Singular Lorenz Measures Method for Seizure Detection using KNN-Scatter Search Optimization Algorithm

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Abstract— **Offline algorithm to detect the intractable epileptic seizure of children has vital role for surgical intervention. In this paper, after preprocessing and windowing procedure by Discrete Wavelet Transform (DWT), EEG signal is decomposed to five brain rhythms. These rhythms are formed to 2D pattern by upsampling idea. We have proposed a novel scenario for feature extraction that is called Singular Lorenz Measures Method (SLMM). In our method, by Chan's Singular Value Decomposition (Chan's SVD) in two phases including of QR factorization and Golub-Kahan-Reinsch algorithm, the singular values as energies of the signal on orthogonal space for pattern of rhythms in all windows are obtained. The Lorenz curve as a depiction of Cumulative Distribution Function (CDF) of singular values set is computed. With regard to the relative inequality measures, the Lorenz inconsistent and consistent features are extracted. Moreover, the hybrid approach of K-Nearest Neighbor (KNN) and Scatter Search (SS) is applied as optimization algorithm. The Multi-Layer Perceptron (MLP) neural network is also optimized on the hidden layer and learning algorithm. The optimal selected attributes using the optimized MLP classifier are employed to recognize the seizure attack. Ultimately, the seizure and non-seizure signals are classified in offline mode with accuracy rate of 90.0% and variance of MSE 1.47×10^{-4}.**

Keywords*— *Epileptic seizure; SVD method; Lorenz curve; KNN algorithm; Scatter search.

I. INTRODUCTION

The seizure diagnosis for decision on surgical intervention and prescribing the drugs using EEG analysis plays the important role [1]. The EEG time series as stochastic process has nondeterministic comportment. The seizure attack as clinical disorder has the symptoms on the recorded brain signals [1, 2]. For diagnosis and prognosis of these anomalies, many offline and online algorithms are frequently used. In recent studies, the common offline algorithm is usually observed [3]. At a glance on these researches, after signal conditioning the signals are decomposed to 5 or 6 dominant rhythms using Discrete Wavelet Transform (DWT) [4], Gabor filter [5] and the periodogram-based methods [6]. In the next step, the convenient features are extracted. This stage is as important section of seizure detection algorithms. For this purpose, the different tools and measures are employed. The time and frequency attributes such as the extracted features of transform-based methods are considered [7]. The features based on the energy or power using the coefficients of the signal decomposition in time-frequency domain [7, 8], applying the periodogram pattern feature on the EEG signals [6], also the entropy features with the definition of higher-order moments and using the statistical distribution of the signal are frequently used [7, 8].

In the developed attitude, these extracted features for improving the classification are optimized. The evolutionary, biotic and abiotic algorithms such as Genetic Algorithm (GA) [1], Ant Colony Optimization (ACO) [6], Particle Swarm Optimization (PSO) algorithms [8] in combination with neural network such as MLP [6] and probabilistic nets [4] or statistical pattern recognizer [9] and the different approximations of the Bayesian classifier are used to select the optimal features for final classification step. With regard to the specified frequency band width of EEG signal and randomly behavior of it, the robust algorithm for different patients and the different types of seizure attack is necessary. In this paper, our first main challenge is proposing a novel method based on the signal decomposition and providing a basis for feature extraction. The second issue is introducing the suitable features with exclusive specifications to detect the seizure and non-seizure signals.

II. PROPOSED OFFLINE SEIZURE DETECTION ALGORITHM

Our offline seizure detection algorithm has been represented in Fig. 1. Each epoch of the EEG signal is denoised then by applying the windowing procedure the signal is decomposed to five rhythms using DWT filter bank in the each window. The 2D pattern of rhythms is formed with naive upsampling. We have introduced a novel algorithm for feature extraction that is named Singular Lorenz Measures Method (SLMM). In this method, the mean of singular values for the patterns of all windows are computed based on the Chan's SVD. Then, the Lorenz curve of this set is plotted and two models of statistical attributes using consistent and inconsistent measures are extracted. Ultimately, 8 features for each EEG signal are attained. These features with hybrid optimization algorithm of KNN-SS are reduced and the optimal features with high efficiency are selected. Moreover, the optimized MLP classifier with Levenberg-Marquardt training algorithm is employed for diagnosing the seizure attack. The stages of our proposed algorithm are presented following in details.

