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Highlights (for review)

Highlights

1. Classification of seizure and non-seizure multi-channel EEG signals from different surface EEG databases

2. Evaluation of efficiency of Iterative Filtering decomposition in seizure detection

3. Hidden Markov Model implemented for seizure classification.

4. The proposed approach achieved accuracy as 99.60% and 99.74% in seizure detection for online CHB-MIT surface EEG database and AIIMS Patna EEG database, respectively.

Multi-channel EEG based Automatic Epileptic Seizure Detection Using Iterative Filtering Decomposition and Hidden Markov Model

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Abstract

Electroencephalography (EEG) is a non-invasive method for the analysis of neurological disorders. Epilepsy is one of the most widespread neurological disorders and often characterized by repeated seizures. This paper intends to conduct an iterative filtering based decomposition of EEG signals to improve upon the accuracy of seizure detection. The proposed approach is evaluated using All India Institute of Medical Science (AIIMS) Patna EEG database and online CHB-MIT surface EEG database. The iterative filtering decomposition technique is applied to extract sub-components from the EEG signal. The feature set obtained from each segmented intrinsic mode function consists of 2-D power spectral density and time-domain features dynamic mode decomposition power, variance, and Katz fractal dimension. The Hidden Markov Model (HMM) based probabilistic model has been designed using the above-stated features representing the seizure and non-seizure EEG events. The EEG signal is classified based on the maximum score obtained from the individual feature-based classifiers. The maximum score derived from each HMM classifier gives the final class information. The proposed decomposition of EEG signals achieved 99.60% and 99.74% accuracy in seizure detection for the online CHB-MIT surface EEG database and AIIMS Patna EEG database, respectively.

Keywords: `EEG`, `Epilepsy`, `Iterative filtering decomposition`, `Spectral features`, `Dynamic mode decomposition power`, `Hidden Markov Model`

1. Introduction

EEG has a wide application in the diagnosis of neurological diseases such as dementia, migraine, and epilepsy [1]. Epilepsy is a non-communicable disease that can affect people of different ages. Nearly 70 million people are affected by epilepsy all over the world, and in India alone, 12 million people are suffering from epilepsy [2]. The unexpected simultaneous activity of groups of neurons is called a seizure. The duration of seizure in continuous EEG signals varies from 1 to 10 seconds. Depending on the seizure condition, the recording duration varies from minutes to hours. At present, the seizure detection is manual, and accuracy depends largely on the doctor's experience. There is an urgent requirement to develop an efficient algorithm which can detect seizure efficiently from continuous EEG signal. There are different state-of-the-art methods proposed for seizure detection. Discrete wavelet transform (DWT) and empirical mode decomposition (EMD) are widely used techniques for data decomposition. EMD time-domain features and frequency domain features with a linear discriminant analysis classifier are used for seizure classification [3]. Multivariate empirical mode decomposition, instantaneous rate, instantaneous amplitude, and artificial neural network are efficient in seizure detection [4]. EMD intrinsic mode function (IMF) and Higher-order moment features are found to be effective in seizure detection [5].

DWT coefficients are found to be efficient in seizure and non-seizure classification [6]. Energy ratio from wavelet coefficients and ant colony classifier achieved good classification accuracy [7]. Stationary wavelet transform has a good application in seizure detection. The features power spectral density (PSD), mean and peak frequency, relative band energy feature, and linear discriminant classifier achieved good accuracy in

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seizure classification [8]. The grey level co-occurrence matrix, texture feature coding method, and local binary pattern features extracted from time-frequency image are efficient in seizure detection [9]. Multi-scale radial basis function and modified particle swarm optimization technique have useful applications in seizure detection [10].

HMM, and features such as signal length, half-wave, and area under the curve achieved good accuracy in seizure detection [11]. In [12], DWT coefficients along with HMM classifier achieved good classification accuracy in seizure classification. DWT and HMM with a mixture of Gaussian observation model techniques have found a good result in seizure prediction [13]. HMM along with Higuchi's fractal dimension, Shannon, collision, minimum entropy features extracted from EMD IMFs are found to be efficient in seizure and non-seizure classification [14]. Support vector machine (SVM), along with entropy and complexity features extracted from the EEG signal, is proposed for seizure and healthy EEG classification [15]. Abeg Kumar *et al.* have compared sub-pattern based principal component analysis (SpPCA) and cross-sub-pattern correlation-based principal component analysis (SubXPCA) along with SVM for seizure detection [16]. Recently deep learning technology has a good application in seizure detection [17]. Multi-channel EEG segments along with convolutional neural network are used for seizure and non-seizure EEG segment classification [18].

In the proposed approach, iterative filtering (IF) decomposition is used to extract sub-components from the signal. The authors have observed the efficiency of different sub-components for seizure detection. The features extracted from the sub-components are Dynamic mode decomposition (DMD), PSD, and statistical parameters. HMM is trained using features extracted from IF sub-components and verified using two different databases. The method generated higher accuracy in detecting different types of seizures with various intensity.

The organization of the paper is as follows. Section 2 presents the proposed approach, and section 3 explains the signal processing techniques used in the proposed approach. Section 4 and 5 present the overall results and summarize the paper with future scope.

2. Proposed Approach

Initially, 50 Hz power line interference noise is removed from the EEG signal using an IIR notch filter. EEG signal is filtered using the Butterworth band-pass filter to keep the data within the desired frequency range. Moving average (MA) filter is used to remove the sudden spike artifacts. In the online CHB-MIT surface EEG database, features are extracted from the common 18 EEG channels across all subjects. In AIIMS Patna EEG database, the channels are selected by manual observations as some of the channels are noisy and contain no EEG information. IF decomposition is used to extract five sub-components from the EEG signal, and smaller blocks are created by dividing sub-components. The process of segmenting the IF sub-components into smaller blocks is called the windowing approach. Authors have extracted DMD power, the 2D PSD, Katz fractal dimension (KFD), and variance feature from the IF sub-components for every 5 seconds from the online CHB-MIT surface EEG database and every 1 second for AIIMS Patna EEG database. The length of the feature vector remains the same irrespective of the variations in the number of channels as 2D PSD, DMD power, variance, and KFD features get extracted from all the EEG channels simultaneously. The feature vector is converted into a symbol sequence using a fuzzy c-means (FCM) clustering algorithm. The Sugeno fuzzy inference system is used in FCM clustering. The singleton output membership functions are either constant or a linear function of the input values. The symbol sequence generated using the FCM clustering algorithm is used to train the HMM classifier. The HMM Viterbi algorithm is used for testing purposes. Different HMM classifiers are trained using each feature vector. The final EEG event classification is achieved based on the maximum score across different classifiers. Figures 1 and 2 show the training and testing Flowchart for the proposed approaches, respectively.

