have subtle motor manifestations that are challenging to recognize at the bedside. Of all ES in critically ill children, around one-third is subclinical and another one-third only have subtle motor manifestations, making a significant proportion of ES challenging to recognize clinically at the bedside.

IMPACT OF ELECTROGRAPHIC SEIZURES

Electrographic seizures are associated with adverse short- and long-term outcomes in critically ill children.[4,5] Although there is a debate regarding causality, the association between ES and poor outcomes in critically ill patients has been well recognized. Studies using cerebral microdialysis in patients with traumatic brain injury have shown an increase in lactate–pyruvate ratio during episodes of ictal activity in the brain.[6] Payne et al.[7] demonstrated an association between increasing ES burden and likelihood of neurologic decline in critically ill children. Most importantly, long-term follow-up studies in children with congenital heart disease and ESs in the perioperative period have established a relationship between electrographic status epilepticus and worse long-term executive function, adaptive behavior, and functional outcomes.[8,9]

THE CLINICAL PROBLEM

Despite recent advances in our understanding regarding the impact of ESs in children, even institutions in the developed world are still unable to perform round-the-clock review of the continuously recorded EEG signals in critically ill children. This is because of several challenges. First, raw EEG data, especially those recorded in critically ill patients, are lengthy, complex, and voluminous. Manual review and interpretation by EEG experts are time-consuming.[10] Second, most centers are experiencing a growing mismatch between increasing demand for EEG monitoring and the limited availability of board-certified neurophysiologists or EEG experts. Because of these two factors, even though the EEG recording is continuous, expert review of EEG is

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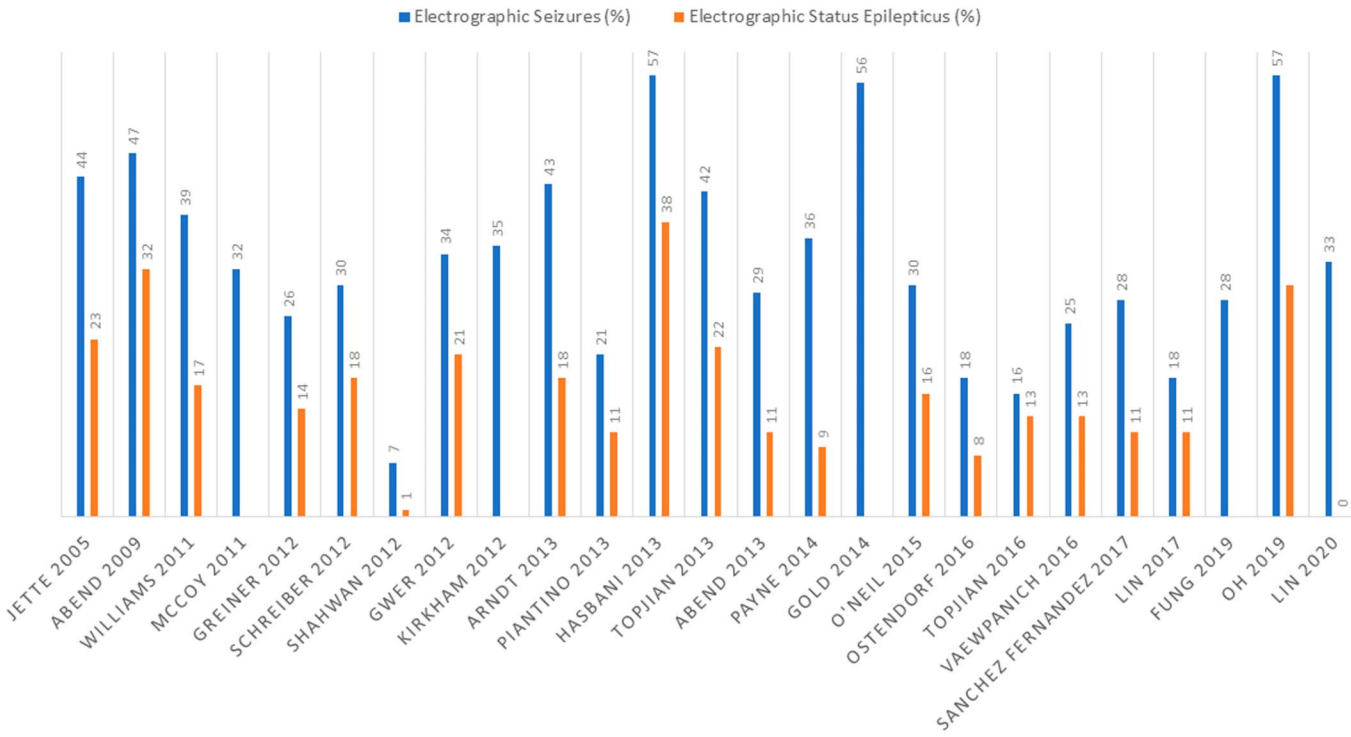