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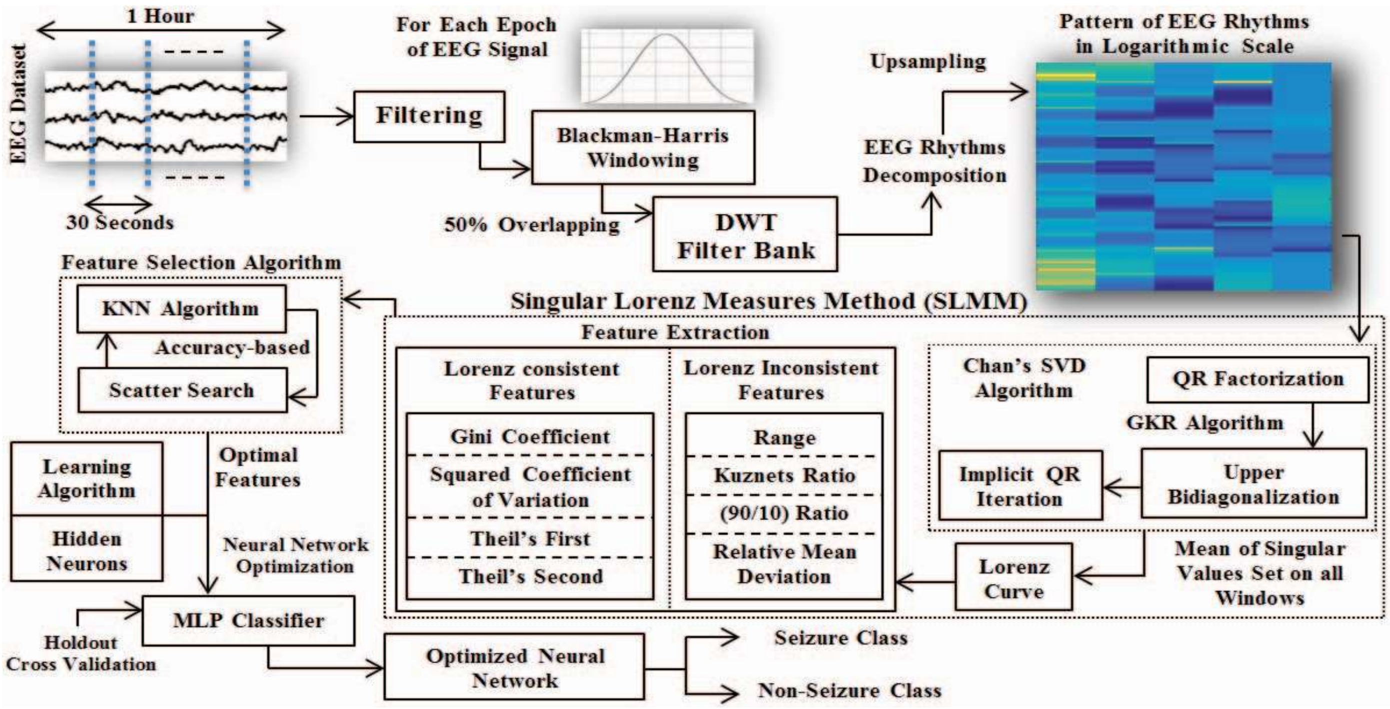

Fig. 1. Block diagram of offline epileptic seizure detection algorithm.

III. Feature Extraction

For offline EEG signal detection into seizure and non-seizure classes, after preprocessing the convenient features for describing the comportment of signal during the attack should be extracted. In this section of paper, our proposed features with novel combination of statistical measures and algebraic-based methods are represented.

