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Epliptic Seizure Detection and Classification Using Cumulative Sum Average Filter TT-Transform and Harmony Search Algorithm Based LLRBFN Model

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ABSTRACT

Seizure detection becomes complex and difficult task for neurologists from electroencephalogram (EEG) signals. Therefore, It is essential to develop an automated detection and classification task to make detection and classification task easier for neurologist for the clinical diagnosis. This paper presents a novel hybrid Harmony search for optimization of weights of LLRBFNN (Local Linear Radial Basis Function Neural Network) model. The preprocessing has been adopted for noise removal and motion artifacts. Further, the Cumulative sum average filter and TT-transform has been used for noise removal and feature extraction from EEG elliptic seizure signals. Three features, namely power spectral density, Shannon entropy, and energy, were extracted. The dataset has been considered from University of Bonn database. The hybrid HS-LLRBFNN obtained an accuracy of 99.45% and the results are compared with HS-RBFNN, HS-LLWNN (Local Linear Wavelet neural network) models. Further, the results depicts the proposed model is appropriate for real-time seizure acknowledgement from EEG recording.

1. Introduction

Epilepsy neurological disorders incline individuals to experience irregular electrical activities in the brain. Seizures are a sudden, disordered neurological functions [1]. The unexpected nature of seizures makes unconsciousness of the daily life task which leads to an increased risk of injury or death [2, 3]. Abbasi and Esmaeilpour [4] proposed statistical characteristics EEG signals for detection of epileptic seizures using "DWT and perceptron neural netwo".

Around 2% of populations of the world are identified with epilepsy and unfortunately, the process of seizure occurrence is very poorly understood. 5,6] .Yuan et al.[6] proposed a novel feature — diffusion distance (DD) algorithm in intracranial Electroencephalograph (iEEG) recordings. Guo et al. [7] proposed a ANN based classifierfor automated and “periodogram and autoregressive” features was proposed in [8]. Gurwinder et al. [10] proposed wavelet transformation and spikebased features for detection, and achieved an accuracy of 98.6% .DWT-based features along with MLPNN model proposed by Orhan et al. [11] d and achieved an accuracy of 84.2%,. wavelet packet entropy in [12] achieved accuracy of 98.33%. The automated detection using k-means clustering utilized for epileptic seizure detection in [13].Gupta et.al [14] proposed multi-scale Renyil permutation entropy (WMRPE) and improves signal to noise ratio (SNR) levels. Bogaarts et al. [15] prposed Empirical mode decomposition (EMD) and DWT compute log energy entropy and K-NN classifier and achieved an accuracy of 89.4% [16]. In the recent study [17], with classification accuracy of 96.1% are achieved. LS-SVM classifier [18] obtained an accuracy of 97.7%. The fragmented feature extraction proposed in [19] achieved classification accuracy 97.1%. In [20], the analytic TF flexible “wavelet transform (ATFFWT)” and achieved 97.9%. s[21]. The “kernel robust probabilistic collaborative representation based classifier (KRPCRBC” has been proposed in [22] and obtained an accuracy of 99.3%. EMD and “power spectral density (PSD” has been executed in [23] for classification and obtained 96.4%. Coifman et al. [24] presented entropy-based wavelet packet decomposition for detection. There are several methods of decomposition and classification available, but it is found that the detection and classification are complex and difficult. Motivated by this above deficiencies we are proposing a hybrid cumulative sum average filter and TT –Transform for seizure detection and “HS-LLRBFNN Model” for classification of seizure, non-seizure and normal categories of EEG signal.

The rest of the paper is divided as follows: Section -2 presents the materials and methods which includes research step block diagram, proposed cumulative sum TT-Transform and HS-LLRBFNN model, Section -3 presents results of the research, section -4 presents discussions on results and section-5 presents conclusion and reference.All manuscripts must be in English. These guidelines include complete descriptions of the fonts, spacing, and related information for producing your proceedings manuscripts. Please follow them and if you have any questions, direct them to the production editor in charge of your proceedings at Conference Publishing Services (CPS): Phone +1 (714) 821-8380 or Fax +1 (714) 761-1784.