FIG. 1. Studies reporting prevalence of electrographic seizures and status epilepticus in critically ill children. The histogram depicts the prevalence of electrographic seizures in each study in blue and prevalence of electrographic status epilepticus in orange.

currently intermittent and infrequent in most centers even in North America.[11] As a result, delays between seizure occurrence, recognition, and treatment are common, as illustrated in Fig. 2. Given the potential deleterious consequences of uncontrolled ESs in the critically ill population, this delay in seizure recognition and therapy may have adverse consequences on both short- and long-term neurologic outcomes in critically ill children.[7,9,12]

QUANTITATIVE EEG (SPECTROGRAMS) AS A SOLUTION

Quantitative EEG is a term that encompasses all mathematically processed, time-compressed visual representations derived from raw EEG signals. Quantitative EEG can function as a sensitive and efficient screening tool for ictal abnormalities, when accompanied by expert review of the corresponding segments of raw EEG to confirm or refute the initial suspicion for seizures. Quantitative EEG trends can be broadly classified as those derived from time domain and time–frequency domain analyses. Examples of the former would include amplitude-integrated EEG and envelope trends, whereas the latter category includes the various types of spectrogram.

What Is a Spectrogram?

A spectrogram is a visual time–frequency representation of the range of frequencies of a signal as it varies over time.[13] Spectrograms are used in a variety of fields including cognitive neuroscience, music, radar, sonar, and seismology. A spectrogram can be generated through one of the following approaches: an optical spectrometer, a bank of band-pass filters, by Fourier transform or by a wavelet transform, and is usually depicted as a "heat map," an image with the intensity shown by varying the color or brightness. It is usually geometrically two-dimensional but contains three-dimensional information. Time is represented on the x-axis, frequency on the y-axis, and another frequency and time-specific characteristic of the signal (e.g., power, rhythmicity, symmetry) is represented by the intensity of color of that point on the spectrogram, constituting its third dimension.[14] Spectrograms are derived from the original signal and there is significant loss of information in the derivation process; therefore, our ability to reverse engineer the raw signal from the spectrogram is limited.

Types of Spectrograms

Some of the common spectrograms included in qEEG panels are Fast Fourier Transform (FFT) spectrogram, rhythmicity spectrogram, and asymmetry spectrogram:

1. An *FFT Spectrogram a.k.a. color spectral array or color density spectral array* represents time on the x-axis, frequency on the y-axis, and a color scale on the z-axis that represents the power (amplitude-squared) within each frequency band. This spectral array of power as a function of time is derived through an FFT analysis of the amplitude of component frequencies from the raw EEG signal.

2. A *rhythmicity spectrogram* represents time on the x-axis and frequency on the y-axis, and a color scale on the z-axis that represents the amplitude of the primary rhythmic EEG components present in each canonical frequency band; for example: delta (1–3 Hz), theta (4–7 Hz), alpha (8–13 Hz) and beta (14–31 Hz).
3. An *asymmetry spectrogram* represents time on the x-axis, frequency on the y-axis, and a color scale on the z-axis that represents the frequency-specific power difference between homologous electrodes, with shades of red usually depicting higher power in the right hemisphere and shades of blue depicting higher power in the left.

Any spectrogram type can be customized in terms of power spectra, montages, and color palette to optimize the sensitivity of seizure detection and to facilitate ease of screening as per the preference of individual users.

It is important to understand that physiologic and nonphysiologic artifacts can significantly affect the quality of the spectrograms. Some EEG review software include the ability to filter out or exclude channels with various types of noncerebral (artefactual) signals in the EEG.[15] These tools work in near-real-time to detect and reduce muscle, electrode, and eye movement artifacts, which high-cut or low-cut filters may not be sufficient to deal with.[15–17] However, these algorithms could potentially attenuate or alter the underlying brain-derived signals.[18] Although the algorithms used by commercially available spectrogram software are proprietary, artifact removal algorithms using second-order blind identification, extended information maximization (InfoMax), or adaptive mixture of independent component analyzers are considered reliable. The best performing algorithm, however, is highly dependent on the type of EEG signal, specific artifacts, and the signal-to-artifact ratio; experts opine that the optimal method for removing artifacts from the EEG consists in combining more than one algorithm to correct the signal using multiple processing stages.[19]

SPECTROGRAM PATTERNS

There have been attempts to standardize the terminology used to describe visually identified spectrogram patterns.[20–22] Most recently, seven categories of spectrogram patterns have been defined for critically ill adults, summarized in Table 1.

Safar et al. also evaluated the interrater agreement for classification into these different spectrogram patterns and estimated the probability distribution of IIC patterns versus other EEG patterns within each category of this new terminology. With 10 experienced electroencephalographers reviewing 230 images (115 raw EEG samples and 115 corresponding spectrogram images), they were able to demonstrate a "near-perfect" agreement for solid flames, low power, and artifact categories, and a "substantial" agreement for all other categories. Most importantly, solid flames demonstrated sensitivity of 87.5%, specificity of 92.5%, and accuracy of 92.2% for identification of seizures. Because these spectrogram patterns have been derived from and validated in EEGs of adult critically ill patients, their applicability to the pediatric population still needs to be evaluated. However, such standardization of the terminology for spectrogram patterns holds promise for facilitating better communication among neurophysiologists, critical care providers, and other non-EEG experts.