3. Techniques

3.1. Preprocessing

The preprocessing step is one of the critical steps in EEG signal processing. Usually, the EEG signal gets affected by the 50 Hz power-line signal. In the proposed approach, authors have used limited frequency bands for event classification. IIR notch filter is used to remove the power line interference. The signal is filtered between 1-40 Hz using Butterworth band-pass filter to keep data up to high beta band. The sudden spikes in the EEG signal are removed using the MA filter with twenty signal points.

3.2. Iterative Filtering Decomposition

Practically, significant amount of signals are non-stationary and non-linear. In the analysis of the signal, it is important to extract the sub-components. DWT and

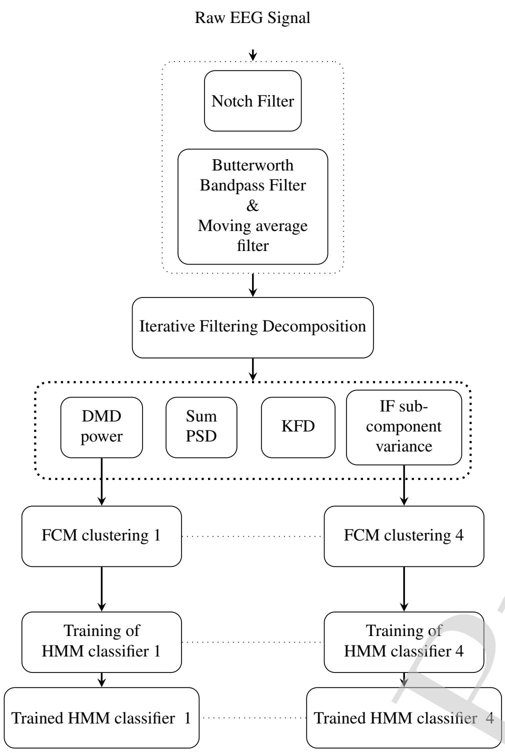

Figure 1: Proposed EEG signal training approach

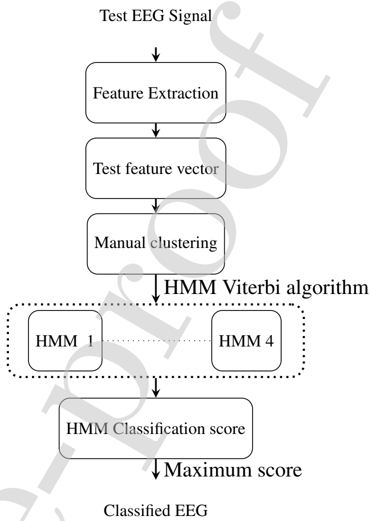

Figure 2: Proposed EEG signal testing approach

Fourier transform have wide usage in biomedical signal processing for the extraction of the subcomponent. EMD decomposes the signal into several IMF based on the following two conditions.

- The number of zero-crossing and extrema of an IMF must be equal or differ maximum by 1.
- The mean of the envelopes defined by the local extrema is 0, at any point of the IMF.

In the IF decomposition technique [19], the IMF extraction approach is largely inspired by EMD. The algorithm 1 explains the IF decomposition approach. The window length is kept constant for the entire iteration of IMF extraction. Here S represents the signal, and m represents the iteration number. In algorithm 1, w represents the window used for filtering purposes. Threshold (Th) is used as stopping criteria for iteration. The stopping criteria are as follows.

$$S_{th} = \frac{|S_{m+1} - S_m|^2}{|S_m|^2} \tag{1}$$

3.3. Dynamic Mode Decomposition Power

DMD is a data-driven approach used to extract Spatio-temporal components from a multidimensional data [20]. DMD is a data reduction technique originally introduced in fluid mechanics. In the present research work, DMD is extracted using singular value decomposition (SVD). The Algorithm 2 explains the steps of DMD power feature extraction. DMD power is evaluated from each IF sub-component.

3.4. Power Spectral Density

PSD is the distribution of power across the frequency components of the signal [21]. The spectrum of a stochastic process is real and even function of the frequency. The PSD is evaluated by finding the Fourier transform of the signal and evaluating the square magnitude of the Fourier transform. In this work, PSD is calculated across all channels IF sub-components at a time. Two dimensional Fourier transform is used for 2D

Algorithm 1 Iterative Filtering Decomposition

1. **Input**: Raw EEG Data
2. **Output**: IMF
3. **Initialize**: IMF

while the number of extrema ≥2 **do**

$S_1 = S$

while $S_{th} \geq$ Th **do**

$$S_{m+1}(x_i) = S_m(x_i) - \sum_{j=0}^{n-1} S_m(x_j) \times w_m(x_i - x_j)^{\frac{1}{n}}$$

i=0,...n-1,

m=m+1

end

$IMF = IMF \cup (S_m)$

$S = S - S_m$

end

$IMF = IMF \cup S$

Algorithm 2 DMD Power

1. **Input**: Signal S
2. **Output**: DMD Power
3. **initialize**: S_h, s=101

Find SVD of the matrix $S_h(1 : end - 1)$.

