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Overhauled Approach to Effectuate the Amelioration in EEG Analysis

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Abstract: Discovering the information about several disorders prevailing in brain and neurology is by no means a new scientific technique. A neurological disorder of any human being can be analyzed using EEG (Electroencephalography) signal from the electrode's output. Epilepsy (spontaneous recurrent seizure) detection is usually carried out by the physicians using a visual scanning of the signals produced by EEG, which is onerous and may be inaccurate. EEG signal is often used to determine epilepsy, for its merits, such as non-invasive, portable, and economical, can exhibit superior temporal tenacity. This paper surveys the existing artifact removal methods. It puts a new-fangled mode forward to confiscate artifacts and hauls informative derived values from EEG to automate Epilepsy detection. The automated Epilepsy detection has to precisely indicate and detect the neural abnormality of the brain. This indication and detection process necessitates a proficient approach for the prompt removal of artifacts of the EEG signals. An effective artifact removal of EEG signals can alone enable the useful features of the original signals for further processing. Once the original signals excluding the noise is obtained, a delicate strategy for extracting the features of the signals, becomes mandatory in order to accomplish robust classification of the signal. Then an expert classification technique is implemented to aid the automated analysis process to correctly distinguish the EEG signal features.

Keywords: ACAR (Adaptive common average reference); electroencephalography (EEG); epilepsy; ICA (Independent component analysis); 1D-LBP (One dimensional-local binary pattern); seizure detection

1 Introduction

Neurons are an enormous magnitude of individual brain cells. Electrical firings hold the responsibility of ensuring communication within the neurons. Each neuron is connected to a small subset of other neurons. Neurons can be analyzed using the EEG signal since the EEG signal is non-invasive, economical, portable, and has a temporal resolution. The neuron's structure is depicted below in Fig. 1. The oscillations at a range of frequencies are indicated using Scalp EEG activity. Approximately these oscillations exhibit distinctive frequency ranges. The resulting EEG signal may also contain some signals from eye movements (EOG), nearby muscle activities (EMG), etc., So, for accurate analysis, EEG signals are to be split into frequency bands that vary from high to low frequencies.
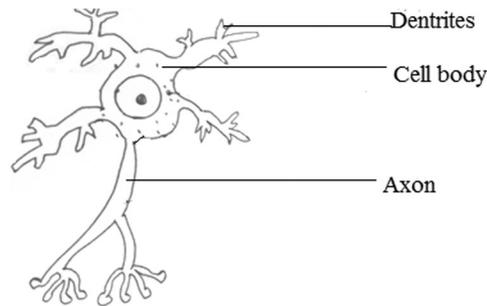
Figure 1: Structure of a neuron

On analyzing the burst suppression, epilepsy and seizure detection can be done. The seizure is nothing but a simple neurological disorder in which excessive neurons are jittered simultaneously. Epilepsy is another neurological disorder where the spontaneous recurrent seizure occurs. Tab. 1 defines the range of frequencies. If the frequency level goes above the range other than that specified in Tab. 1, then neurological disorders can arise.

Table 1: Signal frequencies

Type of EEG	Frequency (Hz)
Gamma (γ)	>30
Beta (β)	14–30
Alpha (α)	8–13
Theta (θ)	4–7
Delta (δ)	1–3

Epileptic EEG activity has been classified as ictal (during a seizure), postictal (after a seizure) and interictal (between seizures). Interictal EEG data is viewed as a collection of isolated spikes, spike trains, sharp waves, or spike-wave complexes. The monitoring of the relative energy flanked by the frequency bands highly assists in decoding the dominant activity and states such as relaxed, excited, drowsy, muscle activities. In this paper, first, an overview of pre-processing techniques is presented, and it provides insights on the challenges in this area. Later Feature extraction methods. Finally, the paper is concluded with classification methods.

1.1 Related Work

Many techniques for catching a glimpse of an epileptic seizure have been invented. Feature extraction by which the informative values are derived and classification of EEG signal plays vitally a crucial role in detecting ictal and interictal signals. They assist in the treatment of epileptic patients and indicate the precautionary measures. Existing methods were not adequately sufficient to endow the accurate data about Epilepsy detection. Conventional diagnostic methods techniques rely on the expert's knowledge for visually inspecting lengthy EEG recordings which is often timely protracted and highly prone to errors. So, in the research of epilepsy detection, Supriya et al. delved into the effect such as the average weighted degree of a complex network [1]. They employed a Complex network for its higher performance and used a single feature to minimize computation cost.

Parvez et al. Enhanced seizure detection was carried out utilizing the temporal correlation within the EEG signals. According to their approach, the EEG signal is parted into a few epochs and then arranged

into a 2D matrix and different transformation/decomposition methods are applied to dig out a few statistical features and these features are then applied as input into LS-SVM (Least Square-Support Vector Machine) for further classification [2]. The reason for using LS-SVM is the minimized operational error, maximized margin hyperplane, and the better classification obtained by taking into consideration by the accuracy of the ictal and interictal period of epilepsy. Wang detected the seizure intervals of epilepsy patients by employing the basis of Partial Directed Coherence (PDC). They implemented Support vector machine to discriminate interictal periods from ictal periods of EEG signals [3].

