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Adaptive median feature baseline correction for improving recognition of epileptic seizures in ICU EEG

S. Raghu [a,b], Natarajan Sriraam [b,*], Erik D. Gommer [c], Danny M.W. Hilkman [c], Yasin Temel [d], Shyam Vasudeva Rao [e], Pieter L. Kubben [d]

[a] Department of Neurosurgery, School for Mental Health and Neuroscience of the Faculty of Health, Medicine and Life Sciences, Maastricht University, Maastricht, The Netherlands
[b] Center for Medical Electronics and Computing, M S Ramaiah Institute of Technology, Bengaluru, India
[c] Department of Clinical Neurophysiology, Maastricht University Medical Center, Maastricht, The Netherlands
[d] Department of Neurosurgery, Maastricht University Medical Center, Maastricht, The Netherlands
[e] Technical Director, Maastricht University, Maastricht, The Netherlands

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ABSTRACT

Automated classification of epileptic seizures surrogates the manual interventions required for analyzing long-term electroencephalographic (EEG) signals and helps to speed up the treatment in epilepsy patients. Developing a patient independent algorithm is a great challenge due to the differences in EEG characteristics. Feature distribution among many subjects results in inter-subject variability, which leads to poor classification performance. Therefore, in order to overcome this limitation, we have proposed a novel adaptive median feature baseline correction (AM-FBC) method to update the feature distribution. Two recently proposed features referred to as successive decomposition index (SDI) and matrix determinant (MD) were extracted from 40 intensive care unit patients EEG at a segmentation length of 4 s with 50% overlap. We have investigated the influence of outliers removal and correction, AM-FBC, and post-processing of classifier output to improve the seizure detection results. The classification was performed using a support vector machine classifier with leave-one-subject-out cross-validation. With the application of above-mentioned methods, the highest area under the curve (AUC) of 0.9663 (sensitivity S^+ = 0.9661, specificity (S^- = 0.8446) and 0.9812 S^+ = 0.9822, S^- = 0.8705) was achieved using SDI and MD features respectively. Further, the AUC of 0.9593 (S^+ = 0.9069, S^- = 0.8695) was achieved when both SDI and MD features were used with the application of the outliers correction method. The findings of the study suggest (1) Outliers correction method does not improve results (2) AM-FBC enhances the results (3) Post-processing method improved the classification results at least 2 to 5% and reduced false detections (4) Lowering the outlier removal factor showed good AUC at the cost of loss of feature samples.

1. Introduction

Epilepsy is a neurological disorder that affects the brain cortical network that in turn affects one's daily life [1]. It is a chronic disease that causes unprovoked recurrent seizures and is characterized by unpredictable seizures that leads to health problems [2,3,1]. It is the fourth most common neurological disorder, which affects 65 million people of all ages around the world [4]. In certain critical situations, epilepsy patients undergo pre-surgical investigation prior to surgery that determines the localization and nature of a seizure. Seizures are a common occurrence in traumatic brain injury patients in the intensive care unit (ICU) [5]. Although estimates of the overall incidence of seizures in the ICU vary, the risk of seizures is higher than in patients at other hospital departments, perhaps with the exception of the emergency department [5]. One of the goals of therapy in the ICU is to suppress seizures to obtain a better patient outcome [5]. Monitoring the long-term electroencephalographic (EEG) signals that belong to epilepsy patients is essential for pre-surgical evaluation, which is found to be a tedious and time-consuming process due to the need for visual interpretation. Accordingly, a reliable patient independent real-time epileptic seizure detection model helps towards long-term monitoring of patients with epilepsy. The high variability in time-varying EEG characteristics between subjects leads to poor classification performance [6,7]. Therefore, we propose an adaptive median feature baseline correction (AM-FBC) method to reduce the

* Corresponding author.
E-mail addresses: r.raghu@maastrichtuniversity.nl (S. Raghu), sriraam@msrit.edu (N. Sriraam).

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inter-subject variability by making use of median values of extracted features.

Several patient independent automatic detection of epileptic seizure algorithms have been proposed in recent years. A patient-specific model using wavelet packet based combined seizure index revealed the sensitivity of 90.5%, a false detection rate of 0.51/h and median detection delay of 7 s [8]. A threshold based seizure detection method was proposed using the minimum variance modified fuzzy entropy showed classification accuracy of 100% [9]. Another threshold-based decision-making algorithm for artifact removal showed good results using a support vector machine (SVM) [10]. Subasi et al. [11] have compared the performance of principal component analysis, independent component analysis (ICA) and linear discrimination analysis for seizure detection using the SVM classifier. A patient-specific seizure detection algorithm using wavelet decomposition and SVM classifier [12] detected 131 of 139 seizures. Another patient-specific algorithm using spectral parameters, time domain parameters, and wavelet analysis predicted 14 of the 25 seizures [13]. The changes in absence seizure were classified using permutation entropy [14].

Acharya et al. [15] showed the highest accuracy of 98.1% using fuzzy classifier when classified using approximation entropy (ApEn), sample entropy, phase entropy 1 and phase entropy 2. Further, the application of different entropy methods has been reviewed to differentiate normal, interictal, and ictal EEG signals [16]. In [17–19], normal, pre-ictal, and seizure activities were classified using the convolution neural network. Automatic epileptogenic zone recognition and localization on scalp EEG using long-term recurrent convolutional network showed the sensitivity, specificity, and accuracy of 84.0%, 99.0%, and 99.0% respectively [20]. Wave2Vec was proposed to learn the deep representation of epileptic seizures temporal data [21]. Different transformation techniques like discrete cosine transformation, singular value decomposition, discrete wavelet transformation (DWT) were studied for epileptic seizure detection [22]. Improved correlation-based feature selection method with random forest classifier achieved an accuracy of 100.0% between normal and epileptic [23]. Mahalanobis-similarity-based feature extraction method using extreme learning machine classifier showed an accuracy of 97.53% [24]. Classification of epileptic and non-epileptic EEG events using time domain and frequency domain features achieved an accuracy of 95.0% using Bayesian network [25]. Different algorithms for analysis of epilepsy [26] and wavelet-based EEG processing [27] for seizure detection have been reviewed. Different entropy methods like log energy and norm entropy [28], approximate entropy [29,30], weighted permutation entropy [31], Renyi, spectral, Shannon and wavelet entropy [32–34], sample and permutation entropy [35], and sigmoid entropy [36] have been successfully used for seizure detection. K-nearest neighbor entropy estimator, log energy entropy, Shannon entropy, and Poincaré plot parameters were extracted from Empirical mode decomposition (EMD) [37]. Intrinsic mode functions from empirical wavelet transform has been studied to improve time–frequency representation of non-stationary signals in [38–40]. Time–frequency localization of scaling functions and design of three-band biorthogonal linear phase wavelet filter banks has been studied for classification of seizure and seizure-free EEG signals [41,42].

In a recent study [7], feature normalization procedure based on median decaying memory (MDM) showed promising improvements towards seizure detection. In this method, in order to correct the feature baseline, initial 5 s of non-seizure EEG segment was used. The same approach was applied in [6] using 1 min EEG to update the baseline to evaluate seizure detection performance in 17 ICU patients. Five feature normalization techniques, namely MDM, mean memory, standard deviation memory, peak detector, and signal range was applied to a line length feature that proved MDM was outperformed [43]. Bogaarts et al. [44] have proposed an algorithm to improve the area under the curve from 0.767 to 0.902 using average non-seizure feature values (ANSFV) and an optimal threshold for feature baseline correction (FBC) and a Kalman filter to classifier output for post-processing. This feature normalization based patient independent approach showed the AUC of 0.90 and 0.93 for neonatal and adult patients respectively [45]. Further, Temko et al. [46] proposed post-processing of the SVM classifier output using a central linear moving average filter (MAF). Ahmed et al. [47] suggested a post-processing approach using the MAX operator and MAF that significantly improved the seizure detection results.

SVM classifier have been widely used for seizure detection studies [48,49,45,44,6,46,47,11,12]. In our recent study, successive decomposition index (SDI) showed the highest sensitivity of 97.53% using the SVM classifier [50]. Further, matrix determinant (MD) was evaluated on eleven classification problems derived from University of Bonn database [51]. These two features have been tested on the Ramaiah Medical College and Hospitals, CHB-MIT, Temple University Hospital databases in our previous studies [51,50]. Therefore, in this paper, we have used these two novel features (SDI and MD) to validate against new EEG recordings using the most widely used and suitable SVM classifier for seizure detection [50,51].

The significant contributions of our study are: (1) We have proposed a novel approach called AM-FBC to reduce the inter-subject variability in feature distribution (2) Effect of outliers removal and correction (3) Effect of post-processing to improve the seizure detection performance (4) Two recently proposed novel features, namely SDI and MD were tested against new EEG recordings.