SEIZURE IDENTIFICATION ON SPECTROGRAMS IN CRITICALLY ILL CHILDREN BY EEG EXPERTS

Several studies have shown that neurologists, neurophysiologists, and epileptologists can identify seizures on spectrograms derived from critically ill patients more efficiently with acceptable sensitivity and false-positive rates.[10,23–26] Stewart et al.[23] were the first to report the diagnostic accuracy of spectrogram for seizure identification in critically ill children. A subsequent study by Akman et al.[24] evaluated seizure detection using digital trend analysis but focused more on factors affecting utility of the trends for rapid seizure identification. Pensirikul et al.[25] incorporated insights gained from these two studies to conduct an elegant study focused on evaluating spectrograms in critically ill children. All three studies confirmed that EEG experts were able to identify seizures on spectrograms in critically ill children with acceptable sensitivity, specificity, and false-positive rates (Table 2).

SEIZURE IDENTIFICATION ON SPECTROGRAMS BY NON-EEG EXPERTS

Most institutions lack sufficient numbers of board-certified EEG experts to permit round-the-clock review of either raw EEG or spectrograms. In this context, if critical care providers who are

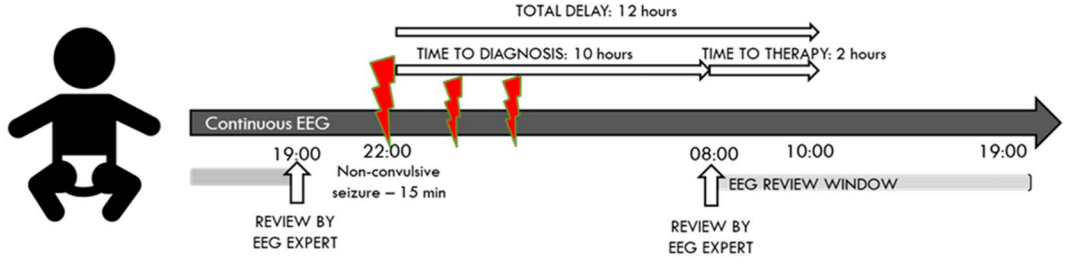
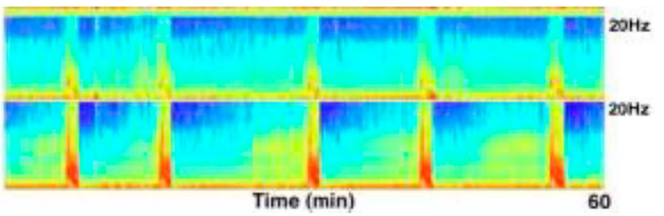
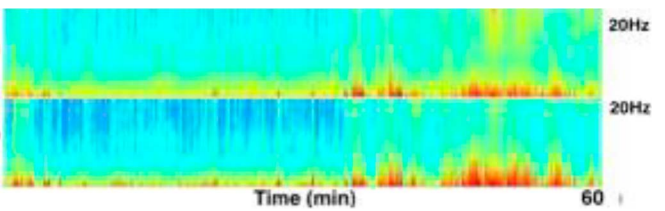
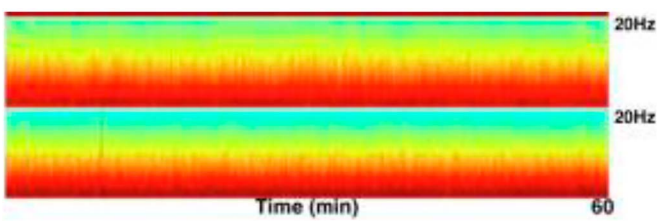
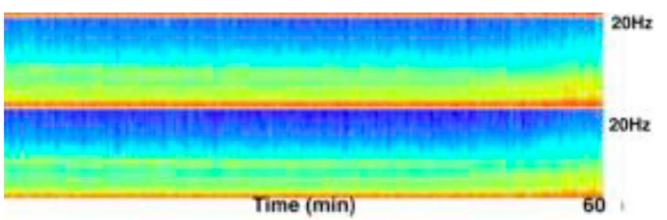