$[U_1, V_1, S_1] = svd(S_h(1 : end - 1))$,

Evaluate the value of r, the number of modes of SVD

Evaluate the expression:

$A_1 = U_1(:, 1 : r) \times X_h \times V_1(:, 1 : r) \times S_1(1 : r, 1 : r)^{-1}$,

$[W, \lambda] = eigen\ (A_1)$

Frequency and amplitude of the modes:

$$DMD_{freq} = \frac{2 \times \log_{10}(diag(\lambda))}{\pi \times dt}$$

$$Phi = X_h(:, 2 : end) \times V_1(:, 1 : r) \times S_1(1 : r, 1 : r)^{-1} \times W$$

$$b = \frac{\Phi}{X_h(:, 1)}$$

DMD power is evaluated by the Equation given below.

$$DMD_{power} = \frac{abs(b) \times 2}{\sqrt{s}}$$

PSD calculation. Mathematically 2D Fourier transform can be written as:

$$FFT(x, y) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} S(m, n) \times e^{-i2\pi \times (x\frac{m}{M} + y\frac{n}{N})}, \quad (2)$$

Here M, N presents row and column value of the multichannel IF sub-components. Two-dimensional power spectral density is mathematically presented as follows.

$$PSD = \frac{2}{M \times N} \times abs(FFT)^2. \quad (3)$$

3.5. Variance

The statistical parameter variance is used as a feature for seizure identification [22]. Here variance is calculated from IF sub-components of multi-channel EEG signal. Mathematically, variance is represented by the following Equation.

$$\sigma^2 = \frac{\sum_{n=1}^{N} (S - \overline{S})}{N}. \quad (4)$$

S is the signal and N is the total number of samples. In this work, the variance is calculated for multichannel IF sub-components.

3.6. Katz Fractal Dimension

KFD [23] is calculated from the IMF sub-components. It has a good application in measuring the complexity of the signal. Mathematically, fractal dimension is defined as shown in Equation 3.

$$Fractal\ Dimension = \frac{\log_{10}(L/a)}{\log_{10}(d/a)}. \quad (5)$$

Where variable L represents total length of the EEG signal and variable d represents the diameter of the curve. Katz has proposed normalized L and d. The point a is normalized as: $a = \frac{L}{n}$. n is the amount of steps in the curve. The KFD is defined as follows.

$$KFD = \frac{\log_{10}(n)}{\log_{10}(d/L) + \log_{10}(n)}. \quad (6)$$

3.7. Feature Normalization

Since the seizure amplitude varies from person to person, features before classification are normalized between 0-1. Mathematically the feature normalization is defined as shown below.

$$S_{Nf} = \frac{(S_f - \overline{S_f})}{(S_{fmax} - S_{fmin})} \quad (7)$$

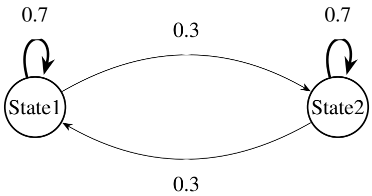

Figure 3: Initial transition matrix for 2 state HMM classifier (State 1=seizure EEG event, State 2=non-seizure EEG event)

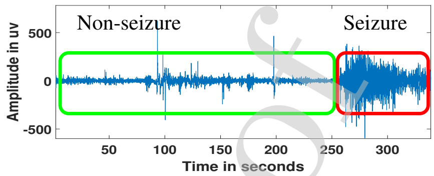

Figure 4: seizure and non-seizure EEG signal, green box represents non-seizure and red box represents seizure EEG signal. The EEG signal is from subject 3 channel T7 of online CHB-MIT surface EEG database

Where S_f is the feature vector used for classification. The factor S_{fmax} represents the maximum value of S_f, S_{fmin} represents the minimum value of S_f and $\overline{S_f}$ represents the mean value of S_f.

3.8. Fuzzy C-Means Clustering

The clustering involves assigning similar points to one group. The similarity between the data points is verified based on the distance factor. In the FCM clustering approach, each feature vector is assigned membership of the cluster based on the degree of closeness to clusters [24]. The cluster numbers are used as a symbol sequence for the training of the HMM classifier.

3.9. Hidden Markov Model

HMM [25] is based on the Markov chain rule. Markov chain rule states that the probability of shifting from one state to other depends only on the present state and not on the previous state.

$$P(d_n = y_n | d_{n-1} = y_{n-1}) = P(d_n = y_n |\, d_0 = y_0, d_1 = y_1, ..., d_{n-1} = y_{n-1}) \tag{8}$$

Here possible states are $y_i, i = 0, 1, ..., n$. In HMM, the states are hidden and the outputs are the observations from the state. HMM is trained using the Baum-Welch algorithm. In this work, two states ergodic HMM is considered for designing the seizure and non-seizure HMM classifier. The size of the training feature vector for AIIMS Patna EEG database and online surface EEG database is 32×1 and 44×1, respectively. HMM classifier is trained for each feature vector separately. The training feature vector is clustered using the FCM clustering algorithm. The vector with the cluster numbers of training feature vector forms the codebook of the model. Euclidean distance is calculated to find the similarity between the train and the test feature vector. The index number of the train feature vector is assigned to the test feature vector based on similarity. Figure 3 represents the HMM initial transition matrix. In the initial transition matrix, self-transition is considered higher as compared to the transition from one state to another. The Baum-Welch and Viterbi algorithm are explained in Algorithm 3 and 4, respectively. The initial transition matrix is selected as shown in Figure 3. The initial emission probability is determined from the repetition of the train feature vector cluster number. The symbol $aatr_i$ represents the initial transition matrix and the $bbtr_j$ represents the emission matrix in Algorithm 2. A total number of 100 iterations are considered for the training of the HMM classifier. The Viterbi algorithm is used to evaluate the state sequence of the HMM classifier, given the symbol sequence.