Fig. 1 depicts the flow of the proposed algorithm for the epileptic seizure detection. The raw EEG recordings were pre-processed using a notch filter and bandpass filter followed by artifacts removal. The two features (SDI and MD) were classified using the SVM classifier with leave-one-subject-out cross-validation followed by post-processing.

The goal of this paper is to evaluate both the SDI and MD features and the effects of baseline correction, outlier removal and correction, and post-processing of the SVM classifier output on classification performance. We hypothesize that the application of the above-mentioned methods would improve the performance of seizure detection using ICU EEG in epilepsy patients.

2. Materials and methods

2.1. Clinical EEG recordings

The clinical data for the study were obtained from the Department of Clinical Neurophysiology, Maastricht University Medical Centre (MUMC+), Maastricht, The Netherlands for research purpose after approved by the hospital ethics committee. The dataset consists of 40 EEG registrations (22 female and 18 male) from an ICU with the age ranges between 22 and 89 years with a mean age of 54.47 years. The 19 unipolar electrodes Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, and O2 were placed according to International 10–20 system electrode configuration. The scalp EEG was recorded using BrainLab EEG recording system at a sampling rate of 250 Hz using a common average montage. In total, 21 h of EEG (mean duration 0.5243 h) consist of 1273 seizure epochs that varied per subject from 1 to 228 with a minimum and maximum seizure duration of 12 s and 1949 s respectively. The minimum duration of seizure epoch was considered 10 s as per the International Federation of Clinical Neurophysiology [52]. Experts at MUMC + Hospital annotated the seizure and non-seizure epochs. The EEG data was not scored in accordance to type

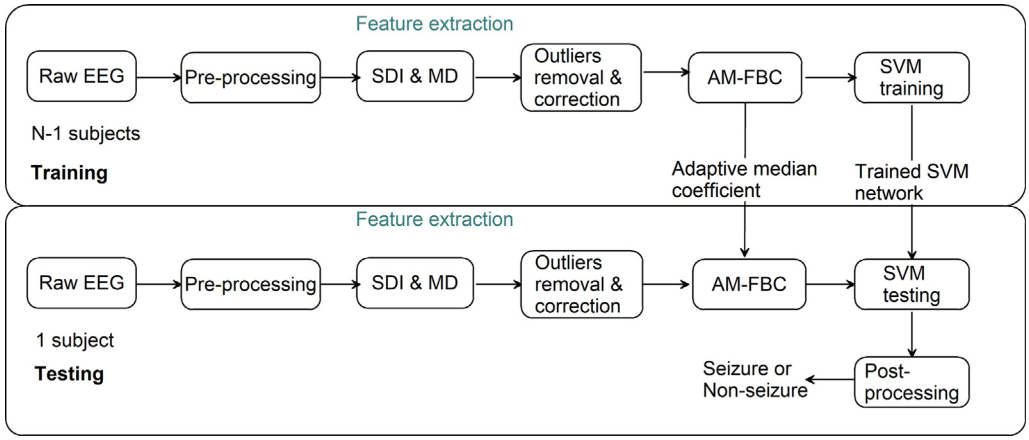

Fig. 1. The flow of the proposed seizure detection algorithm. The SVM classifier was trained using $(N-1)$ subjects and tested on the left out subject. The adaptive median coefficient estimated from the trained subject was used to correct the feature baseline of the test subject.

of seizures. But in many seizures, the majority of the channels were involved, so most seizures were generalized. Table A.3 shows the EEG database details used for the proposed study.

2.2. Pre-processing

A 50 Hz IIR notch filter was applied to eliminate the power line noise at 50 Hz and the EEG signals were bandpass filtered between 0.5 to 32 Hz. Further, ICA was applied to filtered EEG to eliminate the artifacts like eye blinks, muscle artifacts, and electrode movements [53]. The ICA toolbox available in EEGlab was used to remove the artifacts [54].

2.3. Feature extraction

In this study, two features, namely SDI [50] and MD [51] reported recently by our group were used for seizure detection. One can refer to [50,51] for more details on these novel feature extraction methods. Both features were extracted at a segmentation length of 4 s with 50% overlap.

2.3.1. Successive decomposition index

Consider the EEG time series $x = \{x_1, x_2, x_3, x_4, \ldots\ldots, x_n\}$, where n is the total number of the EEG samples in the time series x. Since the sampling frequency is 250 Hz, n becomes 1000 (4s x 250 samples).

In order to define SDI coefficients, first, we define two terms X^+ and X^- which are average of $|x|$ and difference average of x respectively. The coefficient X^+ is given by [50],

$$X^+ = \frac{1}{n}\sum_{i=1}^{n}|x_i| \tag{1}$$

In the subsequent step, the second coefficient X^- was calculated by the iterative process. In the first level ($x^{(1)}$), EEG samples were arranged into $n/2$ non-overlapping pairs as shown below [50],

$$x^{(1)} = \left\{\frac{x_1 - x_2}{2}, \frac{x_3 - x_4}{2}, \ldots, \frac{x_{n-3} - x_{n-2}}{2}, \frac{x_{n-1} - x_n}{2}\right\} \tag{2}$$

Here, if n is not a power of 2 then zeros can be padded towards the end of the x which does not affect on results. After decomposition, $x^{(1)}$of length $n/2$ (n is updated in each level) is represented as [50],

$$x^{(1)} = \{x_1^{(1)}, x_2^{(1)}, \ldots\ldots, x_{n/2-1}^{(1)}, x_{n/2}^{(1)}\} \tag{3}$$

It can be simplified and written as follows,

$$X_i^L = (x_{2i-1}^L - x_{2i}^L)/2 \tag{4}$$

The coefficient remained in the last level ($L = 3.33\log_{10}(n)$) of decomposition was taken as X^-.

Our next aim was to define two new terms X^{++}, and X^{--} using X^+ and X^- as follows [50],

$$X^{++} = \frac{X^+ + X^-}{2} \tag{5}$$

$$X^{--} = \frac{X^+ - X^-}{2} \tag{6}$$

The square matrix A was formed using the four coefficients X^+, X^-, X^{++}, and X^{--} as follows [50],

$$A = \begin{bmatrix} X^+ & X^{--} \\ X^- & X^{++} \end{bmatrix} \tag{7}$$

The basis for forming a square matrix and estimating determinant of same for seizure detection was given in [51]. Thus, SDI was calculated using determinant of the square matrix A [50].

$$SDI = \log_{10}\left(\frac{n}{L}(X^+X^{++} - X^-X^{--})\right) \tag{8}$$

The term n/L is a scalar parameter. Our previous study [50] has proven that SDI better tracks the seizure activity in EEG along with the amplitudes of the EEG samples.

2.3.2. Matrix determinant

Our recent study [51] has proven that the amount of information captured by matrix determinant during epileptic activity increases its measure to acts as a biomarker to identify those events.

The EEG time series were arranged sequentially to form a square matrix by considering the total elements in the square matrix represent a segmentation length. Let the EEG time series be $x = \{x_1, x_2, x_3, x_4, \ldots\ldots, x_n\}$ and apply absolute square i.e. $x = |x|^2$. The absolute was taken because positive and negative EEG samples gets vanishes when their magnitude is same. Defining the matrix with an order of $N(N = r = c)$ and sequentially arrange x into matrix form as follows [51],

$$A = \begin{bmatrix} x_1 & x_2 & .. & x_r \\ x_{r+1} & x_{r+2} & .. & x_{r+r} \\ x_{2r+1} & x_{2r+2} & .. & x_{2r+r} \\ . & . & .. & . \\ x_{(r-1)r+1} & x_{(r-1)r+2} & .. & x_{(r-1)r+r} \end{bmatrix} \tag{9}$$

where r and c are the square matrix order.

The matrix determinant feature was estimated as follows [51],

$$MD = \log_{10}|A| \tag{10}$$

In our study, the square matrix was formed with an order of 32 to estimate the determinant feature.

2.4. Outliers removal and correction

An outlier is a data sample that is distinctly separate from the rest of the data [55,48]. It may be due to variability in the measurement, electrode displacement, fluctuation in data and it may indicate the experimental error. As reported in [55–57,48], it can be noted that the outliers removal improves the classification results for EEG signal classification without losing much diagnostic information. In this study, we have applied outliers removal using Tukey's range test and outliers were replaced using different methods (refer to Table 1). According to Tukey's range test [56], an outlier is an observation which is outside the range of $[Q1 - k* IQR, Q3 + k* \ IQR]$, where k is a non-negative integer. Where, $Q1$ is 25th percentile, $Q3$ is 75th percentile and inter quartile range (IQR) is the difference between $Q3$ and $Q1$. In our study, k was varied as 0.5, 1, 1.5, 2 and 3 to study the effect of outliers removal on classification results with respect to the percentage of loss of feature samples. For outliers correction approach, three methods for detecting outliers, namely mean, median and quartiles were used. The detected outliers were replaced using spline and nearest methods [58].