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2. Materials And Methods

A. Preprocessing

Cumulative sum average filter [25] has been applied to eliminate noise and artifacts which has been has been calculated in "one cycle back fashion". Mathematically the filter equation for the given signal S (k), is defined as

$$EEG_{SUM}(k)=\sum_{l=k-N+1}^{K} EEG(l) \tag{1}$$

The above equation (1) can be written in "recursive form" as

$$EEG_{SUM}(k)=EEG_{SUM}(k-1)+EEG(k)-EEG(k-N) \tag{2}$$

Where, N represents number of samples in the signal

B. Research flow diagram

The research is following steps such as (1) the EEG signals are collected from university of Boon and under gone preprocessing through cumulative sum average filter(ii) the preprocessed signals are fed as input to the TT-Transform for localization of seizure from the signals. (iii) Further the preprocessed signals are undergone feature extraction, the proposed HS-LLRBFNN algorithm acquires the features for classification and corresponding results are compared with the HS-RBFNN,HS-LLWNN models. The proposed algorithm flow is shown in Fig.1.

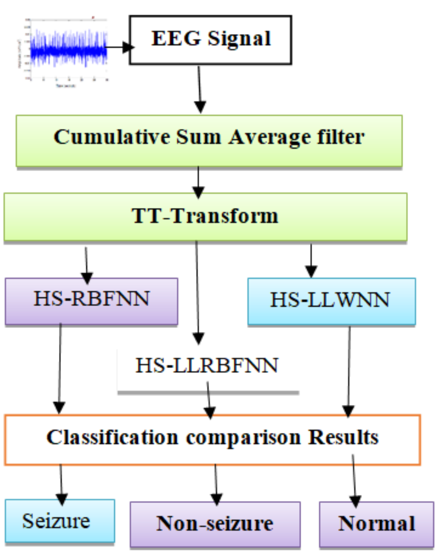

Fig-1 Research flow diagram

C. Dataset

In this study, EEG signals are collected from University of Bonn, Germany [26,27]. The dataset includes five sets of single-channel EEG recordings denoted by "A, B, C, D and E". The samples dataset is presented Fig. 2.

D. Feature extraction

The features such as "power spectral density(PSD)", "Shannon entropy[5], energy [28]" are considered. In this work, PSD[5] referred as power of the EEG signal ,Entropy is referred as measure of the complexity and energy depends on the amplitude of the epileptic data.

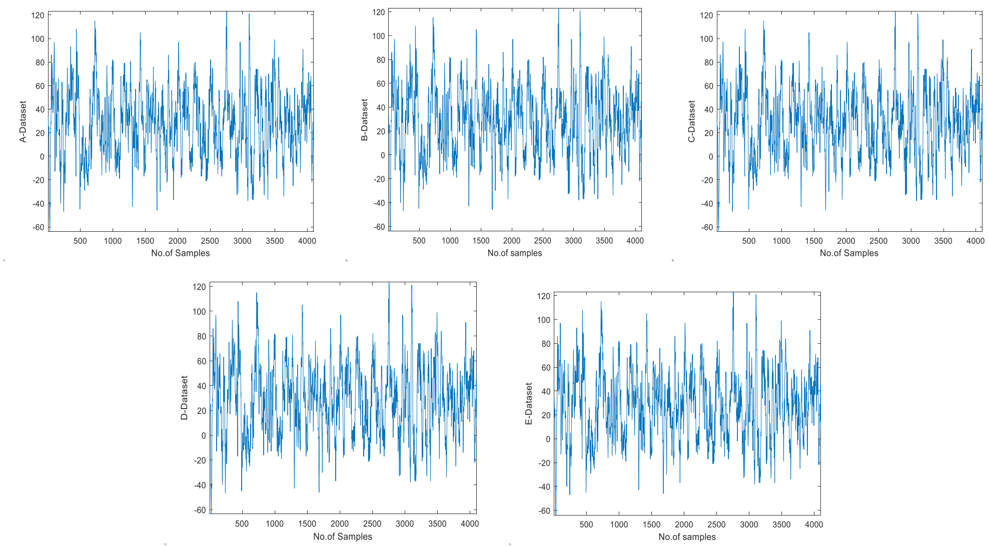

Fig-2 Bonn data A,B,C,D,E

Feature extraction of A,B,C,D,E EEG Dataset

Dataset	Entropy	Energy	PSD
	0.887506	0.569364	0.879636
A	0.852769	0.57378	0.991137
	0.916419	0.397825	0.890395
	0.938259	0.37203	0.373532
B	0.91062	0.356365	0.355168
	0.899218	0.395496	0.3965
	0.915593	0.477471	0.477058
C	0.88666	0.561656	0.561779
	0.858701	0.453925	0.45397
	0.840499	0.061097	0.061349
D	0.863302	0.300907	0.302073
	0.818666	0.195486	0.19631
	0.853131	0.877219	0.568954
E	0.858506	0.988383	0.573816
	0.915385	0.890897	0.397223

E. TT-Transform

Inverse of the S-Transform is treated as "TT-Transform" which has good capability in gathering frequency in diagonal position.