A. Dataset Preprocessing

In this paper, the EEG dataset of pediatric patients and the children with intractable seizure disease that collected at the Children's Hospital Boston (CHB-MIT) is considered [10]. To decide surgical intervention, the subjects for up to several days following withdrawal of anti-seizure medication are monitored. In our application, 104 hours of dataset have been employed. The sampling frequency of signal is 256 Hz with 16-bit resolution [10]. Each signal with the length of 1 hour is divided to $L = 120$ epochs with time of 30 seconds. In totally, 10440 normal signals and 2040 epochs with the symptoms of seizure (about 16.3% of used dataset) are investigated.

1) EEG Signal Filtering

To eliminate the noise, motion artifacts and the undesirable components the EEG signal using band pass Kaiser-Bessel window as a FIR method is filtered [11]. The cutoff frequencies f_{C1} and f_{C2} are tuned on 0.5 and 35 Hz, respectively. The authorized ripples of $\delta_{PB} = 0.05$ for passband and $\delta_{SB} = 0.01$ for stopbands are considered [6].

2) Windowing and Rhythms Decomposition by DWT

The 4-term Blackman-Harris window as Hamming family with truncating on $N = 60$ samples and overlapping of 50% for unbiased estimation of signal and obtaining the minimum loss of information is periodically used [6]. This windowing procedure for $0 \le n \le N-1$ is applied on the signal $S(n)$,

$$S_W(n) = \underbrace{\left\{ c_0 - \sum_{i=1}^{3} (-1)^{i+1} c_i . \cos\left(\frac{2\pi n\, i}{N-1}\right) \right\}}_{Blackman-Harris\,Window} . S(n) \qquad (1)$$

where c_0, c_1, c_2 and c_3 are equal to 0.35875, 0.48829, 0.14128 and 0.01168, respectively. By supposing the $S(n)$ as a Wide Sense Stationary (W.S.S.) and Mean Ergodic (M.E.) stochastic process the windowed epoch is determined [12].

The static DWT filter bank is used for EEG rhythms decomposition [12]. By performing the filter bank in the first level on the windowed epoch, the detail and approximation sequences of two half-band filters are attained. For the next level, DWT is applied on the approximation time series to decompose the rhythm. In four levels and Daubechies of order 4 (Daub4) as a kernel of DWT the five brain rhythms: Delta [0.5,4] Hz, Theta [4,8] Hz, Alpha [8,13] Hz, Beta [13,22] Hz and Gamma [22,30] Hz are obtained by these details and the final approximation [4, 12]. With lowpass interpolation algorithm as upsampling method the number of time-sample for each rhythm is equaled to N'. With regard to Fig. 1 a pattern of the interpolated rhythms is formed as,

$$\underline{\underline{PR}} = \begin{pmatrix} \underline{R}_1(n) \\ \underline{R}_2(n) \\ \vdots \\ \underline{R}_5(n) \end{pmatrix}^T = \begin{pmatrix} \overbrace{}^{Delta} & \overbrace{}^{Theta} & \overbrace{}^{Rhythm\ i} & \overbrace{}^{Gamma} \\ r_{11} & r_{21} & \cdots & r_{51} \\ r_{12} & r_{22} & \cdots & r_{52} \\ \vdots & \vdots & \ddots & \vdots \\ r_{1N'} & r_{2N'} & \cdots & r_{5N'} \end{pmatrix} \qquad (2)$$

where $\underline{R}_i(n)$ is the rhythm i-th (for $i = 1, 2, \ldots, 5$) and n is the sample number of rhythm sequences. This presented 2D pattern is used as a basis of our proposed feature extraction method.

B. Singular Lorenz Measures Method (SLMM)

Here, we introduce a novel scenario for feature extraction to detect the seizure attack in offline mode. The eigenvalues or in the extensive concept the singular values of the pattern demonestrate the energies on each axis of the orthogonal space.