2.5. Adaptive median feature baseline correction

The high variability in time-varying EEG characteristics between patients leads to poor classification performance [6,7]. Therefore, AM-FBC was proposed using the median values of features SDI and MD. AM-FBC was applied individually for each feature and the procedure is give below:

Table 1
Different classification scenarios considered for the study.

Classification scenario	Outliers removal and correction	**AM-FBC**	Post-processing
1	No	No	No
		No	Yes
2	No	Yes	No
		Yes	Yes
3	Replace (Nearest- Mean)	Yes	No
		Yes	Yes
4	Replace (Spline-Median)	Yes	No
		Yes	Yes
5	Replace (Spline-Quartile)	Yes	No
		Yes	Yes
6	Yes (k = 3)	Yes	No
		Yes	Yes
7	Yes (k = 2)	Yes	No
		Yes	Yes
8	Yes (k = 1.5)	Yes	No
		Yes	Yes
9	Yes (k = 1)	Yes	No
		Yes	Yes
10	Yes (k = 0.5)	Yes	No
		Yes	Yes

Note: CS3 to CS5 are outliers correction and CS6 to CS10 are outliers removal methods.
Spline and nearest are outlier correction methods. Median, Mean and Quartile are outlier detect methods.

1. Consider the features of all the subjects $f(sub_1, sub_2, \ldots, sub_n)$ from training data. Here, sub_1, sub_2 are subjects and f is a feature (f may be SDI or MD).
2. Calculate the $f(Median_{seizure})$ and $f(Median_{non-seizure})$ of all the training subjects using seizure and non-seizure feature respectively. The length of the $f(Median_{seizure})$ and $f(Median_{non-seizure})$ are the same as a number of subjects.
3. Estimate global median ($f(Median_{global})$) using median values of seizure and non-seizure.
$$f(Median_{global}) = Median\{f(Median_{seizure})f(Median_{non-seizure})\} \tag{11}$$
4. Now estimate the median of single subject $f(Median_{subi})$, where $i = 1, 2, 3, \ldots, n$ subjects.
5. Now finding the adaptive median coefficient (λ) using $f(Median_{global})$ and $f(Median_{subi})$.
$$\lambda = f(Median_{global}) - f(Median_{subi}) \tag{12}$$
6. Now correct the feature baseline of $subi$ using λ as follows:
$$f_{newi} = \lambda + f_{subi} \tag{13}$$
7. Repeat step 4 to step 6 for all the training subjects (n).
8. Repeat step 4 to step 6 for the testing subjects using the $f(Median_{global})$ calculated from the training data.

The λ can be either negative or positive depends on the inter-subject median variability.

2.6. Classification

The classification of the proposed method was performed using the SVM classifier due to its better performance in previous studies [59,60,30,61,51,48,49]. During the simulation, the radial basis function kernel showed better performance in terms of classification results. The classifier was assessed using leave-one-subject-out cross-validation to achieve the robustness of the method. The trained SVM classifier was tested on each single left out subject and the process repeated so that all the subjects have been used for testing. Further, SVM classifier tuning parameters were set as follows in MATLAB 2018b: Kernel function = radial basis function, Kernel Scale = 1, Box Constraint = 1, and Standardize = true.

The simulations were performed on MATLAB 2018b using 8 GB RAM, CPU 2 GHz with an Intel i3 processor.

2.7. Post-processing

As reported in [46,47], post-processing was performed using a 5-tap MAF to the SVM classifier output. This helps to reduce the random noise without disturbing the sharp step response during seizure activity. The filtered output [0, 1] was compared with a threshold of 0.5 to make the final decision as seizure and non-seizure. After the threshold, the decision was made as seizure and non-seizure if the threshold was greater than and less than of 0.5 respectively. Post-processing of the classifier output helps to reduce the false alarms in real-time seizure detection for ICU patient monitoring.

2.8. Performance measures

The algorithm performance was calculated by the mean results across all the 40 subjects using leave-one-subject-out cross validation. The algorithm was assessed using performance parameters, namely sensitivity, specificity, the area under the curve (AUC) and false detection rate (FDR).

$$Sensitivity\ (S^{+}) = \frac{TP}{TP + FN} \tag{14}$$

$$Specificity\ (S^{-}) = \frac{TN}{TN + FP} \tag{15}$$

where, *TP* is seizure detected as seizure, *FN* is seizure detected as non-seizure, *TN* is non seizure detected as non-seizure and *FP* is non-seizure detected as seizure. The area under the receiver operating characteristic (ROC) curve was reported using sensitivity and 1-specificity. An FDR was calculated by using the ratio of a total number of false detections to the total duration of the data in hours in all the epochs.

2.9. Classification scenarios

The proposed seizure detection approach was evaluated using 10 different classification scenarios (CS) in terms of outliers removal and correction, AM-FBC, and post-processing and same is depicted in Table 1.

3. Results

3.1. Analysis of AM-FBC

Fig. 2 shows the example of the raw EEG signal, pre-processed EEG and spectra of channel Fp2 from subject 2. The SDI and MD values for all the 40 subjects were shown using the boxplot in Figs. 3a & c respectively. The inter-subject variability in SDI and MD features can be observed in most of the subjects (high variability in subjects 3, 4, 10, 16, 22, 25, 27, 28, 31, 32, 33, 34, 35, 36, 37 38 and 39), which leads to poor classification performance. In order to correct the feature baseline among different subjects, we have applied a novel AM-FBC (refer to 2.5) and results are shown in Figs. 3b & d for each subject. We observe that the SDI and MD

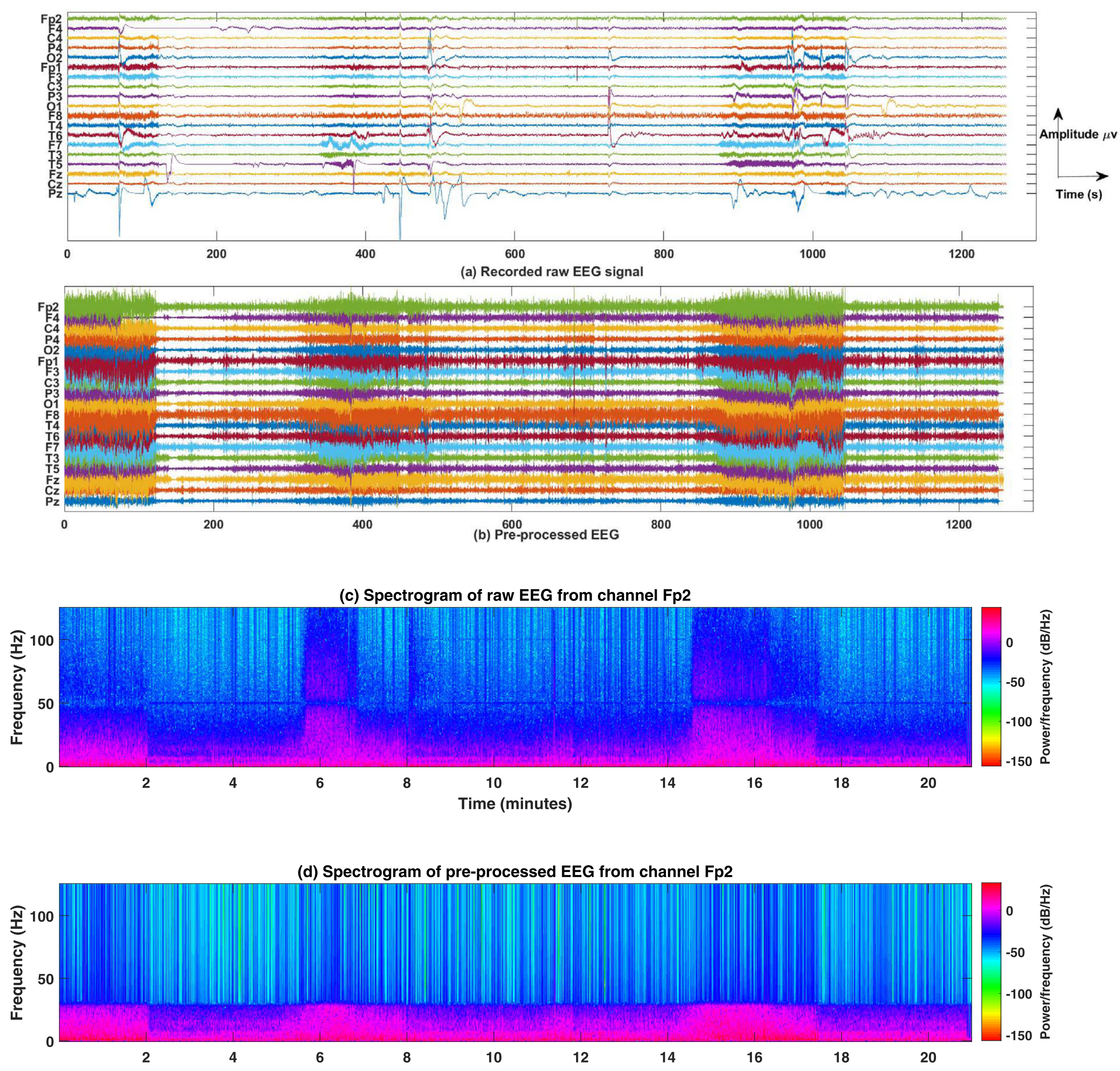

Fig. 2. **(a)** Raw EEG from subject 2. **(b)** Pre-processed EEG using a notch filter, bandpass filter and ICA for artifacts removal. **(c)** Spectrogram of raw EEG from channel Fp2. **(d)** Spectrogram of pre-processed EEG from channel Fp2.