Riaz et al. (2016) used the approach of Empirical Mode Decomposition (EMD) for feature extraction. Intrinsic mode function (IMF) is a yield of EMD [4]. Sharpley et al. implemented EMD since the frequency components of EEG signals change from one interval to the other [5]. Wavelet CSP (Common Spatial Pattern) algorithm is a widely used algorithm for EEG signal processing and the best results were obtained using their proposed methodology. Zabihi et al. (2015) proposed another approach to detect seizures by using the CHB-MIT database to achieve precise classification over competing techniques without any pre-processing [6]. Their approach achieved the highest accuracy and minimum rate of fake alarms among the existing extraction methods and achieved detection accuracy.

To detect the seizures Gajic et al. suggested Wavelet transform and Statistical pattern recognition which was implemented by three stages which are 1. Extracting features using wavelet transform. 2. Reduction of feature space dimension 3. Classification using quadratic classifiers. The cons of their approach are reduced noise level and achieved very good specificity, sensitivity, and accuracy [7]. Das et al. used Discrete Wavelet Transform (DWT) and/neural network to detect epilepsy [8,9]. By using these methods, they achieved better accuracy. The classifiers such as Linear Discriminant Analysis (LDA), Multi-Layer Perceptron Neural Network (MLPNN), Probabilistic Neural Network (PNN), Elman Neural Network (ENN), Radial Basis Function Neural Network (RBFNN), Naive Bayes, Mahalanobis Distance, K-Nearest Neighbor (K-NN), Decision Tress, Logistic Regression, Bayes Quadratic, Hidden Markov Model (HMM), Support Vector Machine (SVM) are prominently used in EEG classification techniques for epileptic seizure detection [10–12]. They defined SVM as the powerful and popular method for better seizure detection performance [13–15]. There are multi-class SVMs [16–18] OneV$_s$One, OneV$_s$Rest and DAG MSVMs, but take more computation time. Among the various classifiers support vector machine and neural networks support most of the characteristics and are popularly used by many researchers. In classification algorithms, a normal task is to suit a model to a collection of data. This model is later used for classifying new samples. Regularization is a technique used to avoid the over-fitting problem.

1.2 Motivation and Justification of the Proposed Work

Burst suppression is a pattern of electroencephalogram that contains quasi-periodic fluctuation between isoelectric suppressions. It is the characteristic of an extremely inactivated brain, happening in the circumstances together with general anesthesia, infant encephalopathy, and coma. The electroencephalographic Burst Suppression Pattern (BSP) is a combination of high amplitude bursts and low amplitude suppressions. Electroencephalography is one of the main tools used for recording brain activity. The primary motivation of using the electroencephalogram is flexible to use, which results in outstanding time resolution and low cost. The recorded EEG signals are more often contaminated with the different types of noises, which can be associated with the EEG signal's frequency band. Hence it is the biggest challenge to remove the noise from the recorded EEG signal, and the various sources of noise are discussed. The prime drive in this paper is to come up with a hybridized instigative artifact removal analysis, feature extraction and classification techniques.

2 Analysis of EEG Signal for the Detection of Brain Abnormalities

This research investigates the pre-processing of the EEG signal, a feature extraction technique, and different classifiers to classify the EEG signals into the Epilepsy Disease patients and Healthy Control. In

the pre-processing of the EEG signal, artifacts are removed. The feature extraction technique utilizes the wavelet transform, and the dimensionality reduction techniques are carried out by the Independent Component Analysis (ICA). The dimensionally reduced EEG signals are additionally processed by utilizing distinct classifiers such as K-Nearest Neighbor, Support Vector Machine (SVM).

The performance measures of the classifiers are compared based on their metrics like Accuracy, Sensitivity, Specificity, Precision, Recall, and F-measure. A very requiring process is epilepsy using the EEG signal. Three main stages are involved in the automated EEG detection process: artifact removal (pre-processing), feature extraction, and classification. The raw EEG signals are provided as input to the pre-processing to perform noise removal and decompose the EEG signal into five sub-band signals in order to do the analysis. From each of the six EEG signals, such as the original EEG, delta, theta, alpha, beta, and gamma, the nonlinear parameters (time and frequency) were extracted. The nonlinear parameters extracted are then fed into a classifier that can classify either normal or abnormal as the same.