Let "x[kT], k=0,1,….N-1" signify a time series[29] , related to x(t), with sampling time interval of T.

The DFT is given by

$$X\left(\frac{n}{NT}\right)=\sum_{k=0}^{N-1}x(kT)e^{\frac{-j2\pi nk}{N}} \tag{3}$$

The "S-Transform" is given by

$$S(t,f)=\int_{-\infty}^{\infty}X(\alpha+f)\ e^{\frac{-2\pi^2\alpha^2}{f^2}}.e^{+j2\pi\alpha\tau}\ d\alpha \tag{4}$$

Using equation (4), the "S-Transform[29] of a discrete time series x(kT)" is given by "f→n/NT" and "τ →pT"where T=1/N

$$S[pT,\frac{n}{NT}]=\sum_{m=0}^{N-1}X\left[\frac{m+n}{NT}\right]e^{\frac{-2\pi^2m^2}{n^2}}\cdot e^{\frac{j2\pi mp}{N}} \tag{5}$$

Where p , "m" and "n=0,1,…N-1". The modified S-Transform is given by

$$\hat{S}(pT,\frac{n}{NT})=\sum_{m=0}^{N-1}\hat{X}(\frac{m+n}{NT})\ .e^{\frac{-2\pi^2m^2}{n^{2\gamma}}}.e^{\frac{j2\pi mp}{N}} \tag{6}$$

Thus, the discrete TT -Transform is given by

$$\hat{T}T(pT,kT)=\sum_{n=0}^{N-1}\hat{S}(pT,\frac{n}{NT}).e^{\frac{+j2\pi nk}{N}} \tag{7}$$

The "discrete TT-Transform [30]" which is the inversion of $\hat{T}T$ is given by

$$\hat{X}(k)=\sum_{p=0}^{N-1}\hat{T}T(pT,kT) \tag{8}$$

F. Proposed Harmonic search LLRBFNN model

The proposed harmonic search based LLRBFNN model is presented in this section for classification. The weights are updated by APSO algorithm.

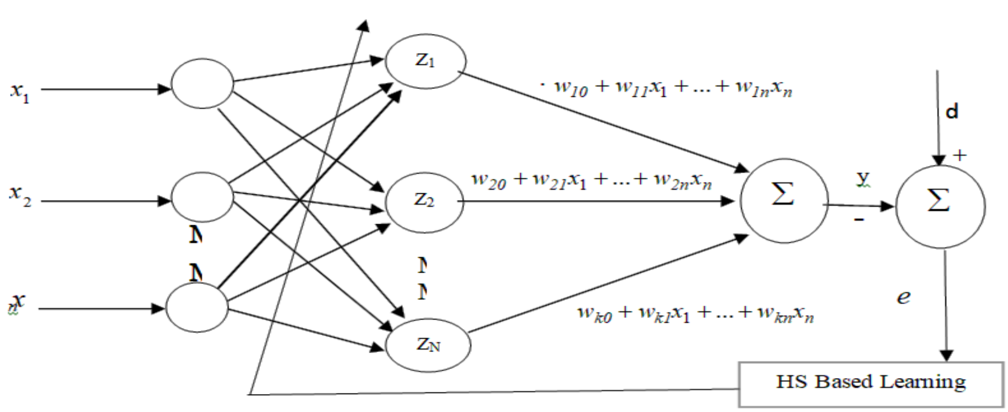

Fig: 3 HS Based LLRBFNN Model

The HS[31] algorithm has been applied for the optimization of weights of the LLRBFNN [32] model. Considering the $x_1, x_2, \ldots\ldots x_n$ data points are inputs as feature and the "activation function" Z_N of the n[th] hidden neuron is defined by a "Gaussian Kernel" as

$$Z_n(x) = e^{\left(\frac{-\|x - v_i(n)\|^2}{2\sigma_n^2}\right)} \tag{9}$$

Where "σ_n^2 is the parameter for smoothness of the activation function" and "C_M is the center of the hidden node and "$\|x - v_i(n)\|$" indicates the "Euclidean distance" and with the desired vector "d", the "objective function" is termed as "mean square erro" which is given by

$$MSE(e) = \frac{1}{N}\sum_{n=1}^{N}(d_n - y_n)^2 \tag{10}$$

G. Harmony Search Algorithm weight optimization

Since the optimization technique HS[31] pursues a best global optimum value, we are considered for weight optimization of LLRBFNN model.Generate random vectors (w_1, w_2, …, w_{HMS}) up to the "harmony memory size (HMS)" and store them in the "harmony memory (HM) matrix":