1) Chan's SVD

To compute the SVD the Golub-Kahan-Reinsch algorithm when $N' \geq 5$ can be enhanced if the matrix $\underline{\underline{PR}}$ is decomposed to QR then the bidiagonalization procedure is performed on the smaller upper triangular matrix of decomposition [13]. This method is frequently presented in two steps.

a) QR Factorization

The QR decomposition of matrix $\underline{\underline{PR}}$ is calculated by [14],

$$\underline{\underline{Q}}^T \underline{\underline{PR}} = \begin{bmatrix} \underline{\underline{R_1}} \\ \underline{\underline{0}} \end{bmatrix} \tag{3}$$

b) Golub-Kahan-Reinsch Algorithm

The Golub-Kahan-Reinsch (GKR) is standard algorithm to compute the singular values and singular vectors. This algorithm as a stage of Chan's SVD procedure is accomplished in two phases. Phase I: the matrix $\underline{\underline{R_1}}$ with order of $N' \times 5$ using the orthogonal equivalence is converted to upper bidiagonal matrix with [13],

$$\underline{\underline{U_0^T}}\,\underline{\underline{R_1}}\,\underline{\underline{V_0}} = \begin{bmatrix} \underline{\underline{B}} \\ \underline{\underline{0}} \end{bmatrix} = \underline{\underline{\tilde{B}}} \tag{4}$$

where $\underline{\underline{B}}$ as the 5×5 bidiagonal matrix with elements b_{ij} is:

$$\underline{\underline{B}} = \begin{bmatrix} b_{11} & b_{12} & 0 & \cdots & 0 \\ & b_{22} & b_{23} & \ddots & \vdots \\ 0 & & b_{33} & b_{34} & 0 \\ \vdots & \ddots & & b_{44} & b_{45} \\ 0 & \cdots & 0 & & b_{55} \end{bmatrix} \tag{5}$$

Phase II: by using the Implicit QR Iteration algorithm in suitable repetitions [14], the matrix $\underline{\underline{PR}}$ is converted to upper Hessenberg matrix by right shift also with proving the algebraic relationships and computing the Givens rotations the bidiagonal matrix $\underline{\underline{B}}$ is reduced to diagonal matrix $\underline{\underline{\Sigma}}$ as follows [13, 14]:

$$\underline{\underline{U_1^T}}\,\underline{\underline{B}}\,\underline{\underline{V_1}} = \underline{\underline{\Sigma}} = diag\left(\sigma_1,\ldots,\sigma_n\right) \tag{6}$$

where singular decomposition of matrix $\underline{\underline{PR}}$ is carried out to form of:

$$\underline{\underline{U}}^T \underline{\underline{PR}}\,\underline{\underline{V}} = \begin{bmatrix} \underline{\underline{\Sigma}} \\ \underline{\underline{0}} \end{bmatrix} \tag{7}$$

where $U = U_0 diag\left(U_1, I_{(N'-5)}\right)$ and $V = V_0 V_1$. The singular values of $\underline{\underline{R_1}}$ are the same singular values of matrix $\underline{\underline{PR}}$ that are assigned by the specific set of $\{\sigma_1,\ldots,\sigma_n\}$ for $n = 5$ [14].

2) Lorenz Curve

The singular values of our proposed pattern of rhythms are obtained. This set is sorted to form of low to the highest value. This new sorted list of singular values is denoted as,

$$\hat{\sigma} = \{\hat{\sigma}_1,\ldots,\hat{\sigma}_i,\ldots,\hat{\sigma}_n\} \tag{8}$$

where $\hat{\sigma}_i$ is representative of sorted singular value i-th. The cumulative probability of singular values population is as,

$$P\{\hat{\sigma}_i\} = \frac{i}{n} \quad , \quad i = 1, 2, \ldots, 5 \tag{9}$$

where in our application $n = 5$. Ultimately, the Cumulative Distribution Function (CDF) using Lorenz method is defined with the following equation [15],

$$L_{\hat{\sigma}_i}\{P\} = \frac{\sum_{i=1}^{k} \hat{\sigma}_i}{\sum_{i=1}^{n} \hat{\sigma}_i} \tag{10}$$

So, the assigned singular values are depicted by graphical presentation using Lorenz curve as a CDF. This CDF is plotted for $L_{\hat{\sigma}_i}$ based on the $P\{\hat{\sigma}_i\}$ [15]. Fig. 2 is a schema of the Lorenz curve as a prototype for distribution of decomposed singular values of a seizure EEG signal.