2.1 Pre-processing

Regrettably, numerous varieties such as artifacts resulting in ocular artifacts, electrode artifacts, motion artifacts, and EMG artifacts resulting from muscle activity are grabbed by EEG signals, which increases the misclassification of recorded EEG signals. The artifacts and their types are shown below in the diagrammatic representation (Fig. 2). During the seizure detection, roughly artifacts can increase the actual negative rate, while some specific types of seizure may be left undiagnosed and regarded as non-epileptic events. Therefore, it is more important to automatically remove such felonious artifacts before a seizure or epilepsy detection to ensure the accurate detection of epilepsy. Many long-established tactics ((S. Barua (2014)) have been proposed to attenuate artifacts from recorded EEG signals [19].
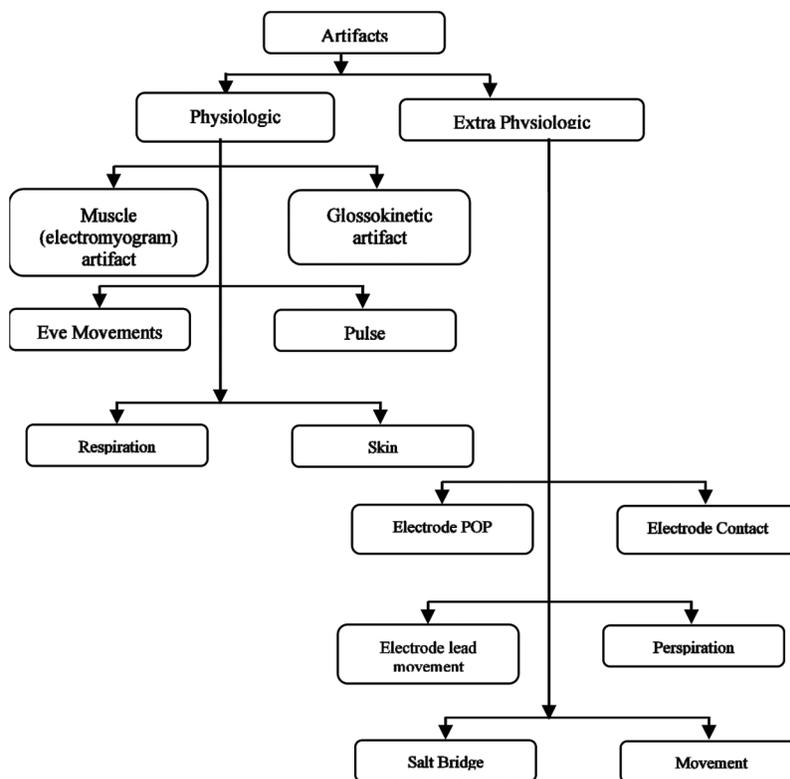
Figure 2: Types of artifacts

Blind source separation (BSS), which includes independent component analysis (ICA) and canonical correlation analysis (CCA), is the most widely used means of decreasing noise in EEG signals [20–22]. Islam et al. mainly concentrated [23] on the methods which can separate artifacts from seizures. They developed an automated program to remove artifacts at their best without distorting the signal of interest. Stationary Wavelet transform has been used to separate artifacts from seizures by considering the spectral band of seizure activities [24]. Their approach reduces false alarms in seizure detection. Mammone et al. (2012) proposed a method to remove artifacts using wavelet independent component analysis, which gives superior results on suppression of artifacts in EEG signals. Artifacts can be removed [25] by several methods such as Regression-based, EMD (Empirical Mode Decomposition), ICA (Independent Component Analysis), etc.

2.1.1 Regression

Regression analysis is a traditional approach to identifying artifact samples and eradicating the same artifact samples from the signal and is the most used method to remove some physiological artifacts such as ocular and cardiac artifacts [26,27] from the Observed artifact-contaminated EEG signal and an artifact reference signal. But this method is case-based that is limited only to particular cases. It is mainly used whenever the reference channel is available, and only those references can be used to eradicate the artifacts. Methodologies for eradicating artifacts include Indexing, Enveloping, Squaring, and thresholding.

2.1.2 Blind Source Separation (BSS)

BSS is a prevalent method of removing eye-related artifacts and some of the muscle artifacts that come from jaw clenching, swallowing, and rising eyebrows [28]. The process of BSS is to extract the individual unfamiliar source signals from their combinations.

Let's consider X as the observed signals in multi-channel recordings and the source, S with additive white noise vector N, that is defined in Eq. (1)

$$X \;=\; AS + N \tag{1}$$

Independent component analysis (ICA)

ICA is a special case of BSS. It is a probabilistic technique for learning a linear transformation of a random vector. Independent component analysis acts as a one-stop solution for all artifacts removal in any EEG signal since the methodology of ICA itself encompasses Indexing, Enveloping, Squaring, Thresholding. ICA addresses EMG artifacts & other Physiologic artifacts. The block diagram of ICA is given below in Fig. 3.
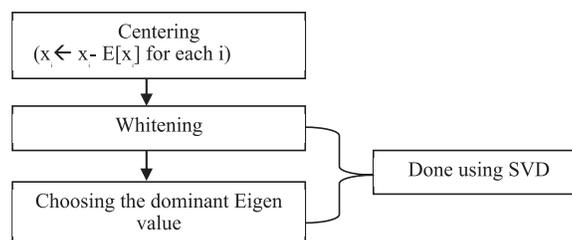
Figure 3: Block diagram of ICA

Steps of ICA process

Centering

The basic idea of Centering is to bring the data to zero means and it is used in the removal of the DC offset from the observations.

Whitening & Singular Value Decomposition (SVD)

Whitening refers to normalizing variance in all the possible directions and treating all the dimensions equally. To perform whitening and to find dominant eigenvalues, Singular Value Decomposition (SVD) can be used.