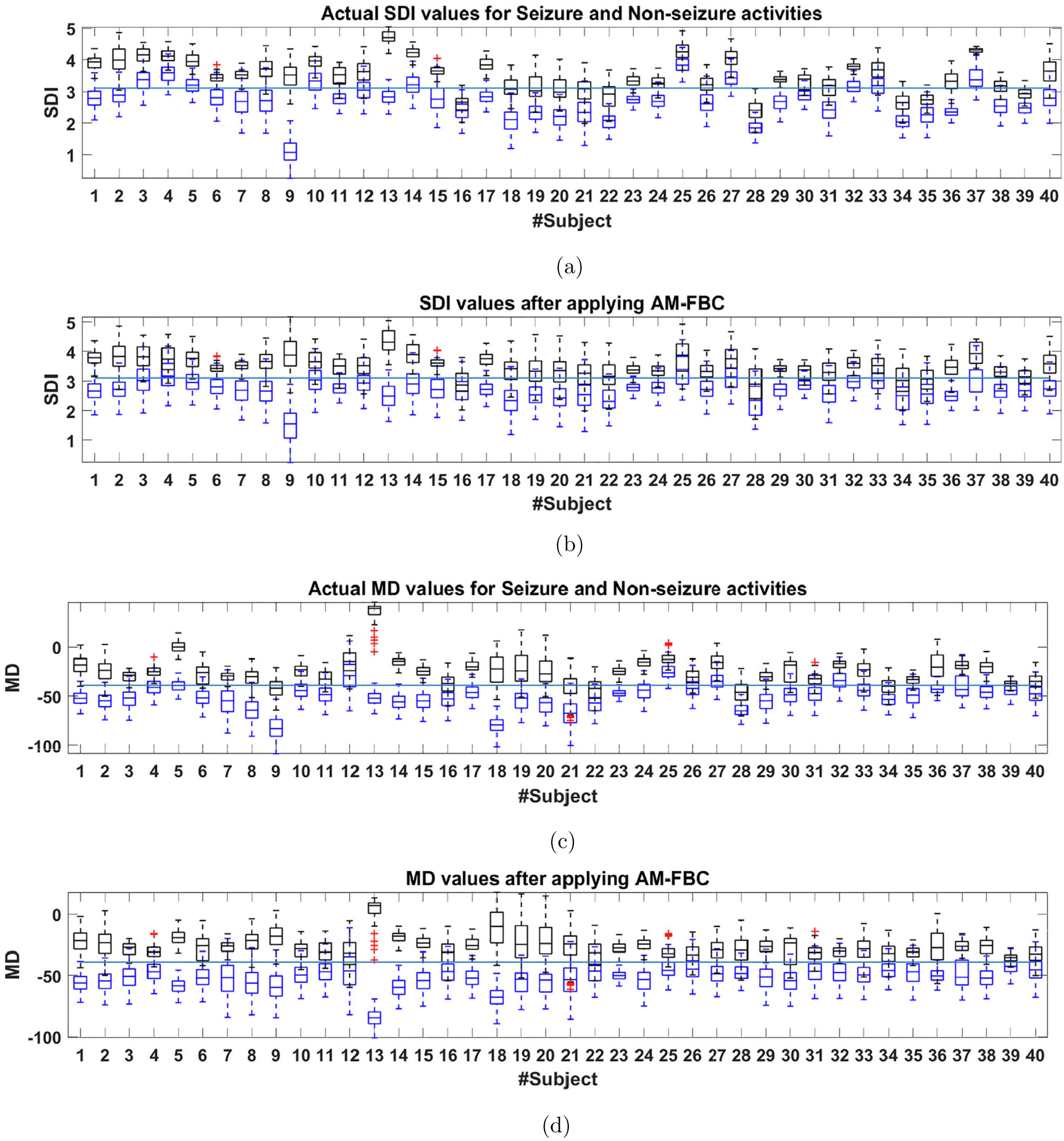

Fig. 3. The boxplot of SDI and MD features for each subject before and after AM-FBC. The boxplot with black boxes indicates seizure and blue boxes indicates non-seizure. The red + indicates the outliers which are beyond the whiskers. The horizontal blue line was drawn as a reference threshold using median values.

features baseline was brought to a common range (indicated in a horizontal line) after applying AM-FBC. We observe some overlap between seizure and non-seizure in SDI and MD features for subjects 4, 10, 12, 16, 21, 25, 27, 28, 30, 33, 34, 35 and 39, which degrades the classification results. After AM-FBC for both SDI and MD seizure and non-seizure features were significantly different ($p < 0.05$) when tested using a Wilcoxon rank sum test.

Fig. 4 shows the resultant features median values before and after AM-FBC. In Fig. 4, the smooth line shows the median values for actual SDI and MD features. It can be seen that high variation of median values among different subjects. In addition, the overlap between seizure and non-seizure median values can be observed for both the features before the AM-FBC. The other line with a circle and plus shows the corrected median values after applying AM-FBC.

3.2. Influence of post-processing

The effect of post-processing of the SVM classifier output is depicted in Fig. 5. The post-processing mechanism involves a 5-tap MAF, thresholding, and binary decision. Figs. 5b & c shows the SDI and MD features respectively for the EEG shown in Fig. 5a. As one can observe that the false alarms in Fig. 5d are high as compared to the ground truth results in Fig. 5g. The SVM classifier output was smoothed using a 5-tap MAF for each channel and applied a threshold at 0.5 as described in [62]. As a result of

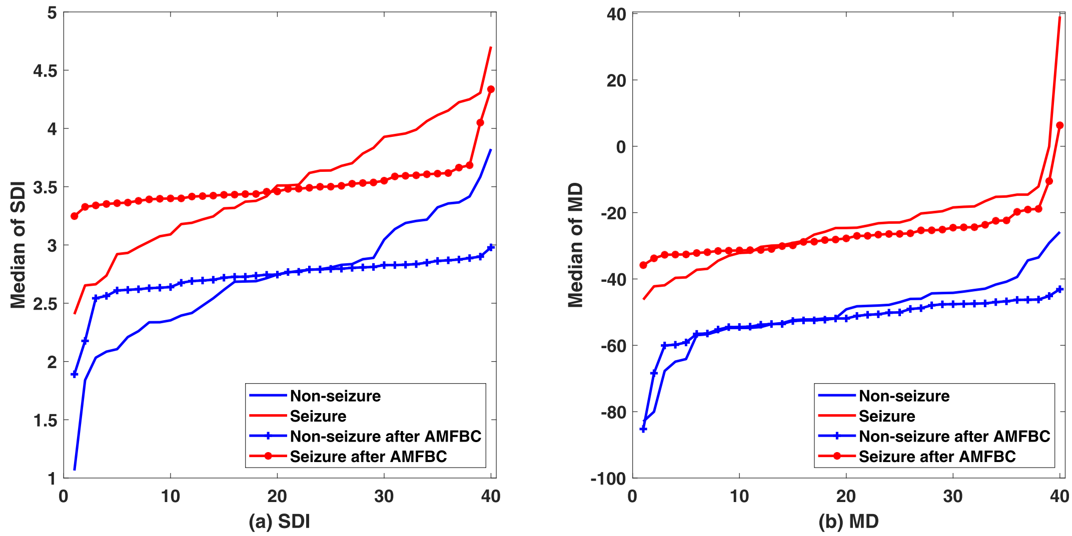

Fig. 4. Median values of SDI and MD before and after AM-FBC. The x-axis is the median values that are sorted for better understanding.