Algorithm 3 Baum Welch Algorithm

1.initialize $\leftarrow aatr_i, bbtr_j, \pi_i$, o
2.Calculate Forward Probability
$\alpha_j(t) \leftarrow 0$, t=0 j $\neq$ initial state
$\alpha_j(t) \leftarrow 1$, t=0 j = initial state
$\alpha_j(t+1) \leftarrow \sum_j [\alpha_i(t) \times aatr_i] \times bbtr_{jo(t)}$ otherwise
3. Calculate Backward Probability
$\beta_i(t) \leftarrow 0, w_i(t) \neq w_0$, t $\neq$ T
$\beta_i(t) \leftarrow 1, w_i(t) = w_0$, t = T
$\beta_i(t) \leftarrow \sum_j [\beta_i(t+1) \times aatr_i] \times bbtr_{jo(t+1)}$ otherwise
4. Calculate $v_{ij}(t) \leftarrow \frac{[\alpha_i(t-1) \times aatr_i \times bbtr_{jo(t)}] \times \beta_j(t)}{P(o^T|\theta)}$
5. Update state transition matrix and emission matrix

$$aatr_i = \leftarrow \frac{\sum_{t=1}^{T} v_{ij}(t)}{\sum_{t=1}^{T} \sum_k v_{ik}(t)}$$

$$bbtr_j \leftarrow \frac{\sum_{t=1}^{T} \sum_l v_{jl}(t)_{v(t)=v_k}}{\sum_{t=1}^{T} \sum_l v_{jl}(t)}$$

6. Repeat till convergence

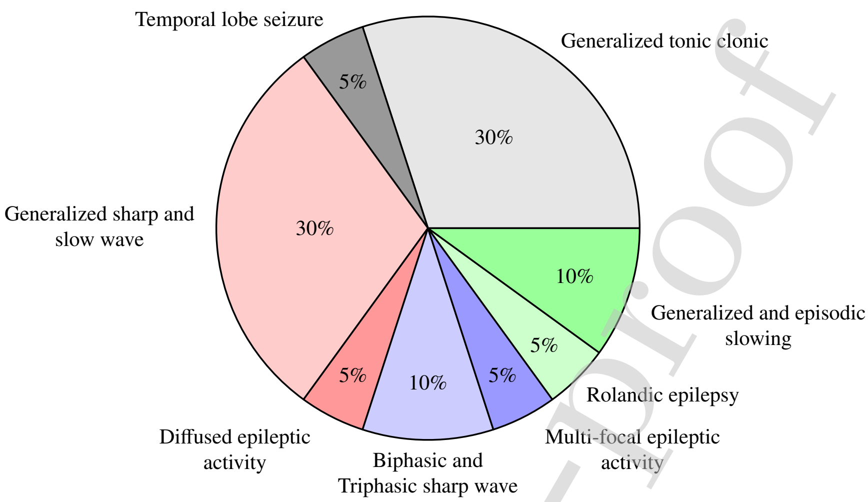

Figure 5: Pie chart of different types of seizures present in AIIMS Patna EEG database

Algorithm 4 Viterbi Algorithm

1.Initialize ← $\delta_1(i) = \pi_i \times bbtr_j(o_1) \quad 1 \leq i \leq N$
2.Recursion ← $\delta_t(j) = \max\limits_{1\leq i\leq N}(\delta_{t-1}(i) \times aatr_i) \times bbtr_j(o_t) \quad 2 \leq t \leq T$
3.Termination ← $p = \max\limits_{1\leq i\leq N}[\delta_t(i)]$
4.Output ← State sequence

4. Results

4.1. Databases Used

4.1.1. Online CHB-MIT Surface EEG Database

The online EEG database is used for experimentation which was collected at the children hospital, Boston [26] [27]. The subjects had drug-resistant seizures. A total number of 24 subject's EEG signals were collected to verify the requirement of surgery after discontinuing the drug intake of patients. EEG of several days was collected from each subject at regular intervals. EEG sampling frequency was 256 Hz with 16-bit resolution. For most of the subjects, there were 23 or more EEG files with several seizure events for a single subject. The International 10-20 EEG system was followed for recording the EEG signal. As it is observed in the database, all the subjects did not have the same electrode arrangement. Therefore, this research selected 18 EEG channels from the above database and used the same for all subjects to maintain a common electrode arrangement. The 18 channels are as follows: C3-P3, C4-P4, CZ-PZ, F3-C3, F4-C4, F7-T7, F8-T8, FP1-F3, FP1-F7, FP2-F4, FP2-F8, FZ-CZ, P3-O1, P4-O2, P7-O1, P8-O2, T7-P7, and T8-P8. Here, EEG signals with seizure events are considered for designing the model. The seizure and non-seizure EEG segments are extracted from these signals. Figure 4 presents the seizure and non-seizure EEG event from the online CHB-MIT surface EEG database.

4.1.2. AIIMS Patna EEG Database

The EEG signal is collected from 20 epilepsy patients at AIIMS Patna. The authors have collected already recorded data from AIIMS Patna. The required permission was sought from the administrative authority of AIIMS Patna before using the database. The EEG system is a 32 channel system, and the recording is done according to the 10-20 electrode system. The sampling frequency of the recorded EEG signal is 256 Hz. The maximum duration of the recording is 20 minutes. Continuous multichannel low noise EEG segments are used for developing and testing the algorithm. Clinicians' inputs are considered in marking seizure, non-seizure segments, and types of seizure events. Many different types of seizures are considered for developing the algorithm. The details are shown in Figure 5. A total number of 17 male and 3 female patients are considered in this seizure database. Age range varies from one year two