3) Relative Inequality Measures

To extract the suitable attributes of the Lorenz curve for feature extraction part of signal classification four basic properties are described [16]. If the $\hat{\sigma}$ as a perfect set has been converted to set $\hat{\xi}$ using an operator on the same space, these properties are defined using the symmetry (anonymity) condition by permutation, replication invariance (population principle) and scale invariance or zero-degree homogeneity are satisfied if $I(\hat{\sigma}) = I(\hat{\xi})$ and the transfer principle is correct when $I(\hat{\sigma}) > I(\hat{\xi})$ [16, 17].

4) Lorenz Inconsistent Features

This section of our proposed features is based on the statistical measures with regard to violate one or more of the four mentioned basics such as transfer principle or scale invariance [17]. For each windowed epoch of signal five singular values are determined, so to detect definitely seizure and non-seizure signals the singular values are averaged on all windows. Therefore, for each signal mean set of singularities is obtained. In this part of paper, four Lorenz inconsistent features are extracted and introduced in details [15, 17].

a) Range

This feature presents the gap of maximum and minimum of the extracted set that is achieved by [15, 17],

$$Range(\tilde{\sigma}) = \frac{\tilde{\sigma}_{Max} - \tilde{\sigma}_{Min}}{\frac{1}{5}\sum_{i=1}^{5}\tilde{\sigma}_i} \tag{11}$$

where $\tilde{\sigma}$ is the sorted set on the averaging singular values with five elements.

b) Simon Kuznets Ratio

A convenient feature for considering the high quility singularity versus the set distribution as a comparison analysis is called Kuznets ratio [16]. This feature is expressed with:

$$KR\left(\tilde{\sigma};\, p, r\right) = \frac{1 - L_{\tilde{\sigma}_i}\left\{1 - r\right\}}{L_{\tilde{\sigma}_i}\left\{P\left(\tilde{\sigma}_i\right) = p\right\}} \tag{12}$$

where r is the highest measure of singular values distribution and p is also the low level values. To extract this feature, it has been supposed that $r = p = P\left(\tilde{\sigma}_3\right)$.

c) $\left(90/10\right)$ Ratio

The ratio of the 90-th and 10-th percentiles of the set proposes the type of distribution and the severity of the slope in the probability distribution function (pdf) of $\tilde{\sigma}$ [16]. This feature is computed by,

$$Ratio_{90/10}\left(\tilde{\sigma}\right) = \frac{Pe_{\tilde{\sigma}}\left(0.9\right)}{Pe_{\tilde{\sigma}}\left(0.1\right)} \tag{13}$$

where $Pe_{\tilde{\sigma}}\left(m\right)$ is the m-th percentile of the data.

d) Relative Mean Deviation

In this section, the feature of relative mean deviation is prefered to use the variance of the singular values for each signal [17]. The relative mean deviation feature is obtained as [16],

$$RMD\left(\tilde{\sigma}\right) = \frac{\sum_{i=1}^{5}\left|\left(\frac{1}{5}\sum_{j=1}^{5}\tilde{\sigma}_j\right) - \tilde{\sigma}_i\right|}{\sum_{j=1}^{5}\tilde{\sigma}_j} \tag{14}$$

5) Lorenz Consistent Features

The consistent inequality measures that achieved from the Lorenz curve satisfy the four basic axioms. Here, in addition to extract the inconsistent measures, four features as consistent features of the set distribution are introduced [15-17].