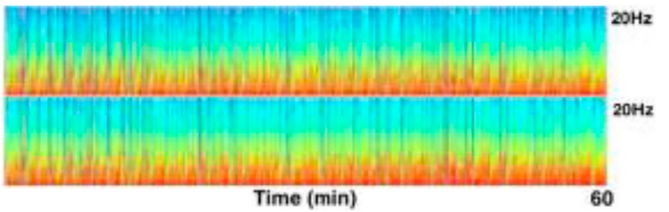
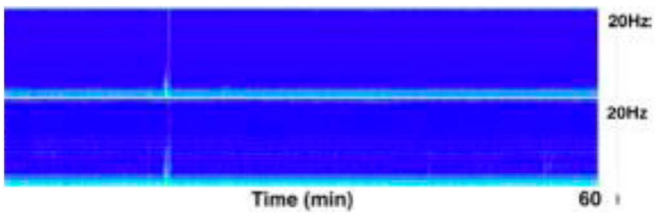
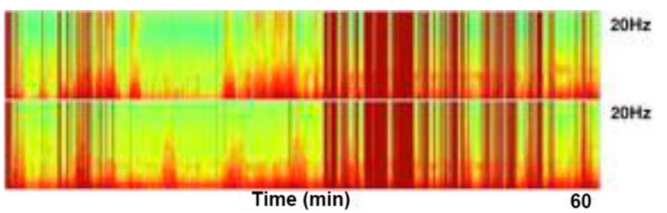
FIG. 2. Illustration of a representative timeline of seizure occurrence, diagnosis, and treatment in a critically ill child under current circumstances. Nonconvulsive seizures are depicted in red. EEG review window is depicted in gray between 08:00 and 19:00. In this case, the three electrographic seizures occurring at 22:00, 23:00, and midnight are not recognized until 08:00 in the morning, leading to institution of appropriate therapy at 10:00, with a total delay of 12 hours.

TABLE 1. Spectrogram Categories, Description, Representative Example and Corresponding Raw EEG Patterns

Spectrogram Pattern	Description	Representative Example[18]	Corresponding Raw EEG Pattern (%)
Solid flames	Abrupt onset of high power and bandwidth with a smooth edge visually resembling a candle flame		Seizures or IIC patterns (69.4%) Seizures only (33.1%) IIC only (36.3%)
Irregular flames	Irregular flame-like shapes that appear to be visually choppy		Seizures or IIC patterns (38.7%) Focal/generalized slowing (32.3%)
Broadband monotonous	Minimal variation or gradual waxing and waning of sustained highpower across a broad range of frequencies		Seizures or IIC patterns (54.3%) Focal/generalized slowing (32.9%)
Narrowband monotonous	Sustained band of high power in lower frequencies with minimal variation, usually yellow/red (high power)		Focal/generalized slowing (43.8%) IIC patterns (24.2%) Seizures or IIC patterns (24.2%)

(*Continued*)

TABLE 1. (*Continued*)

Stripes	Alternating bands of diffuse low and high power across frequencies depicting a burst suppression pattern with bursts contributing to the striped pattern		Burst suppression (37.2%) Generalized suppression (34.4%) Focal/generalized slowing (17.6%)
Low power	Diffuse low power with a monotonous appearance, usually with a narrow band of dark blue/ green (low power)		Generalized suppression (94%)
Artifact	Irregular high power across a broad range of frequencies		Artifact (66%) Generalized suppression (20%)

IIC, ictal–interictal continuum.
Adapted from Zafar et al.[22]

TABLE 2. Summary of Studies Evaluating the Ability of EEG Experts (Neurophysiologists) to Identify Seizures on Spectrograms in Critically Ill Children

First Author	Year	Timing of qEEG Review	Children/ Recording	Reviewers	Reviewer Task	Trends	Sensitivity	Specificity	False-Positive Rate	Other Metrics
Stewart et al.[23]	2010	Retrospective	27 representative critically ill children/ 487 hours of EEG	3 certified neurophysiologists (with no prior qEEG experience)	Identify suspected seizures and mark them using a single-pixel cursor on simulated clinical software	8-channel CDSA (8 hours long)	83.3% (range, 73.3–86.7)	—	0.06/hour (range, 0–0.13)	—
						8-channel aEEG (8 hours long)	81.5% (range, 80.6–83.9)	—	0.05/hour (range, 0–0.19)	—
Akman et al.[24]	2010	Retrospective	14 critically ill children	Reviewer 1 (R1)—experienced user—epileptologist Reviewer 2 (R2)—inexperienced user—neurologist	Classify each image based on whether it contained a seizure (yes/no)	6-channel CDSA (4 hours long)	R1—87% R2—52%	—	—	—
						6-channel CDSA (2 hours long)	R1—78% R2—65%	—	—	—
						6-channel CDSA + envelope trend	R1—100% R2—78%	—	—	—
Pensirikul et al.[25]	2013	Retrospective	21 consecutive critically ill children/ 168 hours of EEG	8 pediatric EEG experts	Circle suspected seizures: Group A—images in random order	8-channel CDSA (2 hours long)	64.8% (95% CI, 54–75)	92.3% (95% CI, 88–95)	—	AUC-ROC—0.79 PPV—75% NPV—88%
					Group B—images from each subject consecutively with seizures in the first 30 minutes circled		75% (95% CI, 65–84)	78.2% (95% CI, 73–82)	—	AUC-ROC—0.77 PPV—55% NPV—90%

AUC-ROC, area under the receiver operating characteristic curve; aEEG, amplitude-integrated EEG; CDSA, color density spectral array; CI, confidence interval; NPV, negative predictive value; PPV, positive predictive value; qEEG, quantitative EEG.