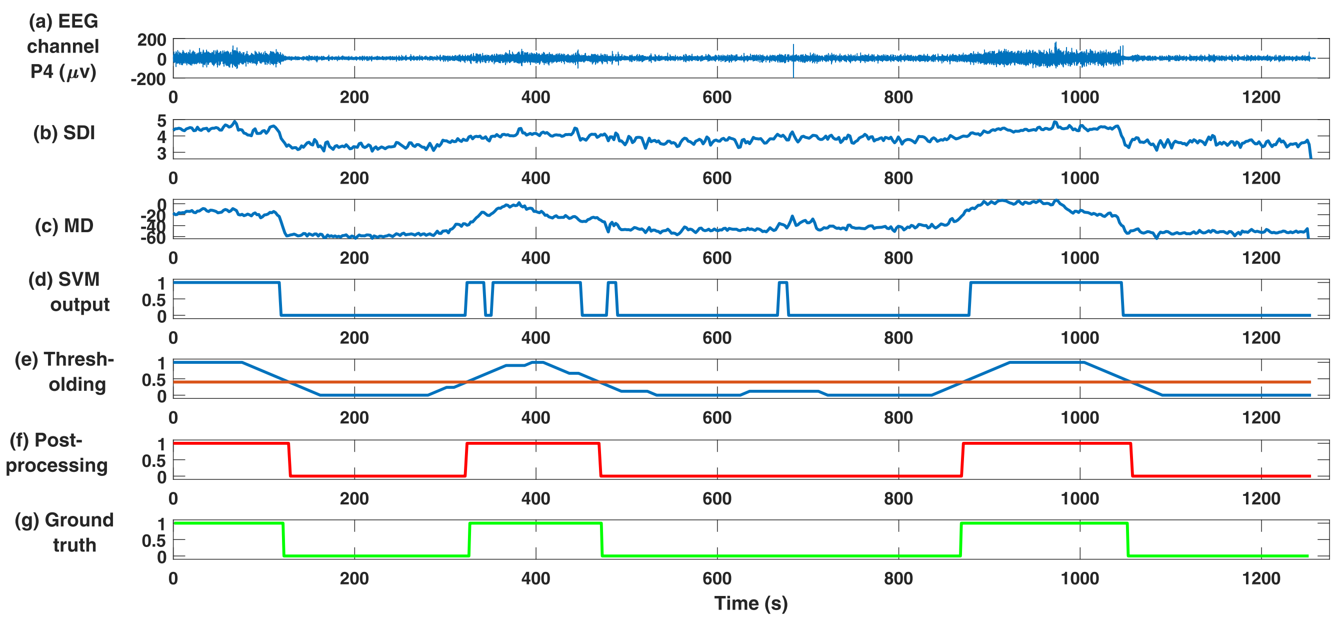

Fig. 5. Effect of post-processing for seizure detection. **(a)** EEG signal belongs to channel P4. **(b)** & **(c)** Corresponding SDI and MD values of channel P4 respectively. **(d)** SVM classifier output. **(e)** The smoothed output after a 5-tap MAF was applied on classifier output when classified using both SDI and MD. The threshold (red line) was set to 0.5 to make a binary decision. **(f)** Binary decision after applying thresholding to smoothed output. **(g)** Ground truth, where 0 and 1 indicate non-seizure and seizure respectively.

filtering, the false detections were reduced (refer to Fig. 5f) and the output was closely matched with ground truth labels (refer to Fig. 5g). The post-processing approach significantly improved the classification results ($p < 0.05$) for seizure detection (refer to Fig. 8).

3.3. Seizure classification results

Fig. 6 shows the ROC curve for different classification scenarios. The best ROC was obtained when both SDI and MD features were classified and post-processing was applied. The estimated area under the ROC curve for each classification scenario is reported in Fig. 7. In the case of both SDI and MD features together, outliers removal was excluded due to an imbalance number of feature segments in SDI and MD.

First, we discuss the classification results obtained using SDI feature. The AUC of 0.6064 (S^+ = 0.2307, S^- = 0.9820) was achieved when outliers removal, AM-FBC, and post-processing techniques (CS1) were not applied. These poor results were due to the inter-subject variability of SDI feature. In CS2, the AUC of 0.9062 (S^+ = 0.8573, S^- = 0.8567) was achieved with AM-FBC, without the outliers removal and post-processing. It was evident that AM-FBC has a significant contribution to classification results. Further, applying post-processing in CS2, the AUC increased to 0.9428 (S^+ = 0.8722, S^- = 0.8770). Hence, it was proven that the application of AM-FBC and post-processing greatly improves seizure detection and reduces the FDR.

In next CS3, CS4 and CS5, outliers were detected using median, mean and quartiles methods respectively and filled using spline and nearest methods [58]. Application of outliers correction methods resulted in the AUC of 0.9388, 0.9445, and 0.9445 for CS3, CS4, and CS5 respectively when post-processing was used. Interestingly, no distinct difference in terms of classification results was

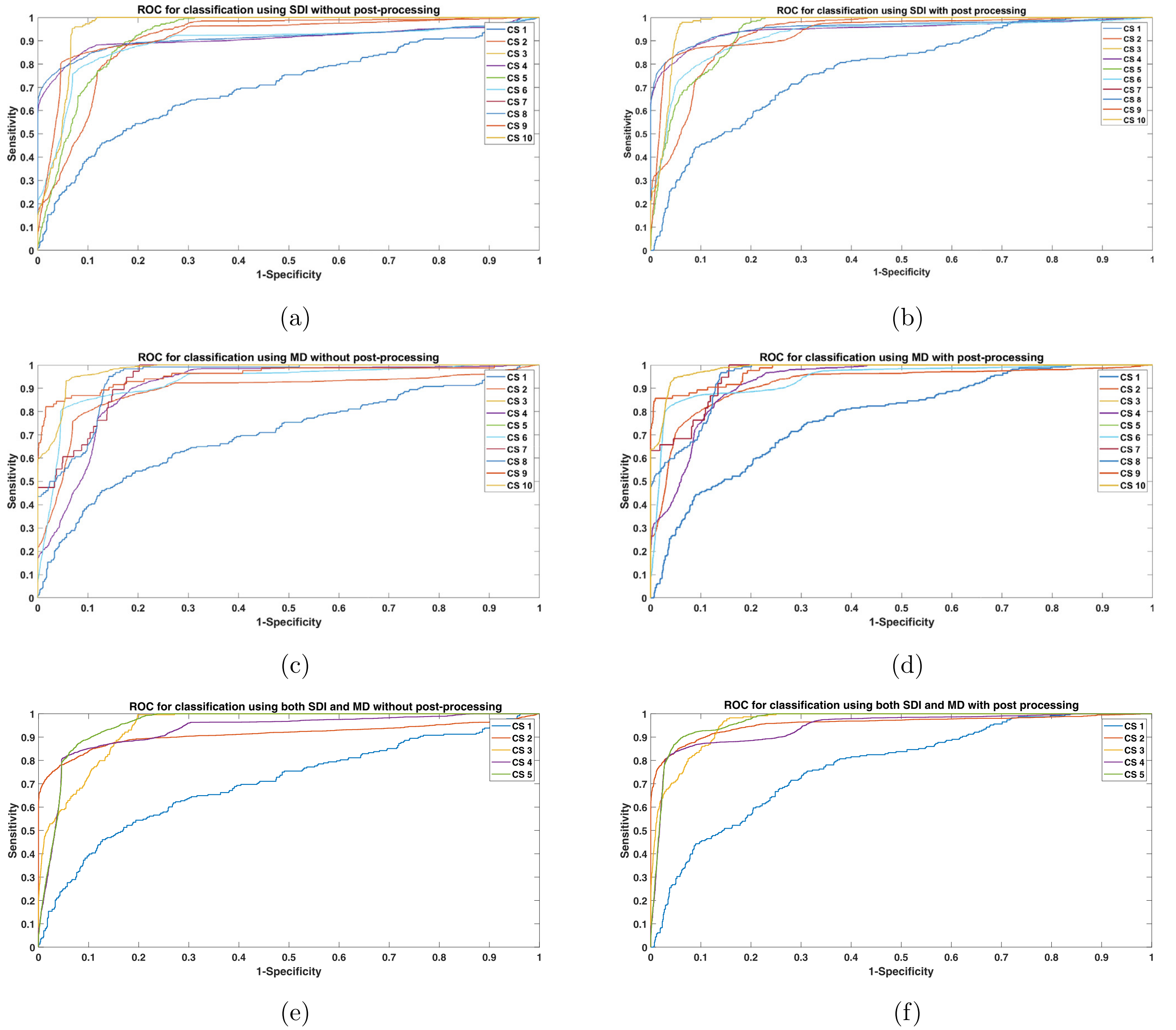

Fig. 6. The ROC curve for different classification scenarios for the proposed method. **(a)** & **(b)** The ROC curve of SDI, **(c)** & **(d)** The ROC curve of MD, **(e)** & **(f)** The ROC curve when both SDI and MD was used for classification. **Left column:** The ROC curve without post-processing, **Right column:** The ROC curve with post-processing. The CS indicates classification scenario.

observed with outliers and outliers correction methods (CS2 to CS4). The AUC of 0.9072 ($S^+ = 0.8578$, $S^- = 0.8566$) and 0.9437 ($S^+ = 0.8734$, $S^- = 0.8764$) were obtained without and with post-processing respectively when $k = 3$ (CS6) for outliers removal which was same as the presence of outliers (CS2). Using the $k = 2, 1.5, 1$ and 0.5, for CS7, CS8, CS9, and CS10 the AUC of 0.9470 ($S^+ = 0.8742$, $S^- = 0.8758$), 0.9525 ($S^+ = 0.8805$, $S^- = 0.8776$), 0.9627 ($S^+ = 0.8984$, $S^- = 0.8805$), and 0.9663 ($S^+ = 0.9661$, $S^- = 0.8446$) was obtained respectively. We observe that the AUC increases as the k value decrease that implies more loss the feature samples. Even though the highest AUC was achieved for CS10 ($k = 0.5$), the S^- drops to 0.8446 which is not a good sign.