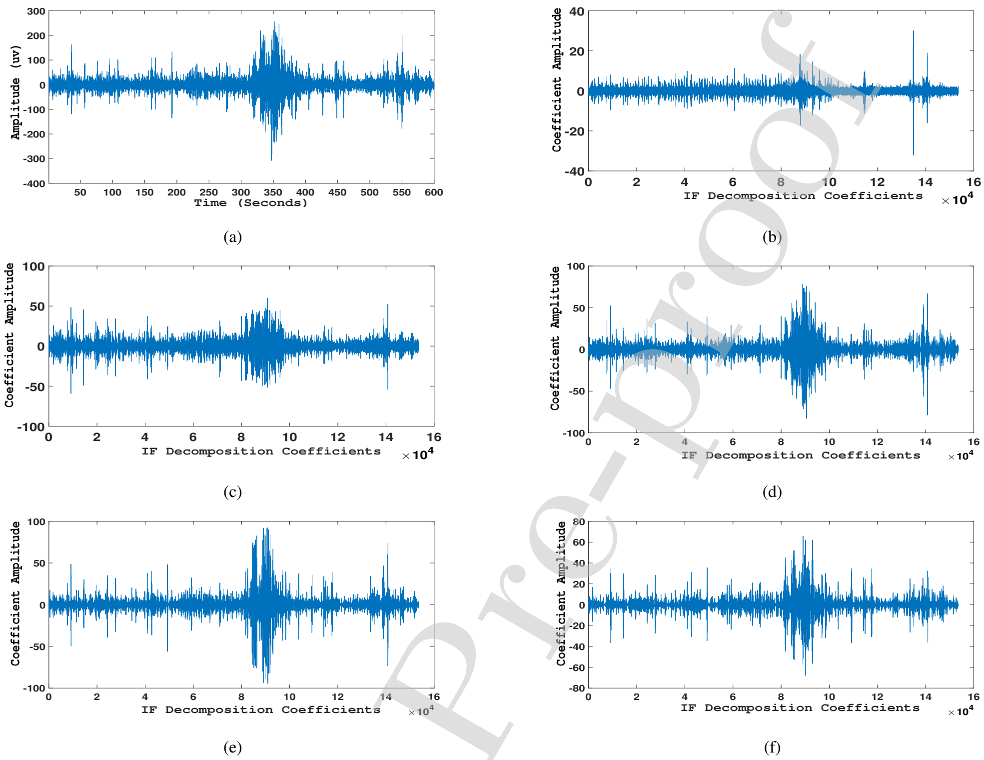

Figure 6: (a) Single channel EEG signal with seizure event, (b), (c), (d), (e), (f) 1^{st} to 5^{th} sub-components after IF decomposition

months to thirty-eight years. As shown in Figure 5, 30% out of the total waveform consists of generalized sharp-slow wave and generalized tonic-clonic seizure patterns. Here seizure events are observed as long as 1 second to a maximum of 4 seconds at a stretch.

4.2. Feature Variation of Online CHB-MIT Surface EEG Database

In this work, DMD power, the sum of 2D PSD, variance, and KFD features are extracted from seizure and non-seizure EEG events. Figure 6 shows the IF sub-components extracted from continuous seizure and non-seizure EEG signal after decomposition. The EEG signal is decomposed up to a maximum of 5 IMFs. The iterative filtering mask length is calculated using the below Equation.

$$Mask\ length = \frac{2 \times X_i \times L}{N} \tag{9}$$

Where X_i is the signal, L is the length of the signal, and N is the number of extrema points.

Figure 6 (a) shows a single EEG channel with a seizure event. The EEG seizure event has a higher amplitude compared to non-seizure EEG events. Figure 6 (b)-(f) shows 5 IF sub-components after decomposition. A significant seizure event amplitude variation is seen among the third, fourth, and fifth IF components. Figure 7 (a) represents the DMD power variation of the EEG signal with a seizure event. The features are extracted from online CHB-MIT surface EEG IF sub-components for every 5 seconds window. The signal features are shown for 10 minutes EEG signal with a seizure event. The features are extracted simultaneously from selected 18 channels. During the seizure event, DMD power is higher compared to the non-seizure event. Figure 7 (a) shows the DMD power 5 minutes before and after a seizure event. Here each window block is of 5 seconds

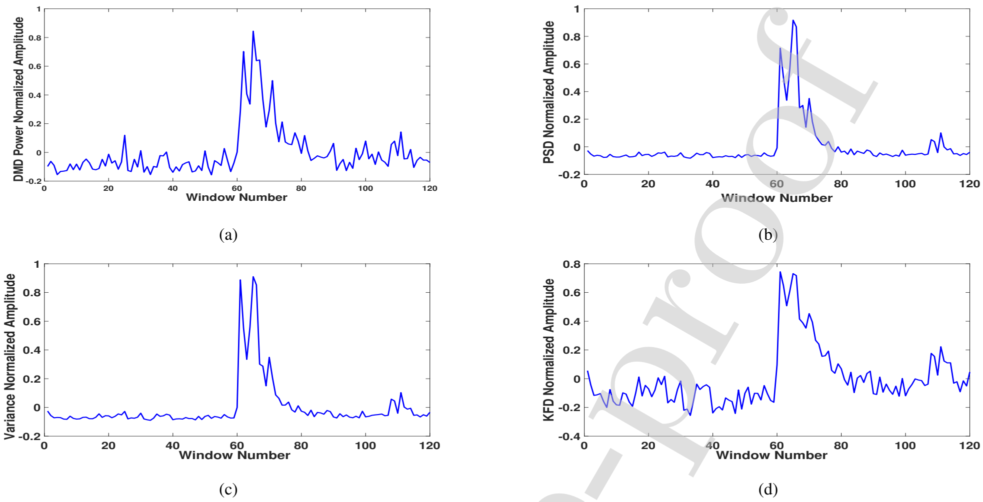

Figure 7: Variation observed in (a) DMD power. (b) 2D PSD. (c) Variance of IF decomposition coefficients. (d) KFD feature extracted from multichannel IF sub-components. The EEG has seizure event.

length. After 60 blocks (300 seconds), a clear uplift is observed in the feature power. Figure 7 (b) shows 2D PSD variation for seizure and non-seizure EEG events. The 4^{th} and 5^{th} lower sub-components have shown good power variation. Figure 7 (c) and (d) represent the coefficient feature variation and KFD feature output for seizure and non-seizure events. The variance and KFD features represent the time domain feature, and PSD represents the frequency domain feature.