TABLE 3. Summary of Studies Evaluating the Ability of Non-EEG experts (Critical Care Providers) to Identify Seizures on Spectrograms in Critically Ill Children

First Author	Year	Timing of qEEG Review	Children/ Recording	Reviewers	Reviewer Task	Trends	Sensitivity	Specificity	False-Positive Rate	Other Metrics
Topjian et al.[27]	2015	Retrospective	39 children post-cardiac arrest	12 PICU attendings 8 PICU fellows 19 nurses	Classify image as having seizure or no seizure on survey monkey	CDSA—100 two-hour trend images	70% (95% CI, 67–73)	68% (95% CI, 67–70)	—	Accuracy—69% PPV—46% NPV—86%
Du Pont-Thibodeau et al.[29]	2017	Retrospective	39 children post-cardiac arrest	6 PICU attendings 12 PICU fellows 5 nurses	Classify image as having seizure or no seizure on survey monkey	aEEG—100 images	77% (95% CI, 74–80)	65% (95% CI, 63–67)	—	PPV—46% NPV—88%
						aEEG + CDSA—100 images	77% (95% CI, 74–81)	68% (95% CI, 66–71)	—	PPV—49% NPV—89%
Lalgudi Ganesan et al.[28]	2018	Retrospective	27 critically ill children—487 hours of cEEG	3 PICU fellows 3 PICU nurses 3 EEG technologists 3 neurologists	Identify suspected seizures and mark them using a single-pixel cursor on simulated clinical software	8-channel CDSA	Fellows: 82.4% (IQR, 75.8–84.9) Nurses: 88.2% (IQR, 85.8–89)	—	Fellows: 7.7 per day (IQR, 3.9–9.3) Nurses: 7.1 per day (IQR, 5.3–7.8)	Fellows: PPV—88% Nurses: PPV—80%
						8-channel aEEG	Fellows: 83.8% (IQR, 81.3–84.2) Nurses: 73.1% (IQR, 72.1–74)	—	Fellows: 2.8 per day (IQR, 2.1–4.5) Nurses: 4.2 per day (IQR, 3.1–4.3)	Fellows: PPV—91% Nurses: PPV—88%
Rowberry et al.[30]	2020	Real-time	101 critically ill children	Nurses and PICU clinicians (doctors and advanced nurse practitioners)	Nurses—review qEEG every hour PICU clinicians—review qEEG every 4 hours	2-channel aEEG + CDSA	100% (95% CI, 74–100)*	88% (95% CI, 79–94)*	—	PPV—52%* NPV—100%*
Swarnalingam et al.[31]	2020	Retrospective	10 critically ill children	6 pediatric residents 5 PICU nurses	Identify suspected seizure on an online quiz platform (Collabshot-Toptal LLC)	45 one-hour qEEG epochs Seizure probability marker aEEG Rhythmicity spectrogram	Residents: 90% (95% CI, 85–95) Nurses: 90% (95% CI, 87–93)	Residents: 87% (95% CI, 80–94) Nurses: 89% (95% CI, 85–93)	—	Residents PPV—87% Nurse PPV—88% Residents NPV—92% Nurses NPV—92%

aEEG, amplitude-integrated EEG; CDSA, color density spectral array; CI, confidence interval; IQR, interquartile range; NPV, negative predictive value; PICU, pediatric intensive care unit; PPV, positive predictive value; qEEG, quantitative EEG.

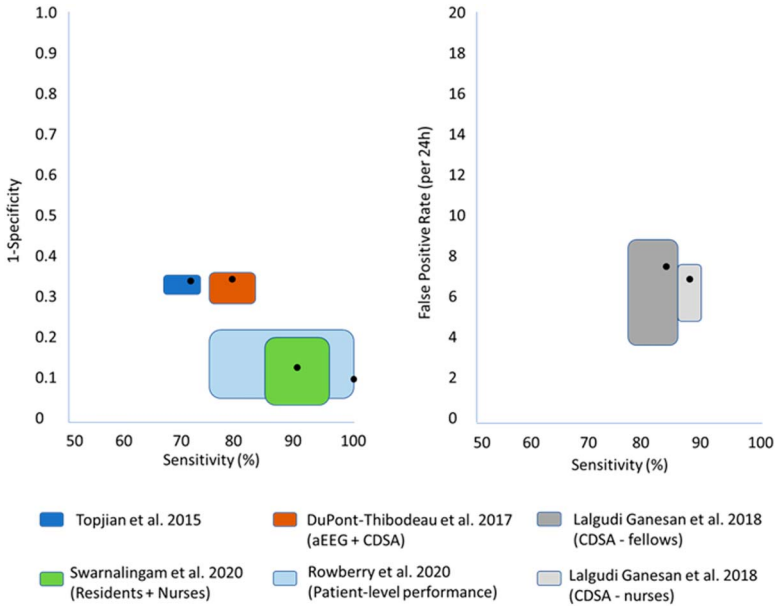


FIG. 3. Illustration of performance of non-EEG experts using spectrograms for seizure identification in critically ill children. The rectangle represents the performance reported in the study. The length of the rectangle represents the dispersion measure (95% CI or IQR) of the sensitivity and the height of the rectangle represents the dispersion measure (95% CI or IQR) of either false-positive rate or 1-specificity, whichever the study has reported. The dark circle inside the rectangle represents the summary measure of sensitivity (x-axis) and one of false positive rate or 1-specificity (y-axis), whichever one the specific study reported. aEEG, amplitude-integrated EEG; CDSA, color density spectral array; CI, confidence interval; IQR, interquartile range.