Similar observations were made when the MD feature was used for classification. The AUC of 0.9332, 0.9000, 0.9475, 0.9476 was obtained for CS2 to CS5 respectively with post-processing. Further, the highest AUC of 0.9757 ($S^+ = 0.9791$, $S^- = 0.8636$) and 0.9812 ($S^+ = 0.9822$, $S^- = 0.8705$) was achieved with $k = 0.5$ (CS10) for without and with post-processing respectively.

The AUC was increased to 0.9158 and 0.9556 without and with post-processing respectively when both SDI and MD features (CS2) were used for classification. Further, the AUC of 0.9619 ($S^+ = 0.9434$, $S^- = 0.8561$), 0.9592 ($S^+ = 0.9062$, $S^- = 0.8702$), and 0.9593 ($S^+ = 0.9069$, $S^- = 0.9069$) were obtained for CS3, CS4, and CS5 respectively using post-processing which was better as compared to results obtained using SDI and MD alone.

Fig. 8 shows the comparison of AUC obtained in case of with and without outliers removal, AM-FBC, and post-processing on SDI and MD features. The overall results from different CS conclude that the application of outliers removal and correction, AM-FBC and post-processing plays a significant role ($p < 0.05$) in improving classification results.

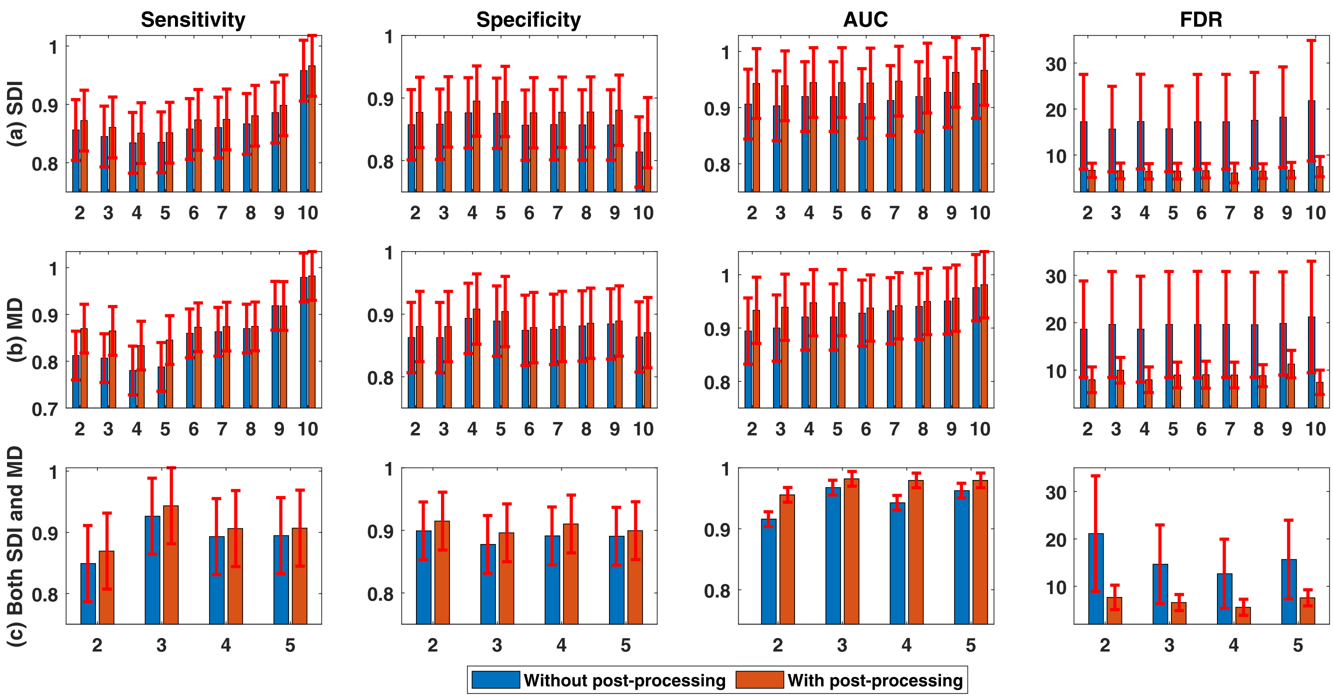

Fig. 7. Classification results in different CS obtained using the proposed seizure detection approach. **First row (a)**: SDI results, **Second row (b):** MD results, **Third row (c):** Results when both SDI and MD were combined. **First column:** Sensitivity (S^{+}), **Second column:** Specificity (S^{-}), **Third column:** AUC, and **Fourth column:** FDR. The X-tick labels indicate different classification scenarios.

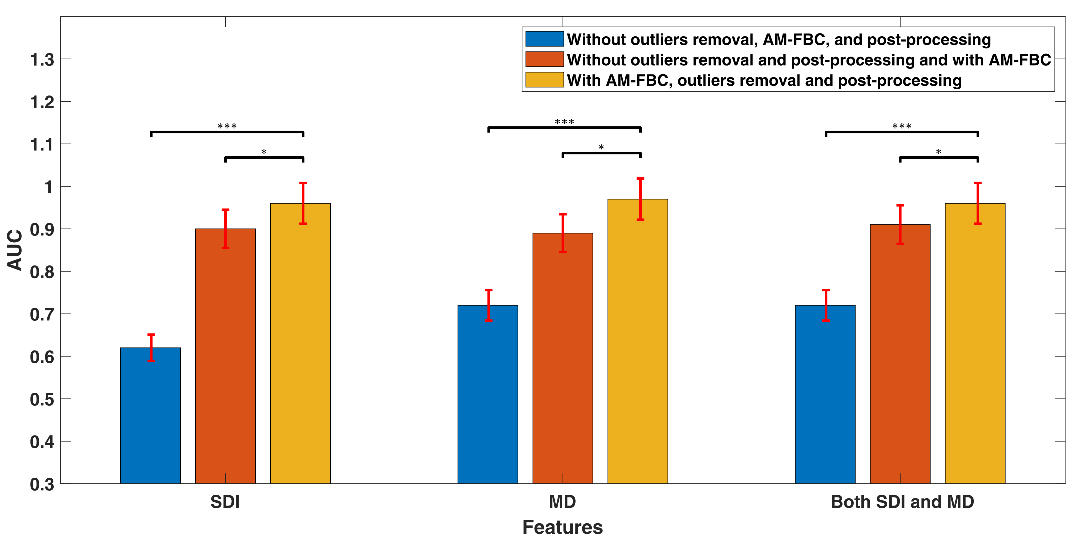

Fig. 8. Significance comparison in terms of with and without outliers removal, AM-FBC, and post-processing on SDI and MD features. $p < 0.05(*), p < 0.01(**)$, $p < 0.001(* * *)$.

4. Discussion

4.1. Effect of outliers removal

We have investigated the effect of outliers on classification results and loss of diagnostic information. In order to accomplish this task, we have considered the CS 6 to 10 and corresponding AUC. The percentage of the feature samples lost after outliers removal was taken into account for the analysis. Fig. 9 shows the effect of outlier removal on AUC and percentage of feature samples lost. As it can be seen, the highest AUC of 0.9663 and 0.9812 was obtained for $k = 0.5$ using SDI and MD features respectively. However, 17% of the feature samples were lost as compared to the original feature set. Similarly, a minimum of 0.3% of samples were lost for $k = 3$ and showed AUC of 0.9023. We observe that as the outlier removal factor k increases, the AUC and percentage of loss of feature samples decreases. In other words, the lower the k, the higher the classification results and loss of diagnostic information. As an optimal setting, $k = 1.5$ can be used for real-time application as that was resulted in the AUC of 0.958 with 1% of samples lost. It concludes that outliers removal factor must be chosen carefully in order to avoid losing diagnostic information.