2.1.3 Adaptive Common Average Reference (ACAR)

Adaptive Common Average Reference combines the merits of CAR and ANC (Adaptive Noise Cancelling) filter. To remove correlated artifacts, ACAR can be used.

CAR

- Common Average Referencing (CAR)-a simple technique in computations.
- It is usually used in EEG signals, where it is essential to detect signal sources at actual noisy recordings.

For 'k' channels, a simple model can be defined in the below equation Eq. (2)

$$d_{k,t} = s_{k,t} + w_k * n_t \tag{2}$$

CAR is calculated by considering sample by sample, which is calculated by the average of all the channels. To remove the artifacts CAR is defined below as a global reference in Eq. (3):

$$\hat{S}_{k,t} = d_{k,t} - \hat{n}_t \tag{3}$$

where $\hat{n}_t = \frac{1}{K} \sum_{k=1}^{K} d_{k,t}$

Theoretically, the anticipated signals are not correlated amid channels and the noises are indistinguishable, i.e., $w_k \sim 1$ for each channel and defined in the below Eq. (4).

$$\hat{n}_t = \frac{1}{K} \sum_{k=1}^{K} (s_{k,t} + w_k * n_t) \approx n_t \tag{4}$$

Since different channel characteristics in CAR enable unpredictable amplitudes in artifacts, the proposed approach adapts ACAR. CAR is considered as X_k/n_t to an ANC filter as a reference signal and the weight for each channel is found by finding the relationship between ANC output and the reference. Adaptive noise canceling (ANC) filter is given below in Fig. 4.
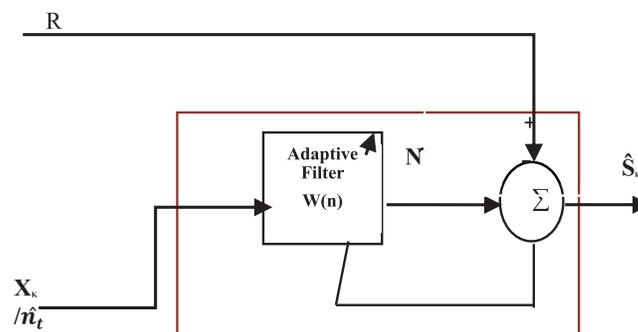
Figure 4: System design for an adaptive noise canceling (ANC) filter

Where

R_k-recorded signal where R_k = S+N.

X-A reference correlated with N, W-FIR filter coefficients to minimize output

Ŝ-Output, $W_{(n)}$ = $[\omega_0(n)\ \omega_1(n)\ ...\omega_{L-1}(n)]^T$

ACAR

The block diagram of ACAR filter is given above in Fig. 5.
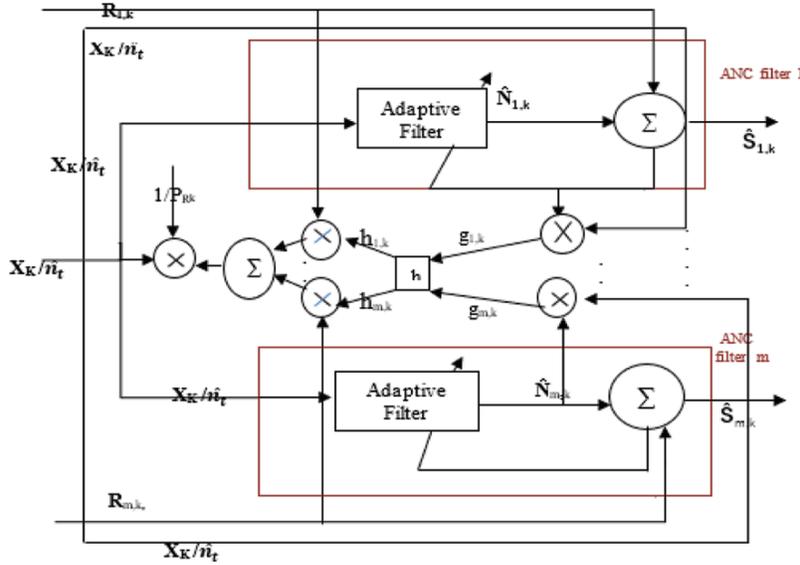
Figure 5: Block diagram of ACAR

$$h_{m,k=}\frac{\overline{g_{m,k}}}{max_m(\overline{g_k})} \tag{5}$$

$$\overline{g_{m,k}} = \frac{1}{T}*\sum_{i=1}^{T}g_{m,k-i+1} \tag{6}$$

$$P_{R_k} = \frac{1}{T*M}*\sum_{j=1}^{M}\sum_{i=1}^{T}R_{j,k-i+1}^2 \tag{7}$$

where

R_k-recorded signal where R_k = S + N.

Ŝ-filtered output

h block-Moving average on g

P_{Rk}-Average signal power of R as given by Eq. (7).

2.2 Feature Extraction

The feature extraction technique can be employed for the dimensionality reduction of the features. The signal characteristics can be best portrayed using the extracted features. The feature extraction can be

performed both in Time and Frequency domains. Feature extraction methods enable the extraction of the relevant features and the features with little or no predictive information are eliminated.