4.3. Classification Result of Online CHB-MIT Surface EEG Database

Table 1 tabulates the classification accuracy between seizure and non-seizure EEG events for online CHB-MIT surface EEG database. The proposed approach is a patient non-specific approach. The system achieved overall 99.60% accuracy and 99.88% specificity in seizure and non-seizure EEG classification. The HMM classifier is designed for each feature separately and the feature vector is classified based on maximum classification score from all the classifiers. Initially HMM is trained by features extracted from subject 1 seizure and non-seizure EEG segments. Four seizure and four non-seizure EEG segment features are used for training the HMM classifier. The accuracy of the system is calculated using the rest of the seizure and non-seizure EEG segments for all other subjects. The system efficiency is evaluated based on the following factors.

$$
\begin{aligned}
Spec. &= \frac{TN}{TN+FP} \times 100.\\
Sen. &= \frac{TP}{TP+FN} \times 100.\\
PPV &= \frac{TP}{TP+FP} \times 100.\\
NPV &= \frac{TN}{TN+FN} \times 100.\\
Accuracy &= \frac{TP+TN}{TP+TN+FP+FN} \times 100.\\
False\ Positive\ Rate &= \frac{FP}{FP+TN} \times 100.\\
F\ Score &= 2 \times \frac{PPV \times Sensitivity}{PPV + Sensitivity}.\\
Kappa\ score &= \frac{P_o - P_e}{1 - P_e}.\\
MCC\ score &= \frac{\frac{TP}{N} - S \times P}{\sqrt{PS(1-S)(1-P)}}.
\end{aligned}
\tag{10}
$$

Where TP: true positive, TN: true negative, FP: false positive, FN: false negative, Specificity (Spec.), Sensitivity (Sen.), Positive Predictive Value (PPV), Negative Predictive Value (NPV), False Positive Rate (FPR).
In Matthews correlation coefficient (MCC) score and kappa score, the variables are calculated by the follow-

Table 1: Classification accuracy between seizure and non-seizure EEG segmented from online CHB-MIT surface EEG database

Subject ID	Total Seizure	Seizure duration (Seconds)	Spec. (%)	Sen. (%)	PPV (%)	NPV (%)	FPR (%)	Kappa Score	MCC Score	Accuracy (%)
2	3	174	98.17	100	84	100	1.83	0.90	0.90	98.34
3	7	286	99.74	100	97.18	100	0.26	0.98	0.98	99.76
4	4	378	100	100	100	100	0	1	1	100
5	5	558	100	96.37	100	99.68	0	0.98	0.98	99.70
6	2	28	100	79.00	100	97.74	0	0.87	0.87	97.92
7	3	325	99.47	87.50	91.30	99.22	0.53	0.88	0.88	98.77
8	5	919	100	85.26	100	97.63	0	0.90	0.91	97.92
9	4	276	100	97.05	100	99.79	0	0.98	0.98	99.80
10	4	377	100	100	100	100	0	1	1	100
11	2	784	100	100	100	100	0	1	1	100
12	25	1167	99.93	93.23	98.41	99.69	0.07	0.95	0.96	99.64
13	7	465	100	95.56	100	99.75	0	0.97	0.97	99.77
14	3	69	100	100	100	100	0	1	1	100
15	17	1637	100	100	100	100	0	1	1	100
16	4	39	100	100	100	100	0	1	1	100
17	3	320	100	100	100	100	0	1	1	100
18	5	249	100	100	100	100	0	1	1	100
19	3	236	100	100	100	100	0	1	1	100
20	8	294	100	100	100	100	0	1	1	100
21	2	131	100	100	100	100	0	1	1	100
22	3	204	100	100	100	100	0	1	1	100
23	7	424	100	96	100	99.62	0	0.98	0.98	99.65
24	16	511	100	92.75	100	99.72	0	0.96	0.96	99.73
Average			99.88	96.64	98.73	99.69	0.12	0.97	0.97	**99.60**

ing formulae.

$$
\begin{aligned}
N &= TN + TP + FN + FP. \\
S &= \frac{TP + FN}{N}. \\
P &= \frac{TP + FP}{N}. \\
P_o &= \frac{TP + TN}{TP + TN + FP + FN}. \\
P_e &= \frac{(TP + FN) \times (TP + FP) + (FP + TN) \times (FN + TN)}{(TP + TN + FP + FN)^2}.
\end{aligned}
\tag{11}
$$

In this work, DMD power feature from 4^{th} and 5^{th} IMFs are fused for classifying seizure and non-seizure EEG segments. PSD and variance features extracted from 1^{st}, 4^{th} and 5^{th} IMFs are fused to train and test the seizure-non-seizure HMM classifier. KFD features from 1^{st}, 3^{rd}, and 4^{th} IMFs are fused for seizure classification. Seizure segments of less than 10 seconds are not considered for the classification. If consecutive two 5 seconds window features are classified as seizure then, the segments are considered as seizure segments. It is observed from Table 1 that subjects 2 and 7 have less PPV. In subject 2, for the 2-19 EEG segment, four 5 seconds window features are wrongly classified as seizure segments. For subject 3, two 5 seconds window features are wrongly classified as a seizure. The lowest sensitivity is observed for subject 6. The proposed approach failed to classify many seizure segments in EEG recording of subject 6. The subjects 4, 10-11 and 14-22 achieved 100% accuracy in detecting seizure and non-seizure EEG events. In this work 164 minutes and 11 seconds, seizure events and other total non-seizure segments are considered for testing the model. A total number of 142 seizure events are used for testing the model. The overall system achieved 96.64% sensitivity and 99.88% specificity in seizure and non-seizure EEG classification. FPR is found to be zero for most of the subjects. Maximum FPR is observed for subject 2 which also has the lowest PPV. The accuracy of the system is evaluated using MCC and kappa scores. The MCC represents the correlation coefficient between the observed and predicted binary classification. The Kappa coefficient represents the statistic that is used to measure the amount of agreement occurring by chance for categorical items. The proposed approach achieved the highest kappa and MCC score for different subjects. The minimum kappa score is achieved for subjects 6 and 7. The MCC score is highest for different subjects. The average MCC score across all the subjects is 0.97 indicating a good correlation between observed and predicted binary classification. The average kappa score observed for online surface EEG is 0.97.

4.4. Classification Result on AIIMS Patna EEG Database

The patient data is collected from the EEG Lab of AIIMS Patna. The EEG signal is recorded for 20 minutes. The seizure is not observed for a longer duration for the patients under medication. The duration of seizure for each subject is mentioned in Table 2. It is essential to detect small seizures from continuous EEG signals. The window length is selected as 1 second for feature extraction to detect small seizure segments. Figure 8 shows the DMD power and 2D PSD feature extracted for the patient with tonic-clonic seizure. In the Figure, there is a distinct difference in the power between seizure and non-seizure EEG segment. It is observed from the graph that there are four seizure events. The feature variation observed for seizure is marked as a seizure feature, and non-seizure feature variation is indicated with a non-seizure mark and arrow mark in Figure 8.