4.2. Effect of a moving average filter

The length of the MAF for post-processing needs to be chosen properly. If the length of the filter is higher, it tends to a delay in seizure detection and short seizures will be missed out. The lower

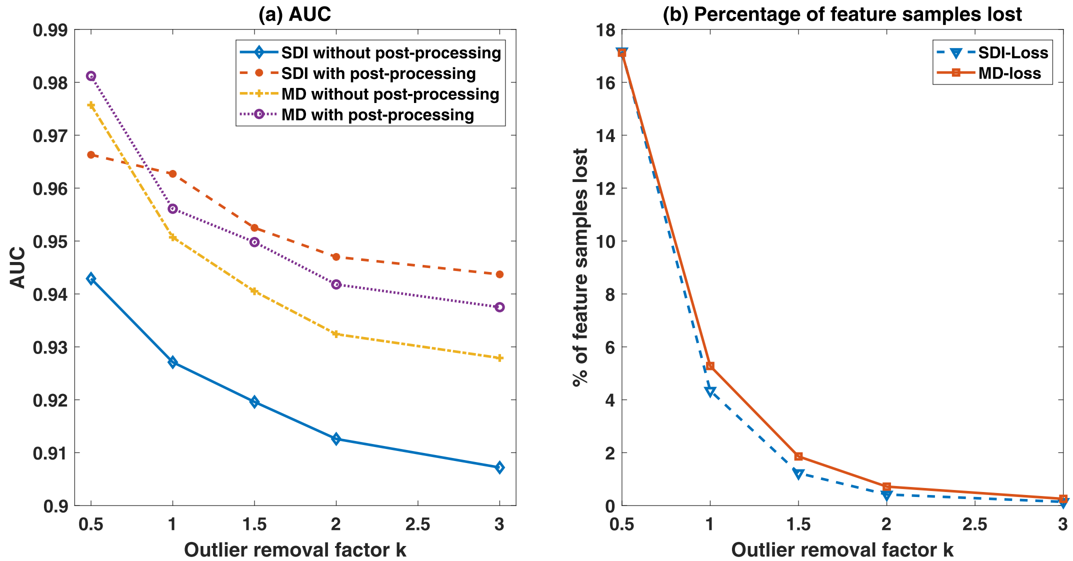

Fig. 9. **(a)** Effect of outliers removal on classification results (AUC). **(b)** Percentage of feature samples lost. The x-axis varied with different k values such as 0.5, 1, 1.5, 2 and 3.

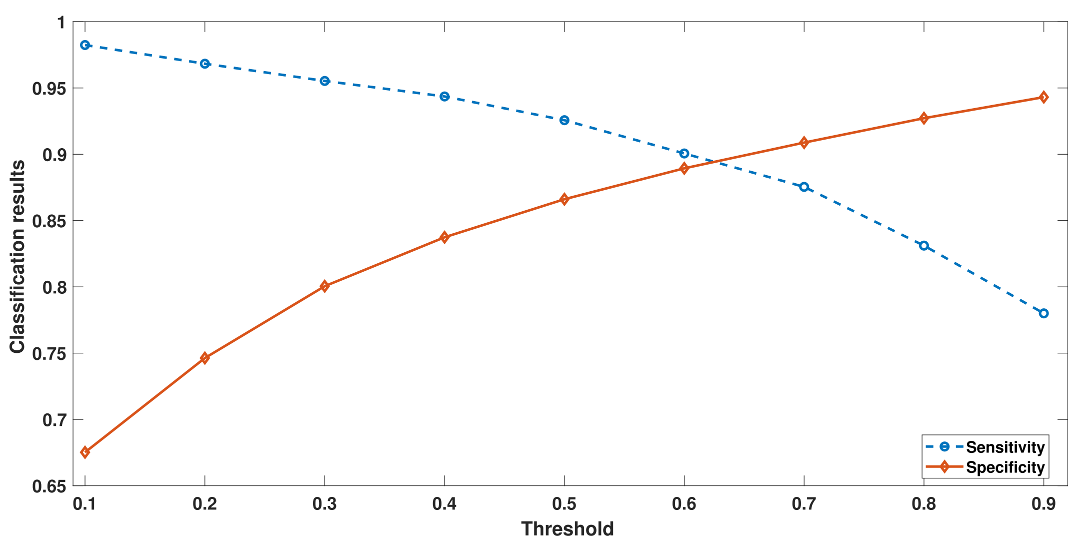

Fig. 10. Effect of threshold in post-processing on sensitivity and specificity. Threshold was varied between 0.1 and 0.9.

length of the filter will not improve the classification results but ideal for lower detection delay. In our study, it needs a delay of 10 s (5th order filter x segmentation length of 4 s = 20 s, due to 50% overlap it becomes 10 s data) to produce classification output of MAF. The 10 s criteria is the same as a minimum seizure duration considered as per International Federation of Clinical Neurophysiology (refer to 2.1) [52]. Hence, our classification results suggest that a 5-tap MAF would be ideal to avoid limitations such as higher detection delay and lower classification performance.

4.3. Effect of threshold in post-processing

With the goal of achieving an acceptable trade-off between sensitivity and specificity, threshold must be fixed accordingly. Fig. 10 shows graph of sensitivity and specificity versus different threshold for post-processing. The higher the sensitivity for lower threshold value results in poor specificity and in contrary for higher threshold values. In order to achieve the good trade-off between sensitivity and specificity, a threshold of 0.5 found to be optimal selection. Further, a threshold of 0.5 provides an equal justification to both the classes (seizure and non-seizure) being a mid-point.

4.4. Comparison with other studies

The comparison was restricted to the studies that have used either or both FBC and post-processing for seizure detection. Ahmed et al. [47] have proven that the post-processing of the SVM classifier output improved the seizure detection rate. Similarly, Temko et al. [46] have used the central linear MAF followed by logical OR operation with collar technique to increase the seizure detection rate and reduce the false detection. In [47,46], post-processing was applied using a 9-tap and 15-tap MAF respectively, which leads to a delay in the final decision of seizure detection. Further, Bogaarts et al. have used a Kalman filter for post-processing in his three studies [45,44,6] proving the need for post-processing and a Kalman smoother for features before classification. Logesparan et al. [43] have proven MDM was better among five methods and improved classification results seen in

[6]. In [7], bitwise logical OR operator was applied on classification output which was obtained from DWT based 65 features. In total, 55 [46,47], 65 [7] and 103 [45,44,6] features were used that leads to the computational expense of the overall algorithm during feature extraction and classification. The results presented in Table 2 shows that the proposed method outperformed other state-of-the-art methods in terms of classification results.

In case of real-time seizure detection, latency of seizure detection also matters to avoid any damages caused to patient. As discussed in previous studies [8,63,62] latency of seizure detection is one of the key metric. The algorithm used to calculate the features and the subsequent classification of the data is possible within 4 s. Therefore, patient treatment can be considered on short notice.

4.5. Significant findings of the study

The significant findings and contributions of our study are summarized as follows:

1. A novel AM-FBC was proposed to overcome the inter-subject variability in feature distribution and a 5-tap MAF for post-processing of the SVM classifier.
2. We observed a significant difference in terms of median values of SDI and MD features before and after AM-FBC.
3. Outliers removal method outperformed outliers correction method.
4. The lower outlier removal factor (say $k = 0.5$) results in high loss of feature samples with improved classification results.
5. When outliers were removed with $k = 0.5$, specificity started decreasing as compared to results of $k = 1$.
6. The classification results revealed that the FDR reduces when post-processing was applied.
7. As compared to the studies [46,47,7,45,44,6] that have used multiple features for seizure detection, our proposed algorithm has shown better classification results using a single feature leading to computationally efficient, which is an ideal for real-time application.
8. The MD performs better than SDI without post-processing and contrary with post-processing (refer to Fig. 9) revealing post-processing has more effect on SDI compared to MD.
9. We have already proven that SDI and MD were computationally efficient in our previous studies [51,50]. AM-FBC and post-processing are simple steps leading to computationally efficient algorithms. Starting from pre-processing to post-processing for off-line seizure detection of a single subject takes on average 2.6 s.
10. Overall, the results of the study suggest that AM-FBC and post-processing has an effect on seizure classification results.

4.6. Clinical significance

This study mainly focuses on FBC to reduce the feature distribution variation using AM-FBC, which has major impact on improving the classification results. Developed algorithm will help to monitor the epilepsy patients admitted to ICU. Further, it reduces the manual intervention of experts for analyzing long term EEG signals.

4.7. Limitations and future direction

For this study, we only used short duration EEG recordings from MUMC. From this it is unknown if there are drawbacks using these

Table 2
Comparison between the state of the art seizure detection algorithms.