2.2.1 Local Binary Pattern (LBP)

After the analysis of different methods, LBP is found to be one of the most powerful methods for feature extraction. LBP can also be used to descript texture and summarizes the local-gray level structure of an image. The fundamental design to develop the LBP operator Chatlani et al. is to use two harmonizing metrics [29]: local spatial patterns and grayscale contrast.

The description of LBP code is given below in Eq. (8):

$$S_c^{LBP} = \sum_{i=0}^{m-1} s(P_i - S_c)2^i \tag{8}$$

where $s(x) = \begin{pmatrix} 1, & if \ x \geq 0 \\ 0, & otherwise \end{pmatrix}$

'm'-surrounding pixels,

Pi-Points (i = 0…m − 1)

2.2.2 One Dimensional Local Binary Pattern (1D-LBP)

1D-LBP is a kind of LBP used to process the signals. 1D-LBP is very akin to LBP, but it is pertinent to use only for a 1D signal. The example of a signal point S_c of 1D-LBP code is shown in Fig. 6.
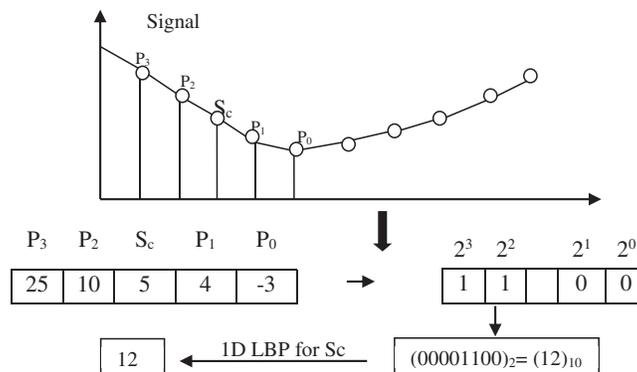
Figure 6: Block diagram of the ACAR filter

One dimensional (1D-LBP) transformation code is given below in Eq. (9):

$$S_c^{1D-LBP} = \sum_{i=0}^{m-1} s(P_i - S_c)2^i \tag{9}$$

where $s(x) = \begin{pmatrix} 1, & if \ x \geq 0 \\ 0, & otherwise \end{pmatrix}$

Sc-signal point

m-Number surrounding points (P_i, i = 0, … m − 1)

In the above technique [30], different weights (2^i, i = 0…m − 1) are assigned to different points.

3 Proposed Approach

To instigative Epilepsy, the combination of different methods to remove artifacts and seizures also detected using an innovative, optimized algorithm founded from the primary research and has come up with innovative changes that abolish the downsides of the previous approaches.

3.1 Methodology

Pre-processing is a vital methodology by which raw data is transformed into a format suitable for upcoming analysis. EEG signals while pre-processed the annihilation of the artifacts from the data and getting the accurate neural signals. Regarding EEG artifacts, this proposed method analyses all the possible artifacts encountered while recording an EEG signal and suggests a one umbrella methodology that at its best annihilates all those possible artifacts. A feature defines a unique property that is quite measurable. Extracted features are intended to minimize the loss of essential information implanted in the signal and simplify the number of incomes required to define a substantial magnitude of data correctly.

The newly suggested ideology for detecting epilepsy is given below in Fig. 7.

```
┌─────────────────────────────┐
│    Acquired EEG signal      │
└─────────────────────────────┘
              │
              ▼
┌─────────────────────────────┐
│  Artifact removal using ICA │
│      coupled with ACAR      │
└─────────────────────────────┘
              │
              ▼
┌─────────────────────────────┐
│  Feature extraction using   │
│  Local Deviation Pattern    │
│          (LDP)              │
└─────────────────────────────┘
              │
              ▼
┌─────────────────────────────┐
│ Classification using        │
│ Ensemble classifier         │
│ (ANN+SVM + Modified Wigner  │
│        distribution)        │
└─────────────────────────────┘
```
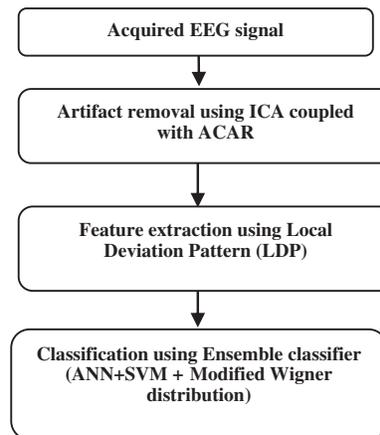
Figure 7: Proposed method for Epilepsy detection

After acquiring the EEG signal, ACAR is mainly employed to remove the noise or artifacts. After removing artifacts, LDP (Local Deviation Pattern) is adapted as its feature extraction technique because of its high discriminative power, computationally simple, invariant to grayscale changes, and exhibits superior performance. The proposed method is to detect epileptic seizures, feature extraction, and classification. Ensemble classifier is the combination of ANN and SVM binary classifier technique with Modified Wigner distribution function to perform better classification. Given a series of training samples, ensemble classifier tries to find which sample goes to first-class and the one that fits the second. It is adapted since the prediction is accurate, is robust, and performs effectively with the noisy data.