present at the bedside of the critically ill child could be trained to review spectrograms in collaboration with EEG experts, the frequency of review of spectrograms could be enhanced. Critical care providers are already trained to recognize pathologic patterns in multiple streams of physiologic signals recorded from critically ill patients. Empowering them to screen spectrograms or other qEEG trends will allow them to participate more actively in the diagnosis of nonconvulsive seizures.

In this context, several studies have focused on educating healthcare providers without prior experience or expertise in EEG interpretation on how to use spectrograms to identify seizures in critically ill children.[27–30] While two studies focused on critically ill children post-cardiac arrest,[27,29] the other three evaluated the general pediatric critical care population at risk for nonconvulsive seizures.[28,30,31] Only one of these is a prospective study with real-time seizure detection at the bedside.[30] These studies varied significantly in their design, educational approach, testing strategies, and measures of performance but agreed that critical care providers (non-EEG experts) can use spectrograms to identify seizures with acceptable sensitivity and specificity with standardized training (Table 3 and Fig. 3). Although not a spectrogram-based trend, amplitude-integrated EEG also showed moderate agreement for seizure identification between bedside nurses and EEG experts for the detection of abnormal amplitude-integrated EEG traces in neonates and children.[32]

NOVEL APPLICATIONS OF SPECTROGRAMS

Although most studies have focused on conventional spectrograms available through commercially available EEG review software, a few researchers have developed novel spectrogram trends for the sole purpose of seizure detection by non-neurophysiologists.[33] For example, the median power spectrogram applies a multispectral estimation algorithm to calculate the median power across electrodes and generate a novel color density spectral array (Fig. 4). Using median power spectrogram, non-neurophysiologists could detect seizures with a sensitivity of 77% and a specificity of 72% comparable with performance on other spectrograms.[33]

Automated Seizure Detection Using Spectrograms

Instead of relying on human healthcare providers to review spectrograms, recently there has been an attempt to develop machine learning algorithms to evaluate spectrogram patterns using image processing solutions to determine if these images contain seizures. Convolutional neural networks are one such form of machine learning and has been used to automate the process of seizure detection on EEG spectrograms.[34] Yan et al. evaluated four convolutional neural network models of increasing complexity on 130 EEG spectrograms from 22 children. For spectrographically visible seizures, two convolutional neural network models (containing four and seven convolution layers) achieved >90% sensitivity and specificity for seizure diagnosis. Although current solutions may be limited by overfitting, the increasing ability to apply advanced image processing techniques such as deep convolutional neural networks and transfer learning on spectrogram images to identify seizures could pave the way for development of highly accurate seizure detection algorithms, as well as the ability to accurately classify seizure subtypes.[35]

IMPLEMENTING A SPECTROGRAM-BASED SEIZURE SCREENING PROGRAM

Although several studies have confirmed the ability of critical care providers (non-EEG experts) to identify seizures on spectrograms in critically ill children retrospectively, there are