For LLRBFNN Model the weight random vector is generated as

$$W_{HM} = \left[\begin{array}{ccc|c} w_1^1 & \cdots & w_n^1 & f(w^1) \\ \vdots & \ddots & \vdots & \vdots \\ w_{HMS}^1 & \cdots & w_n^{HMS} & f(w^{HMS}) \end{array}\right] \tag{11}$$

Step-1 Considering new probability "HMCR (harmony memory considering rate";
"0 ≤ HMCR ≤ 1)", we can write

$$w_i^{'} \leftarrow w_i^{\mathrm{int}(u(0,1)\times HMS)+1} \tag{12}$$

Step-2 With "PAR (pitch adjusting rate; 0 ≤ PAR ≤ 1)" change

$$w_i^{'} \leftarrow w_i^{'} + bw \times (2rand - 1) \tag{13}$$

Where $rand$ is taken as (0,1) and "bw" is the "maximum change in pitch adjustment".

Step-3The weights of the LLRBFNN is updated as

$$w_i^{new} = \begin{cases} \{w_i^{old},\ old \in (1,2\ldots\ldots, HMS), rand < HMCR \\ w_i \in W_i \end{cases} \tag{14}$$

Select the best harmonies until the closure criterion is satisfied.

3. Results

A. EEG Seizure detection

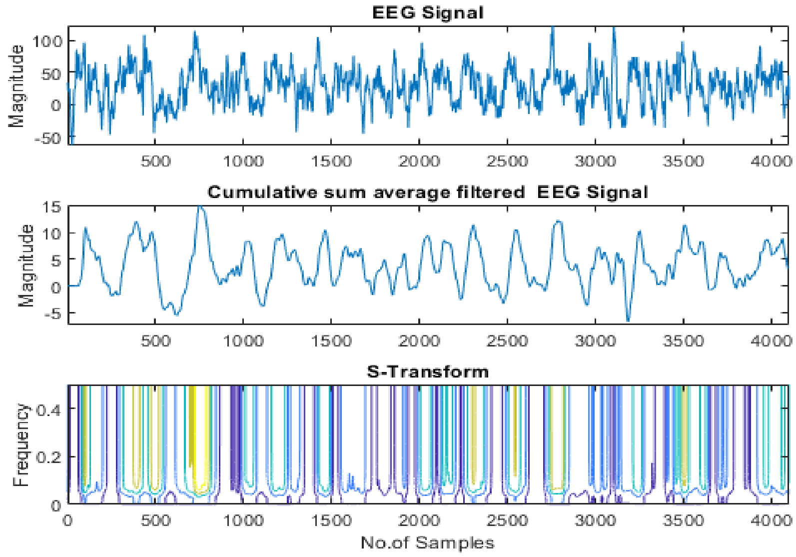

Fig.4 Cumulative sum average filter and s-transform localization

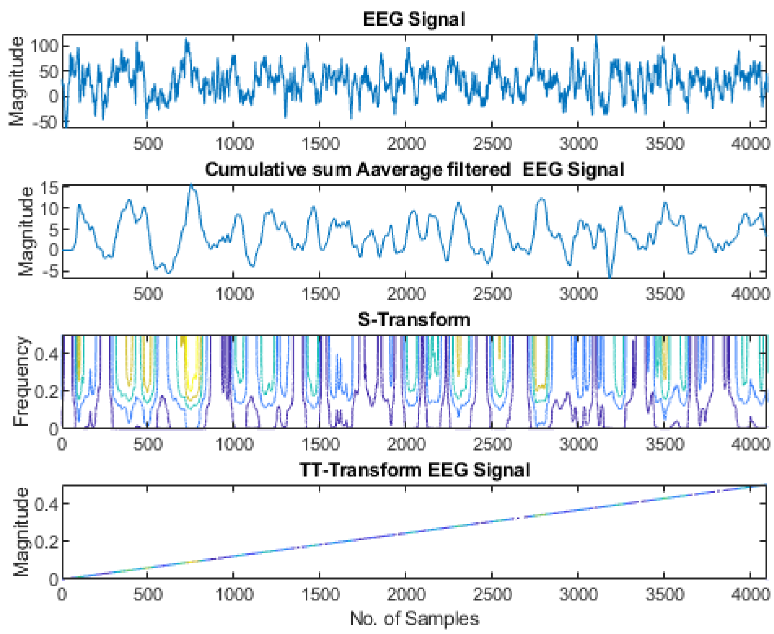

Fig.5 Cumulative sum average filter and TT-transform localization

B. EEG Seizure classification

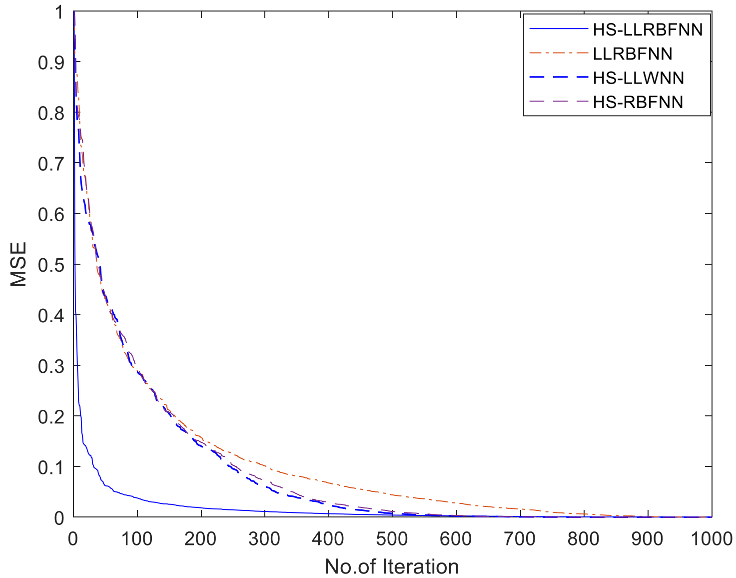

Fig.5 Mean square error results of classification

Performance measure classification

Classifier	Accuracy in (%)		Computational time in sec
	Training	Testing	
LLRBFNN	97.23	96.72	35.1527
HS-RBFNN	97.84	97.12	31.4543
HS-LLWNN	**98.27**	**97.88**	**23.2578**
HS-LLRBFNN	**98.89**	**98.22**	**18.2117**

4. Discussion

Fig.3 shows the seizure EEG signal along with cumulative sum average filter and S-Transform. The cumulative sum average filter removes the noise signal in one cycle back fashion. The s-transform shows the location of different seizures through yellow contours. Fig.4 shows the cumulative