3.1.1 ACAR

It is efficiently used in cases where it is difficult to remove the noise. ACAR tackles EOG artifacts and other extra physiologic artifacts. The basic idea behind ACAR is, a weighted CAR is considered as $X_K/\hat{n}_t$ (a reference signal) to an ANC filter.

3.1.2 One Dimensional Local Deviation Pattern (1D-LDP)

1D-LBP is thin-skinned to noise and, so it exhibits limited of detecting the hidden patterns. To overcome this limitation, 1D-LDP has been proposed. The 1D-LDP technique is concerned with calculating the

Standard deviation of the neighbouring points and finds the comparison among neighbouring points and the deviated value. The code, which is in binary form, has been obtained after the comparison. After getting the code, it must be converted into the transformation code. The standard deviation is the most acceptable way to measure the variation. Each comparison results in a binary value (0 or 1) both in 1D-LBP and LDP.

The 1D-LDP is more descriptive when compared with that of 1 D-LBP. The Example of 1D-LDP is defined in Fig. 8. 1D-LDP is an innovative technique for extracting features by using the standard deviation of the adjacent points. The 1D-LDP feature extraction technique is realized using the following steps:
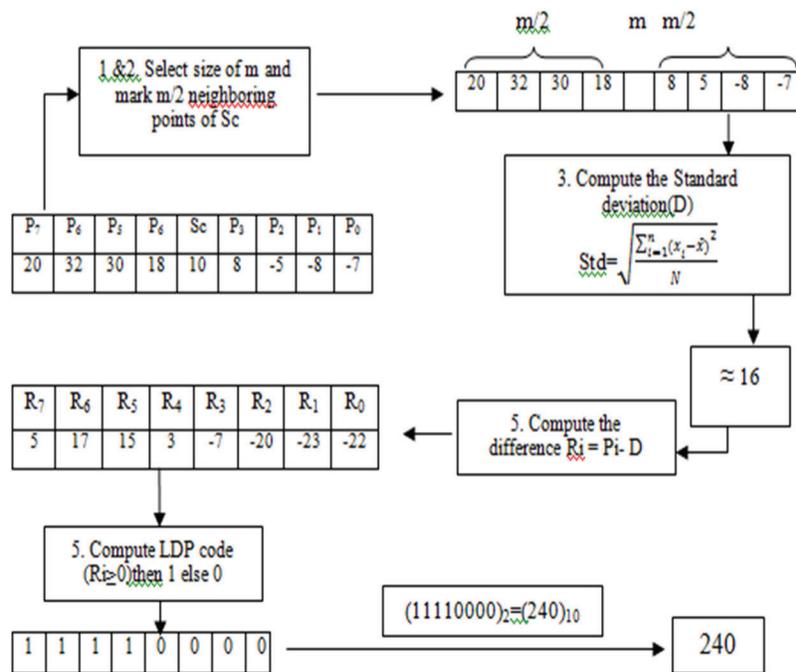
Figure 8: Example of 1D-LDP

1. 'm' is set as the number of neighbouring points.
2. For each S_c (Signal point), consider m/2 neighbour points.
3. The standard deviation (D) of the neighbouring points is computed as below in Eq. (10):

$$D = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{N}} \tag{10}$$

4. The disparity between the neighbouring points and the mid-point is computed below:
   $R_i = P_i - D$; where 'i' varies 0. . .m − 1
5. 1D-LDP code is computed as below in Eq. (11):

$$S_c^{1D-LDP} = \sum_{i=0}^{m-1} s(R_i) 2^i \tag{11}$$

where

$$s(x) = \begin{pmatrix} 1, & \text{if } x \geq 0 \\ 0, & \text{otherwise} \end{pmatrix}$$

3.2 Proposed Ensemble Classifier

This classifier is a combination of ANN and SVM base classifiers with modified Wigner distribution. ANN explained in 2.3.2. SVM performs intense byzantine transformations and then catches out the way of separating the data based on the outputs by which they are defined. A nonlinear classification can be efficiently carried out by the SVM classifier using a kernel trick. Vladmir N. Vapnaik put forth a model for creating nonlinear classifiers by utilizing Kernel trick to maximum-margin hyperplanes. A much more complex relationship can be captured between the data points without performing complex transformations manually. SVM can be defined below by using a training set that contains 'N' training artifact samples and coefficients $\propto\_(1\ldots N)$ learned in the training step, the decision function of $X(1\ldots M)$.

SVM is defined in the below equation Eq. (12):

Decision function

$$f(X) = \sum_i \alpha_i K(X_i,\ F) + z \tag{12}$$

where

K(.)-kernel function, b-input vector.

3.2.1 Modified Wigner Distribution Function

Modified Wigner distribution function as Time-frequency distribution function is a variation of the Wigner distribution function (WD) with reduced or removed cross-terms. A modified Wigner distribution (MWD) can be formulated as

$$C_x(t, f) = \int\limits_{-\infty}^{\infty} \int\limits_{-\infty}^{\infty} W_x(\theta,\ v)\pi(t - \theta,\ f - v)d\theta dv = [W_x * \pi(t, f)] \tag{13}$$

where $\pi(t, f)$-Cohen's kernel function (low-pass function), which usually masks the interference with the original Wigner representation.