The proposed approach is evaluated on the EEG data recorded at AIIMS Patna. A total number of 105 seizure segments are classified with high accuracy. A total of 138 seconds of the duration of the seizure vector is used for testing the model. All four features are found to be efficient in seizure and non-seizure EEG classification. Among all the IMFs, the 3^{rd} IMF is found to be most efficient in seizure classification. The HMM classifier is trained using 7 seizure and 7 non-seizure EEG events. The Viterbi algorithm is used to evaluate the present state of continuous EEG signals from the HMM classifier. It is observed from Table 2 that tonic-clonic seizure is classified with 100% accuracy. In this approach, we have observed seizure events ranging from 1 to 4 seconds. DMD power, on its own, achieved low accuracy. The proposed approach achieved low sensitivity for classifying diffused biphasic waveform. Three seizure events in subject 8 are misclassified as the non-seizure event. Generalized sharp and slow waves are classified with 100% sensitivity. The classification sensitivity is low for biphasic and triphasic sharp waves. In the biphasic and triphasic waveform, PSD and variance individually achieved good accuracy, but the other two features DMD power and KFD failed to classify many seizure events resulting in overall lower sensitivity. The diffused biphasic seizure could not be detected efficiently by DMD power and KFD in many instances. The proposed approach detected seizures with even lower activation. The approach achieved 100% accuracy in classifying other types of seizures such as episodic slowing, sporadic sharp wave, rolandic epilepsy, multi-focal epilepsy, and diffused epilepsy, which can be observed in Table 2. The proposed features are found to be useful in classifying different types of seizures and non-seizure events with 10 different types of seizures being classified with higher accuracy. HMM is found to be well suited for modelling seizure and non-seizure events and classification.

Overall, the system achieved 99.79%, 97.08%, and 99.74% specificity, sensitivity, and accuracy, respectively. The highest FPR is observed for a tonic seizure that is 1.19%. The efficiency of the classifier is evaluated using the MCC score and kappa score. It is observed that out of 20 subjects, 13 subjects achieved perfect 1 score in both MCC score and kappa score indicating excellent classification performance. The seizure and non-seizure classification in subject 4 achieved low kappa score and MCC score. The lower classification efficiency is indicated by low sensitivity in subject 4. In this approach, the binary classification has achieved 0.96 average kappa score and MCC score. Thus, the proposed approach is found to be efficient in classifying seizure and non-seizure EEG signals.

4.5. F score for Online CHB-MIT Surface EEG Database and AIIMS Patna EEG Database

F-value is a measure of classification accuracy. It is measured by the harmonic mean of PPV and sensitivity achieved by the classifier. PPV gives the measure of the sample that can be truly classified as a positive sample. Figures 9 and 10 show the F values of different subjects for AIIMS Patna EEG seizure database and online CHB-MIT surface EEG database, respectively. In Figure 9, it is observed that subjects 2, 6 and 7 have low F value. All other subjects have achieved high F value indicating good classification accuracy. In Figure 10, subject 4 achieved low F-value, also reflected by low sensitivity. The lowest F measure is 0.77 for subject 4. The highest F value 1 is achieved for many subjects in AIIMS Patna EEG database.

Table 2: Accuracy of seizure-non-seizure EEG classification for different types of seizure using AIIMS Patna EEG database

Subject ID	Type of Seizure	No. of Seizures	Seizure duration (seconds)	Spec. (%)	Sen. (%)	PPV (%)	NPV (%)	FPR (%)	Kappa Score	MCC Score	Accuracy (%)
1	Tonic Clonic seizure	2	2	100	100	100	100	0	1	1	100
2	Temporal lobe seizure	3	4	100	100	100	100	0	1	1	100
3	Generalized sharp and slow waves	1	1	100	100	100	100	0	1	1	100
4	Biphasic and triphasic sharp wave	12	14	99.91	66.67	92.30	99.47	0.09	0.77	0.78	99.38
5	Generalized tonic clonic seizure	5	14	100	100	100	100	0	1	1	100
6	Multiple generalized sharp wave	6	8	100	100	100	100	0	1	1	100
7	Generalized sharp wave	4	6	99.42	100	87.50	100	0.58	0.93	0.93	99.44
8	Diffused biphasic wave	6	7	100	75	100	98.25	0	0.85	0.85	98.33
9	Generalized tonic clonic Seizure	5	7	99.13	100	83.34	100	0.87	0.93	0.93	99.17
10	Generalized tonic clonic seizure	4	4	100	100	100	100	0	1	1	100
11	Episodic slowing	5	13	100	100	100	100	0	1	1	100
12	Generalized sharp wave	8	8	100	100	100	100	0	1	1	100
13	Diffused generalized slowing	5	10	100	100	100	100	0	1	1	100
14	Generalized tonic clonic seizure	4	7	99.11	100	87.50	100	0.88	0.93	0.93	99.17
15	Sporadic sharp wave	2	2	100	100	100	100	0	1	1	100
16	Rolandic epilepsy	1	2	100	100	100	100	0	1	1	100
17	Tonic seizure	6	6	98.81	100	83.34	100	1.19	0.91	0.91	99.81
18	Multi focal epileptic activities	4	4	100	100	100	100	0	1	1	100
19	Sharp EEG pattern	18	14	99.58	100	75.00	100	0.42	0.85	0.86	99.58
20	Diffused epileptic activities	4	5	100	100	100	100	0	1	1	100
Average				99.79	97.08	95.45	99.89	0.20	0.96	0.96	**99.74**

4.6. Comparison with State-of-the-art Methods based on Online CHB-MIT Surface EEG Database

Table 3 shows the comparison of the proposed approach with other state-of-the-art methods with surface EEG signals. In [28] DMD power, signal curve length and decision tree classifier are used for seizure detection. In [30] collective network of binary classifiers and particle swarm optimization are used for seizure detection and achieved 94.71% specificity. The STFT based approach achieved 94.37% accuracy in seizure classification [31]. Nowadays, deep neural network-based approaches such as convolutional neural network (CNN) are widely used for classification problem because of the good accuracy. In [32], authors have used CNN based approach for seizure detection and found accuracy as 97.5%. We observed accuracy using the online CHB-MIT surface EEG database as 99.60%, which is slightly higher than the accuracy expressed in [32].