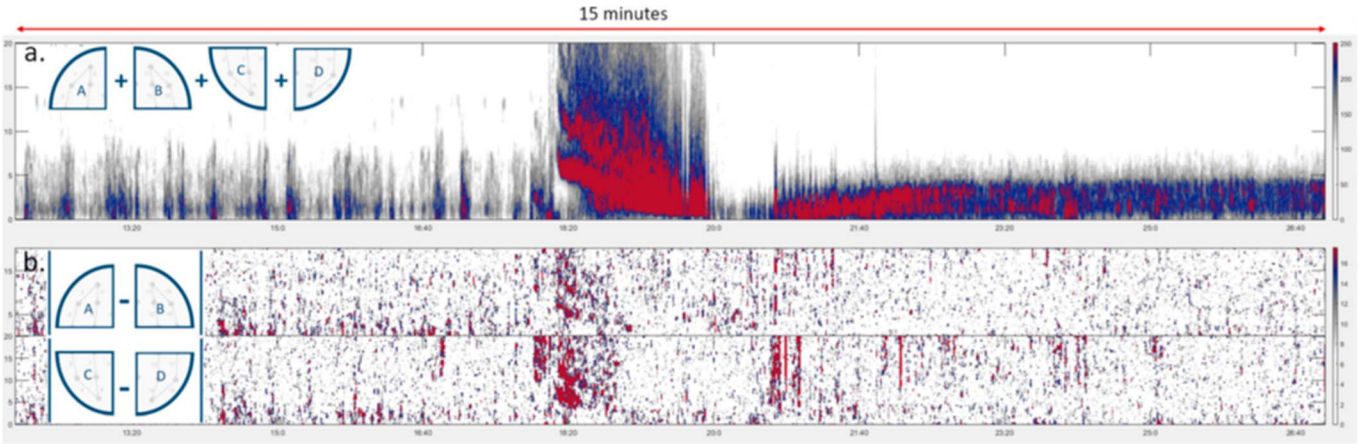


FIG. 4. Representative image of a seizure as depicted on a median power spectrogram (MPS). **A**, shows a single channel that displays the sum of median power spectra from all four scalp quadrants. **B**, has two channels: the top channel shows difference between anterior left and right scalp, whereas the bottom channel shows the difference between posterior left and right scalp [From Yan et al. *Seizure* 2017].[33] The seizure is in the middle of the spectrograms and both panels are time-locked.

several unknowns related to the implementation of a *real-time spectrogram-based seizure-screening program*. In this section, we summarize some of the key components and challenges of a successful program implementation and have presented these as the five Rs:

Right Population

Studies have shown significant variability in sensitivity and false-positive rates among individual EEG recordings, suggesting that in certain patient populations, seizure type or EEG background characteristics influence the utility of qEEG-based seizure screening.[23,24,28] The initial report by Stewart et al.[23] reported that missed seizures usually fell into one of these categories: low voltage (<75 μV), short duration (<1 minute), focal, and those that occurred in the context of abundant interictal epileptiform discharges. A subsequent effort to identify factors affecting utility of spectrograms in critically ill children was undertaken by Akman et al.[24] who reported that interpreter's experience, display size, and type of trend used played a role in addition to seizure and other EEG features. Among seizure factors, the maximum spike amplitude, seizure duration, and seizure frequency also affected accuracy of seizure identification on spectrograms. In a more recent report focused on critically ill children, the likelihood of seizures being identified on spectrograms was low in children younger than 3 years of age, those with brief or focal or infrequent seizures, and those with low signal-to-noise ratios (abnormal EEG backgrounds).[36] In this context, choosing the right patient subgroup for spectrogram-based seizure screening in the pediatric critical care unit is paramount and should help optimize both sensitivity and false-positive rates.

Right Spectrogram Panel

Different seizure types have specific patterns on individual spectrograms, and this may affect their sensitivity for individual seizure types.[37] Goenka et al.[37] were able to show that asymmetry spectrogram was particularly sensitive for picking up focal seizures. Table 4 presents an outline of how different qEEG trends have advantages for specific seizure subtypes based on anatomic distribution.

In addition, most studies have evaluated one type of spectrogram, usually color density spectral array (FFT Spectrogram).[27–29] Newer studies are evaluating the role of a comprehensive panel containing a combination of trends.[31] Even within the same type of spectrogram, the degree of compression, i.e., the time scale (x-axis) makes a difference as demonstrated by Akman et al.[24] Finally, each qEEG software comes with its own set of default settings.[37] For example,

TABLE 4. Comparative Sensitivity of qEEG Spectrograms for Detecting Seizure Subtypes

Seizure Type	FFT Spectrogram	Rhythmicity Spectrogram	Asymmetry Spectrogram	aEEG Trend
Focal ($n = 125$)	43%	29%	**94%**	32%
Focal with secondary generalization ($n = 187$)	**84%**	65%	46%	56%
Generalized ($n = 250$)	**63%**	44%	16%	53%

aEEG, amplitude-integrated EEG; FFT, Fast Fourier Transform; qEEG, quantitative EEG.
Adapted from Goenka et al.[37]
The spectrogram type with greatest sensitivity for a given seizure type is in bold.

those for the FFT spectrogram in the Persyst trend panel are as follows: time constant = 0.16 second, high-frequency filter = 35 Hz, FFT sampling rate = 64 Hz, FFT window duration = 2 seconds, FFT windows per epoch = 8, FFT smoothing = 3; y-axis (frequency display) 0 to 20 Hz, can be customized from 0 to 30 Hz; z-axis (power display and color palette is used) 0 to 2 mV/Hz, can be customized from 0 to 70 mV/Hz. Depending on the preference of the end-users in a pediatric critical care unit, these settings and the color palette can be modified.

Such factors need to be considered while implementing spectrograms for seizure screening in the intensive care unit. The choice of spectrograms may have to be tailored for individual patients based on their seizure phenotype. Alternatively, one could consider using a comprehensive panel comprising of several spectrograms but at the cost of potential cognitive fatigue for critical care providers. Further insights regarding the best combination of spectrogram trends, color palette, and time scale can be obtained through application of human factor analysis methods to test usability of the trends with critical care nurses and other end users.