4 Performance Analysis

Performance evaluation of the methods adopted, enhanced, and developed is the most key step in any research. For the performance analysis, the paper considers the CHB-MIT database Goldberger et al. which is web-based, freely available [31]. This database provides access to all the researchers working on neurological disorders since it offers a wide range of EEG records to augment their research. This paper uses CHB-MIT database. It contains child patients EEG recordings that are collected at Boston Children's Hospital. For up to seven days, subjects are observed to define their seizures. The dataset has 22 subjects, from that, 5 male and 17 females provided recordings divided into 23 cases. Due to hardware restrictions, there are pauses between sequentially numbered .edf files during which the signals are not captured; in most situations, the intervals are shorter than 10 s. All signals are sampled at 256 samples per second, with a resolution of 16 bits. The majority of the files include 23 EEG signals. These recordings were made using the International 10–20 method.

The Performance metrics that aids in evaluating the system performance are mentioned in this section. All types of physiologic artifacts have been considered for performance analysis. For the performance

evaluation, Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), Average Difference (AD), Maximum difference (MD), Laplacian Mean Squared error (LMSE) and Normalized Absolute Error (NAE) are taken. Tabs. 2 and 3 depicts the MSE, PSNR, and performance of the above-specified algorithms. It is identified that (from Tab. 2) high PSNR value can be produced by Proposed approach when compared with supplementary algorithms. Moreover, it also produces low MSE values with good computational speed (from Tab. 3). Tab. 4 shows the average difference values and Tab. 5 shows the maximum difference. Tab. 6 shows the LMSE values and Tab. 7 shows the NAE values. From the tables, it is identified that the proposed approach yields good results. Ensemble classifier performance is shown in Tabs. 8–10. The value of Accuracy, Precision and F-measure are calculated using Cross validation and Partitioning technique as K-FOLD. Ensemble classifier gives better performance in all the three metrics.

Table 2: Performance of ICA & proposed approach based on PSNR

Techniques	Input signal/Case No	Various artifact interferences				
		Respiration	Eye movement	Pulse	Glossokinetic	Muscle
ICA	1	38.6709	35.4111	32.3106	29.5335	27.3276
	2	41.0349	36.468	32.3914	29.2364	27.678
	3	37.8721	34.3517	31.5122	28.6444	26.0195
	4	38.6789	34.112	30.0354	26.8804	25.322
	5	35.4111	33.2928	29.4106	26.8868	25.6463
Proposed (ICA+ACAR)	1	41.4251	38.1653	35.0648	32.2877	30.0818
	2	43.7891	39.2222	35.1456	31.9906	30.4322
	3	40.6263	37.1059	34.2664	31.3986	28.7737
	4	41.4331	36.8662	32.7896	29.6346	28.0762
	5	38.1653	36.047	32.1648	29.641	28.4005

Table 3: Performance of ICA & proposed approach based on MSE

Techniques	Input signal/Case No	Various artifact interferences				
		Respiration	Eye movement	Pulse	Glossokinetic	Muscle
ICA	1	37.3953	80.3311	142.4216	313.7931	522.1349
	2	22.532	62.7631	97.325	162.0159	336.0763
	3	45.1489	102.7997	198.5958	385.3013	705.9939
	4	24.00125	64.23235	98.79425	163.4852	337.5456
	5	80.3311	131.4629	322.824	578.0093	769.4507
Proposed (ICA+ACAR)	1	34.8879	77.8237	139.9142	311.2857	519.6275
	2	20.0246	60.2557	94.8176	159.5085	333.5689
	3	42.6415	100.2923	196.0884	382.7939	703.4865
	4	21.49385	61.72495	96.28685	160.9778	335.0382
	5	77.8237	128.9555	320.3166	575.5019	766.9433

Table 4: Performance of ICA & proposed approach based on AD

Techniques	Input signal/case No	Various artifact interferences				
		Respiration	Eye movement	Pulse	Glossokinetic	Muscle
ICA	1	0.008627	0.008627	0.008627	0.071127	0.196127
	2	0.046337	0.037005	0.021491	0.021491	0.146491
	3	0.015087	0.046337	0.046337	0.046337	0.046337
	4	0.008627	0.008627	0.008627	0.071127	0.196127
	5	0.046337	0.037005	0.021491	0.021491	0.146491
Proposed (ICA+ACAR)	1	0.009627	0.009627	0.009627	0.072127	0.197127
	2	0.047337	0.038005	0.022491	0.022491	0.147491
	3	0.016087	0.047337	0.047337	0.047337	0.047337
	4	0.009627	0.009627	0.009627	0.072127	0.197127
	5	0.047337	0.038005	0.022491	0.022491	0.147491