a) Gini Coefficient

The Gini coefficient as a criterion of distribution based on the Lorenz curve is computed with the following [15]:

$$GC\left(\tilde{\sigma}\right) = 1 + \frac{1}{n} - \left(\frac{2}{n^2\left(\frac{1}{n}\sum_{j=1}^{n}\tilde{\sigma}_j\right)}\right).\left(\tilde{\sigma}_1 + 2\tilde{\sigma}_2 + \cdots + n\tilde{\sigma}_n\right) \tag{15}$$

where n is the length of the $\tilde{\sigma}$ and equal to 5. In this equation, we have $\tilde{\sigma}_1 \ge \tilde{\sigma}_2 \ge \cdots \ge \tilde{\sigma}_n$. At a glance, the Gini coefficient indicates the area between the perfectly equal distribution (Area (2)) and the Lorenz curve (Area (1)) [15]. The *GC* feature is frequently in the interval of [0,1].

b) Squared Coefficient of Variation

The squared coefficient of variation as a feature represents the validity rate of the singular values [15]. This feature is based on the variance of the normalized distribution [15, 16],

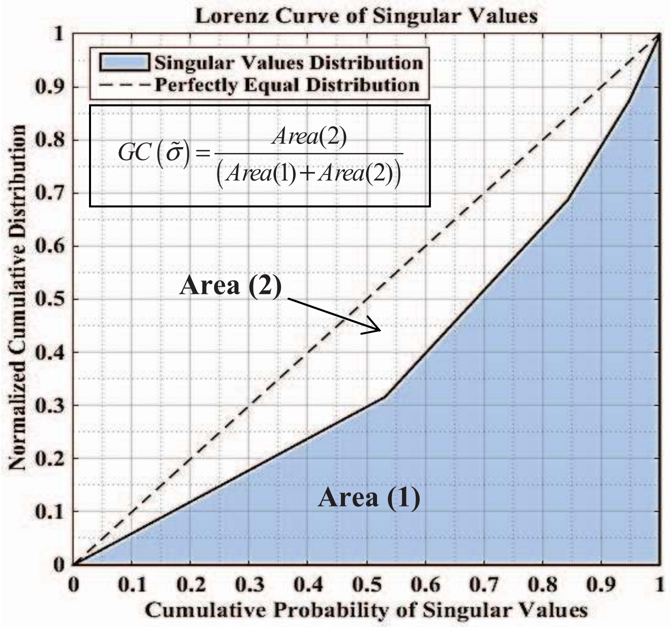

Fig. 2. Lorenz curve as distribution model of sorted singular values for a sample of seizure EEG signal.

$$SCV\left(\tilde{\sigma}\right) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\tilde{\sigma}_i - \frac{1}{n}\sum_{j=1}^{n}\tilde{\sigma}_j}{\frac{1}{n}\sum_{k=1}^{n}\tilde{\sigma}_k}\right)^2 \tag{16}$$

c) Theil's First

Due to the Shannon's entropy measure and as a specific state of the generalized entropy computation the useful feature based on the model of density for singular values in the cumulative content from the Lorenz curve is obtained [15]. This feature is Theil's first with definition of below,

$$ThF\left(\tilde{\sigma}\right) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{n.\tilde{\sigma}_i}{\sum_{j=1}^{n}\tilde{\sigma}_j}\right)\ln\left(\frac{n.\tilde{\sigma}_i}{\sum_{j=1}^{n}\tilde{\sigma}_j}\right) \tag{17}$$

d) Theil's Second

This feature is as another branch of generalized entropy. On the other hand, it is known with mean logarithmic deviation of the set [17]. By considering the *ThS* to form of:

$$ThS\left(\tilde{\sigma}\right) = \frac{1}{n}\sum_{i=1}^{n}\ln\left(\frac{\sum_{j=1}^{n}\tilde{\sigma}_j}{n.\tilde{\sigma}_i}\right) \tag{18}$$

Finally, we have proposed an algebraic-statistical scenario to extract the 8 features based on the decomposition contents for each pattern of the EEG rhythms. In this paper, this algorithm is named Singular Lorenz Measures Method (SLMM). So, for each signal is a feature vector with the length of 8 that is used to detect the seizure and non-seizure classes in the offline mode.