4.7. Comparison with State-of-the-art Methods based on Clinical Surface EEG Database

The proposed approach is evaluated on AIIMS Patna EEG database. Different entropy features and statistical

Table 3: Performance Comparison of Proposed Approach with State-of-the-art methods

State-of-the-art methods	Methodology	EEG Type	Dataset Used	Sen. (%)	Spec. (%)	Accuracy (%)
[30] (2014)	collective network of binary classifier, particle swarm optimization	Surface	CHB-MIT	89.00	94.71	–
[28] (2018)	DMD Power, signal curve length, decision tree classifier			87	98.93	–
[31] (2018)	STFT, stacked sparse denoising autoencoder, convolutional autoencoder			–		94.37
[32] (2018)	FFT and CNN			96.9	98.1	97.5
Proposed approach	**Iterative filtering decomposition**, **PSD, DMD power, variance, KFD, HMM**			96.78	99.85	**99.60**
[29] (2013)	Sample entropy, statistical values, genetic algorithm with SVM		Clinical EEG dataset of 13 patient	–	–	99.77
[28] (2018)	DMD Power, signal curve length, decision tree classifier		KU Leuven	87.5	98.84	–
Proposed approach	**Iterative filtering decomposition**, **PSD, DMD power, variance, KFD, HMM**		**AIIMS Patna EEG**	97.08	99.72	**99.74**
[13] (2014)	Wavelet features, HMM	Intracranial	Rat EEG collected from University of Rostock	90.7	88.9	–
[34] (2017)	Time and DWT based feature, Shannon entropy, random forest classifier		Bonn University	97.4	97.5	97.4
[16] (2018)	SpPCA, SVM			99.00	100	99.66
[33] (2019)	Symlet wavelet processing, Gradient boosting machine, greed search optimizer, SVM			–	–	98.4

values are used for seizure detection [29]. The accuracy observed in [29] is 99.77%, but the number of subjects used in the database is 13. The authors in [28] have used the clinical KU Leuven EEG seizure database for seizure classification and achieved 87.5% sensitivity. The proposed approach achieved 99.74% accuracy and 99.72% specificity using AIIMS Patna EEG database.

4.8. Comparison with State-of-the-art Methods based on Intracranial EEG Database

The seizure detection algorithm based on intracranial EEG signal achieved good accuracy as noise interference is very low as compared to the surface EEG signal. The recording of intracranial EEG signals is an invasive technique. The authors in [16] have used SpPCA and SVM for seizure and non-seizure classification. Although the system has achieved high accuracy, a smaller database of 500 intracranial EEG signals of

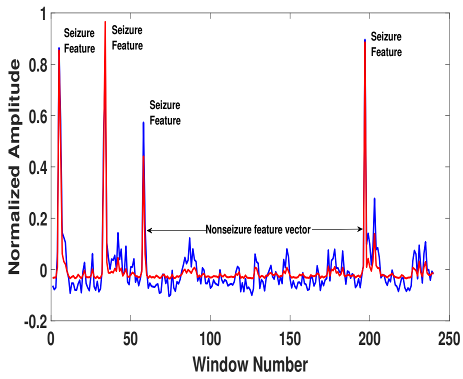

Figure 8: Plot of PSD and DMD power features extracted from 3^{rd} IF subcomponent of generalized tonic clonic seizure EEG signal segment from AIIMS Patna EEG database, red line represents the PSD and blue represents the DMD power feature

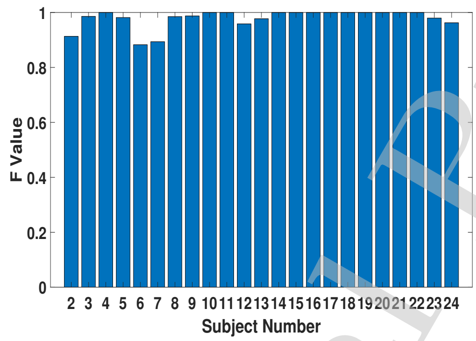

Figure 9: F value for different subjects in online CHB-MIT surface EEG database

small duration is used in the approach. Different wavelet features, SVM, HMM, random forest classifiers have found good classification accuracy in seizure detection [16] [33] [34]. The proposed HMM-based seizure detection approach using online CHB-MIT surface EEG and AIIMS Patna EEG database is overall efficient in classifying seizure and non-seizure EEG signals.

5. Conclusion and Future Scope

In this work, the subject non-specific automated epileptic seizure detection algorithm is proposed. DMD power, 2-D PSD, variance, and KFD features are ex-

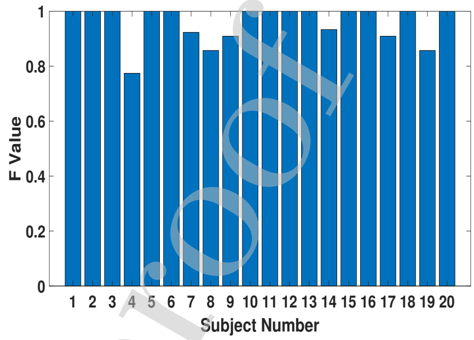

Figure 10: F value for different subjects in AIIMS seizure EEG database

tracted from the EEG signal. The iterative filtering approach is used to find subcomponents of the EEG signal. The EEG signal is decomposed up to level 5. Lower level IMFs are observed experimentally to achieve the maximum difference between a seizure and non-seizure EEG signals features. HMM is used for classifying seizure and non-seizure EEG signals. The proposed approach has achieved higher accuracy compared to other state-of-the-art methods. We evaluated the proposed approach across different types of seizures and two different databases. In the future, the system will be made more noise-robust. Also, we will validate the proposed approach with more AIIMS Patna EEG signals.

Conflict of interest

There is no conflict of interest in this work.

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