Author	EEG database	Duration of EEG (h)	Number of subjects	Number of seizures	Feature extraction	FBC	Classifier	Post-processing	Results
[7]	National Society of Epilepsy (UK), Katholieke Universiteit Leuven (Belgium), and Freiburg University Hospital (Germany).	172	24 adults	47	DWT based Relative power	Normalization	Threshold	Bitwise logical OR operator	AUC = 0.83
[43]	CHB-MIT	884	23	182	Line length	MDM	Threshold	No	AUC = 0.93
[47]	Neonatal Intensive Care Unit (NICU) of Cork University Maternity Hospital, Cork, Ireland	261	17 neonates	821	55 features	No	SVM	MAF	AUC = 0.71
[44]	MUMC The Netherlands	25	39 term and pre-term new borns	360	103 features	ANSFV	SVM	Kalman filter	AUC = 0.902 Sensitivity = 0.801 Specificity = 0.831
[6]	MUMC, The Netherlands	4018	7 ICU patients	1362	103 features	MDM	SVM	Kalman filter	AUC = 0.96
[46]	Neonatal Intensive Care Unit (NICU) of Cork University Maternity Hospital, Cork, Ireland	267	17 new borns	705	55 features	No	SVM	Central linear MAF	Sensitivity = 89%
[45]	MUMC, The Netherlands	613	39 neonatal 39 adults	34898*	103 features	ANSFV	SVM	Kalman filter	AUC = 0.93
Proposed	MUMC, The Netherlands	21	40 ICU patients	1273**	SDI and MD	AM-FBC	SVM	MAF	AUC = 0.9663 (SDI) AUC = 0.9812 (MD) AUC = 0.9593 (Both)

* 34898 Feature vectors derived from 10s epoch,
** 1373 seizure epochs of 10 s duration

classifiers for long-term recordings as in continuous recording on the ICU. Further, outliers removal results in loss of diagnostic information even though good classification results were obtained. Classification of artifacts and epileptiform activities was not done in our study where that has a significant contribution to reduce false detection. As a future expansion, long-term EEG recording will be used to validate the proposed algorithm. Further, deep learning neural network will be explored for seizure detection.

5. Conclusion

In this paper, we propose a novel algorithm called AM-FBC to correct the inter-subject variability in feature distribution for patient-independent seizure detection algorithm in ICU EEG. The results suggest that the application of AM-FBC, outliers removal and post-processing revealed the AUC of 0.9663 and 0.9822 using SDI and MD features respectively. Further, we found that the lower the outlier removal factor improved the seizure detection performance at the cost of loss of feature samples. This study has proven that two novel features SDI and MD were capable of detecting seizures on new EEG dataset leading to algorithm generalization and robustness.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

See Table A.3.

Table A.3
EEG database details used for the study.

Subject #	No. channels has seizures	Age (years)	Gender	Record length (h)	Number of seizure epochs	Mean duration of seizure (s)	Min duration of seizure (s)	sMax duration f seizure (s)
1	4	68	M	0.3694	38	57.92	21	102
2	19	27	M	0.3472	21	125.19	121	184
3	2	33	F	0.3361	4	79.75	29	111
4	2	61	F	0.5861	29	85.72	39	157
5	5	56	F	0.8028	21	35.42	29	42
6	1	47	F	0.4111	1	115	115	115
7	4	84	M	0.7389	8	79.62	53	116
8	19	75	F	0.7361	56	62.35	24	135
9	9	22	M	0.4556	9	311	262	484
10	4	57	F	1.1333	8	950	26	1949
11	2	65	F	0.4528	4	55	38	76
12	19	65	M	0.6583	26	147.57	43	171
13	3	46	F	0.3278	3	31	31	31
14	2	76	M	0.5000	38	33.26	17	43
15	19	40	F	0.4639	52	80.43	38	194
16	19	49	F	0.3861	44	55.51	34	124
17	2	50	F	0.3444	4	132	131	134
18	4	40	M	0.4000	4	87.50	32	106
19	19	49	F	0.8028	43	55.5	34	124
20	19	49	F	1.5750	43	55.5	34	124
21	3	66	M	0.5500	12	140.33	124	150
22	3	29	M	0.3333	30	20.1	20	36
23	3	62	M	0.4556	9	112.33	106	117
24	12	43	M	0.7306	228	19.89	25	32
25	11	40	F	0.6472	44	59	24	119
26	5	71	M	0.3667	10	169	169	169
27	14	84	F	0.4500	224	44.43	18	82
28	19	71	F	0.3611	76	74.25	15	125
29	2	89	F	0.5167	14	84.71	49	135
30	3	79	F	0.5361	3	90	90	90
31	5	29	F	0.3111	9	13.77	13	16
32	3	59	M	0.4472	3	79	79	79
33	19	83	M	0.5194	114	17	12	29
34	7	46	F	0.7111	39	111.6	26	142
35	3	23	F	0.3417	15	45.2	39	52
36	19	46	F	0.3556	19	79	79	79
37	5	50	M	0.4639	10	12	12	12
38	19	27	F	0.3389	38	12	12	12
39	4	68	M	0.3722	8	164.5	150	179
40	3	62	M	0.3344	12	91.5	79	119

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S Raghu is pursuing his Ph.D. at School for Mental Health and Neuroscience of the Faculty of Health, Medicine, and Life Sciences, Maastricht University, The Netherlands, through Ramaiah Institute of Technology. He received M.Tech. Degree in Communication System from Christ University Faculty of Engineering in 2016 and M.Sc. degree from Bangalore University in 2011. He worked as Research Associate at Center for Medical Electronics and Computing, Ramaiah Institute of Technology, Bengaluru, India, from April 2016 to April 2017. His current research included biomedical signal processing, machine learning, epilepsy and telemedicine.

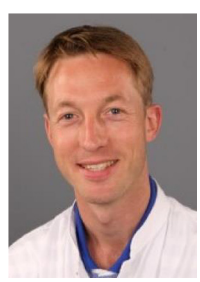
N Sriraam received the B.E. degree in Electronics and Communication Engineering in 1996, the M.Tech degree (with distinction) in Biomedical Engineering from MIT Manipal, India, in 2000, and the Ph.D. degree in Information Technology from the Multimedia University, Cyberjaya, Malaysia, in the area of biomedical signal processing, in 2007. He is currently working as Professor and Head, Department of Medical Electronics, Ramaiah Institute of Technology, Bengaluru, India. His current research interests include biomedical signal processing, data mining, neural networks. He is a senior member of IEEE and IEEE Engineering in Medicine and Biology Society (EMBS), Signal Processing Society, life member of telemedicine Society of India and member of medical computer society of India.

E. D. Gommer graduated in Electrical Engineering at Twente University in 1992. Currently, he works as clinical physicist at the Maastricht University Medical Centre, where he did his Ph.D. in 2013. E. D. Gommer has a PhD in measurement and analysis methods of dynamic cerebral autoregulation. As a researcher he is involved in scientific research in the field of signal analysis and classification methods of electrophysiological signals and applications of functional TCD

D. M. W. Hilkman is a clinical neurophysiologist at the department of clinical neurophysiology at the MUMC+, Maastricht. He monitors the integrity of the nervous system/ brain, including various types of (neuro) surgical procedures. In addition to general clinical neurophysiology, the activities of Dr. Hilkman in healthcare include diagnostics for epilepsy and epilepsy surgery.

Prof. Dr. Y. Temel followed the medical training at Maastricht University from 1995–2001. After completing his PhD research at the Neuroscience Department again at Maastricht University, he started his Neurosurgery training, which was completed in 2010. He is currently working as a neurosurgeon at the academic hospital in Maastricht and as an associate professor at Maastricht University. In addition to practicing general neurosurgery, Dr. Y. Temel two clinical and scientific focus areas, Functional Neurosurgery and Skull Basic Surgery. He leads the Experimental Neurosurgery research team, which is active in these two research fields. He has received international and national prizes because of the promising research results.

Shyam Vasudeva Rao holds a doctorate in Real Time Embedded Systems, specialising in Parallel Computer Architecture from Indian Institute of Science (gold Medal). His first innovation was a hardware antivirus solution called Knox card. He co invented this in 1989 and this let to a start-up called Knoxware which was one the first to come up with such a unique solution to computer virus protection in a generic way. He has published more than 40 technical papers and filed more than 20 international patents with 4 US patent grants.



P. L. Kubben has studied medicine and training as a neurosurgeon in Maastricht. He has been a staff member since 2014 and obtained his PhD in "Ultra low-field strength intraoperative MRI for glioblastoma surgery". In addition to his clinical activities, he is actively involved in various medical IT projects. He developed the NeuroMind app, which became the number 1 app for neurosurgery worldwide. He gave a TEDx talk about medical decision support and was twice named one of the Top 10 Internet smart doctors in the world by the weblog Internetmedicine.com. His current areas of focus are deep brain stimulation, epilepsy surgery, and he coordinates the eHealth program for the Maastricht UMC +.