Table 5: Performance of ICA & proposed approach based on MD

Techniques	Input signal	Various artifact interferences				
		Respiration	Eye movement	Pulse	Glossokinetic	Muscle
ICA	1	91.763241	105.27632	120.92745	136.8606	157.77268
	2	62.963221	67.750221	109.30622	140.74922	147.82222
	3	47.851451	72.968593	113.32478	160.25686	203.26062
	4	47.218	52.005	93.561	125.004	132.077
	5	105.27632	78.260591	108.05029	154.99295	175.94992
Proposed (ICA+ACAR)	1	112.1252	125.6383	141.2895	157.2226	178.1347
	2	83.32522	88.11222	129.6682	161.1112	168.1842
	3	68.21345	93.33059	133.6868	180.6189	223.6226
	4	67.58	72.367	113.923	145.366	152.439
	5	125.6383	98.62259	128.4123	175.355	196.3119

Table 6: Performance of ICA & proposed approach based on LMSE

Techniques	Input signal	Various artifact interferences				
		Respiration	Eye movement	Pulse	Glossokinetic	Muscle
ICA	1	0.7268335	0.8909205	0.9729175	0.9900445	0.9945345
	2	0.1116575	0.2453685	0.5225935	0.9444525	0.9944665
	3	0.2588425	0.5041085	0.7007265	0.8989525	0.9849175
	4	0.112908	0.246619	0.523844	0.945703	0.995717
	5	0.8909205	0.4038215	0.7331905	0.9396325	0.9946815

(Continued)

Table 6 (continued)

Techniques	Input signal	Various artifact interferences				
		Respiration	Eye movement	Pulse	Glossokinetic	Muscle
Proposed (ICA+ACAR)	1	0.746834	0.910921	0.992918	1.010045	1.014535
	2	0.131658	0.265369	0.542594	0.964453	1.014467
	3	0.278843	0.524109	0.720727	0.918953	1.004918
	4	0.132908	0.266619	0.543844	0.965703	1.015717
	5	0.910921	0.423822	0.753191	0.959633	1.014682

Table 7: Performance of ICA & proposed approach based on NAE

Techniques	Input signal	Various artifact interferences				
		Respiration	Eye movement	Pulse	Glossokinetic	Muscle
ICA	1	0.7256935	0.0448365	0.0661495	0.0953845	0.1290625
	2	0.0263105	0.0449175	0.0733355	0.1087585	0.1375145
	3	0.0396925	0.0616445	0.0811185	0.1077665	0.1464535
	4	0.0278645	0.0464715	0.0748895	0.1103125	0.1390685
	5	0.0448365	0.0627275	0.0988375	0.1331535	0.1564605
Proposed (ICA+ACAR)	1	0.723694	0.042837	0.06415	0.093385	0.127063
	2	0.024311	0.042918	0.071336	0.106759	0.135515
	3	0.037693	0.059645	0.079119	0.105767	0.144454
	4	0.025865	0.044472	0.07289	0.108313	0.137069
	5	0.042837	0.060728	0.096838	0.131154	0.154461

Table 8: Performance of ensemble classifier–accuracy

Training data/ testing data	Classifier			
	Modified Wigner distribution	SVM	ANN	Proposed (Ensemble classifier)
90/10	83.72	86.78	89.12	92.72
70/30	80.84	84.13	87.30	90.54
60/40	79.12	82.64	85.11	88.66
50/50	77.34	80.25	82.05	86.26
40/60	76.72	79.17	80.16	84.92

Table 9: Performance of ensemble classifier–precision

Training data/ testing data	Classifier			
	Modified Wigner distribution	SVM	ANN	Proposed (Ensemble classifier)
90/10	81.61	84.67	86.4	90.61
70/30	79.72	82.24	84.45	89.32
60/40	76.24	81.53	82.22	88.75
50/50	73.45	78.16	80.16	87.38
40/60	71.60	76.28	78.28	85.87

Table 10: Performance of ensemble classifier–F-measure

Training data/ testing data	Classifier			
	Modified Wigner distribution	SVM	ANN	Proposed (Ensemble classifier)
90/10	85.51	87.67	90.48	94.66
70/30	81.72	86.46	88.62	92.43
60/40	80.35	83.72	86.33	89.75
50/50	78.48	81.14	83.17	88.14
40/60	77.61	80.26	82.28	87.78

5 Conclusion

The novelty of efficient artifact removal by ICA coupled with ACAR and 1D-LDP visual descriptors and classified using Ensemble classifier makes this proposed paper an optimal and ideal tool for enabling automated epileptic detection of EEG signals at best and at the earliest too. The proposed strategy for automated EEG analysis is found to exhibit superior PSNR value compared with other existing algorithms. The proposed strategy also produces low MSE values with good computational speed. Performance with respect to accuracy, precision and F-measure is also highly better when compared with the existing strategies. Altogether, the proposed strategy has yielded augmented performance and results.

6 Future Enhancement

The future scope of the research includes a varied range of pathologies and to development of lightweight epileptic seizure detection and monitoring system with multi-modal data.

7 Limitations

Ictal EEG may also be uninterpretable or difficult to read if movements generate excessive artifact. To enable the robotic epileptic detection, EEG signals can be combined with multi-modality images. So that it can improve the performance.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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