Right Training

Studies have reported the use of heterogeneous training methods of varying durations to prepare nonexperts for qEEG review. The duration of training for pediatric critical care providers varied from 15 minutes[31] to 30 minutes[27,29] to 120 minutes.[28] A recent systematic review focusing on training intensive care unit providers on EEG highlights much longer durations of reviewer training in the range of hours to days without any evident advantage in performance of the reviewers.[38]

The content and mode of delivery of the training also varied from electronic dissemination of a slide deck[31] to a more comprehensive program consisting of a 30-minute slide-based introduction followed by 90 minutes of hands-on training using qEEG software to examine actual qEEG recordings derived from critically ill children.[28] Despite such wide variability in training provided to non-EEG experts, there was no significant difference in performance of critical care providers among these studies attributable to the training program. However, it is to be noted that none of the pediatric intensive care unit–based studies have formally evaluated the effectiveness of the administered training program using a post-test strategy.

There is also limited information on minimal standards of competence for critical care providers screening spectrograms and maintenance of competence among diverse groups of healthcare providers, especially relevant in institutions with low volumes of patients undergoing continuous EEG monitoring. Future studies should evaluate the role of interactive online learning modules or focusing training on a small group of motivated caregivers with a special interest in neurocritical care to maintain long-term competence.[28]

Right Action Plan

When considering the implementation of a spectrogram-based seizure screening program in a pediatric intensive care unit, it is important to address this practical question—"What happens after a critical care provider identifies an abnormality on the spectrogram?." It is important to develop a pathway that incorporates backup review by a small expert user group of intensivists and/or neurophysiologists before decisions regarding therapy are taken. False-positive flags on spectrograms by non-EEG experts could lead to escalation of therapy and unnecessary exposure to anti-seizure medications with potential for respiratory and/or hemodynamic adverse events. This could also have unrecognized medicolegal consequences. Although Rowberry et al.[30] did not describe this being a significant concern in the early evaluation of their qEEG program, their publication does not provide granular seizure- or event-level data. Similarly, Bourgoin et al.[32] do not comment on false-positive rates or unnecessary interventions based on nurse-identified abnormalities on amplitude-integrated EEG. Future research in this area should prospectively evaluate safety and feasibility of a real-time spectrogram-based seizure screening program for critically ill children.

Right Program

For any spectrogram-based seizure screening program to be successful, it is important to incorporate a stepwise implementation plan with iterative cycles of program monitoring, evaluation, and optimization. The first author is currently leading a multiphase implementation of such a program with the following components: (1) The first phase of the program engages local stakeholders to determine the four Rs outlined earlier. (2) The second (implementation) phase involves roll-out of the program with ongoing monitoring of sensitivity and false-positive rates for seizure diagnosis. These metrics are evaluated at a predetermined frequency to determine if these meet the predefined thresholds of safety acceptable to all stakeholders. In addition, during this phase, qualitative feedback is obtained from stakeholders regarding the program and insights gained from this process are used for continuous quality improvement. (3) The third (post-implementation) phase allows the team to institute anti-seizure treatments based on abnormalities detected on spectrograms by bedside critical care providers with appropriate backup review by a select group of neurocritical care physicians or neurophysiologists. During this phase, there is also a focus on ongoing maintenance of competence of qEEG reviewers and performance standards of the program. (4) The final phase (steady state) focuses on integrating the spectrogram-based seizure screening into the workflow of the stakeholders with minimum need for additional major changes in the program. We recognize that these phases may look very different for each institution. However, a comprehensive collaborative approach is key in ensuring the success of a spectrogram-based seizure-screening program in any intensive care unit.

FUTURE DIRECTIONS

As the demand for continuous EEG in critically ill children increases, existing gaps in our ability to support around-the-clock

real-time review of raw EEG for seizure diagnosis have become more evident. Until automated seizure detection algorithms have better sensitivity and lower false-positive rates,[39] qEEG-based seizure screening by bedside critical care providers is the best path forward to enhance timeliness of seizure diagnosis and therapy. In this context, more research is needed on evaluating feasibility and safety of different real-time qEEG implementation programs and optimal staffing models. Future research in this area should embrace novel approaches from the field of human factors engineering, implementation science, and health services research to understand performance, usability, feasibility, safety, cost-effectiveness, and other facets of various implementational strategies.

CONCLUSIONS

Bedside qEEG is a very good screening tool for seizures but remains an imperfect diagnostic tool. Quantitative EEG trends such as spectrograms are likely to be most beneficial in improving timeliness of seizure diagnosis and treatment in institutions where raw EEG is presently reviewed infrequently. Several retrospective studies have confirmed that non-EEG experts such as critical care providers (attendings, trainees, and nurses) can be trained to identify around four of five ESs in critically ill children. A recent encouraging report of implementation and early evaluation of a qEEG program for real-time seizure detection in critically ill children[30] has brought this one-step closer to more widespread implementation in this population. However, concerns regarding high false-positive rates leading to unnecessary exposure to anti-seizure medications persist. When implementing bedside qEEG monitoring, pediatric intensive care units must be aware of the limitations of the data and carefully consider the five "R"s that we have outlined. Further research is needed on determining the best approaches to implementing a qEEG (spectrogram)-based real-time seizure-screening program in critically ill children ensuring that critically ill children see all or most of the benefits without any or minimal harm.

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