sum average filter and S-Transform and TT-Transform. The TT-Transform gathers the frequency contents in the diagonal position which shows the localization of seizures prominently. Further, the TT-Transform has been applied for feature extarxtion and the features of the dataset A,B,C,D,E are presented in Table-1. Fig.5 shows the mean square error results of HS-LLRBFNN,HS-LLWNN,HS-RBFNN and LLRBFNN. It is found that the LLRBFNN takes nearly 800 iteratios to converge , HS-RBFNN took nearly 530 iterations, HS-LLWNN took 500 iterations to converges to zero. The computational time taken by the proposed HS-LLRBFNN is 18.2117 seconds which shows the improved performance of LLRBFNN algorithm. The performace accuracies are presented in Table-2.

5. Conclusion

In this research work a novel HS-LLRBFNN model has been proposed to classify the seizure signal. Bonn dataset has been utilized for the testing and training process. The EEG signals are denoised through cumulative sum average filter to have better smoothness of the signal. Further the denoised signal has been given as input to S-Transform and TT-Transform for localization of the seizures from the EEG signals. It is observed that the TT-Transform method performs diagonaal localization , reduces the noise level and ready for feature extraction. There are therr features such as PSD, Entropy and Energy has been calculated and presented. The distinct feature entropy plays a vital role in classification. Further the classification has been done by utilizing HS –LLRBFNN model and the results aare compared with HS-LLWNN,HS-RBFNN and LLRBFNN and comparison results are presented. The HS-LLRBFNN shown an accuracy of 98.89 % along with the lesser computational time of 18.2117 seconds.

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