IV. Optimal Feature Selection Algorithm

To improve the performance of the signal classification the optimal features based upon a hybrid approach of K-Nearest Neighbor (KNN) and Scatter Search (SS) algorithm are introduced. By our optimization algorithm the optimal attributes of signal are selected to employ in the final pattern detection.

A. Hybrid Algorithm of KNN and Scatter Search

The KNN algorithm is considered as a particular state of non-parametric estimation of the probability density function (PDF). With choosing the appropriate neighborhood parameter *K*, this method is convenient approximation of Bayesian classifier. To evaluate the classification the hyper-sphere in the feature space with the center of test feature vector so that *K* samples are in the hyper-sphere is analyzed [18]. For class ω_i using the sub feature vector of f the classification duty is carried out by the probability relationship of bellow,

$$P\left(\omega_i \mid f\right) = \frac{K_i}{K_N} \quad , \quad i = 1, 2 \qquad (19)$$

where K_i is the number of samples for class *i*-th and K_N is the total samples in the desired area of space [19]. At first, to combine this method with SS algorithm the eight extracted features are classified one-by-one and eight inverse of accuracy rates of classification by KNN are stored as the weights for implementing in the search algorithm (presented in Table I). In the diversification generating step, the preliminary random sub feature vector by set of binary string is presented [20]. For each sub feature vector the KNN accuracy rate as objective function is evaluated. The mean of the weights for each sub feature vector is also calculated [21]. By using the following recursive method the diverse generation is accomplished using the initial random seeds by,

$$f'_{1+mk} = 1 - f_{1+mk} \quad , \quad m \le n-1 \qquad (20)$$

where $k = 0, 1, \ldots, {}^{n}\!/_{m}$ and the new population are different. To improve the trial solutions with considering the values of objective function based on the mean of the weights for each sub vector, existence of the features in the new iteration are analyzed [20, 21]. Therefore, after updating the reference set, the sub set with dimension of $d = 2$ up to $d = 8$ are generated in this stage. In the solution combination step, the score criterion for mutation in the sub feature vector is returned as,

$$Score\left(FV_i\right) = \frac{\sum_{j \in D} \left\{ Objective\ Value\left(FV_i\right) \times \frac{1}{L} \sum_{k=1}^{L} Weight\left(k\right) \right\}}{\sum_{j \in D} Objective\ Value\left(FV_i\right)} \qquad (21)$$

where FV_i is the sub feature vector *i*-th and *D* is the sub set dimension for the interval of 2 up to 8 [20, 21]. The next iteration of scatter search is run by considering the threshold on the score function to create the sub feature vector FV' for solution combination stage as [20],

$$FV'_i = \begin{cases} 1 & , \quad Score\left(FV_i\right) > Threshold \\ 0 & , \quad Score\left(FV_i\right) \le Threshold \end{cases} \qquad (22)$$

where 0 and 1 return the existence of the special features. So, the hybrid algorithm of KNN and scatter search is converged to the optimal features with the high performance for classifying with KNN method.

V. Experimental Results

A. Optimal Features

Our proposed optimization algorithm is finally converged to the optimal features with suitable complexity in the feature space and high efficiency for seizure detection. These obtained features are: (90/10) ratio, Kuznets ratio, Gini coefficient and Theil's first. The schema of optimal features distribution using the Inter Quartile Range (IQR) interpretation is presented in Fig. 3 for comparing our features in seizure and non-seizure modes.

B. MLP Optimization and Holdout Cross Validation

For final signal classification the Multi-Layer Perceptron (MLP) neural network with a hidden layer is used [6]. In the architecture of net four neurons equal to the length of optimal feature vector in input layer have been applied [3]. To analyze and choose the best method of learning, the net is trained with four training algorithms [11]. In each training procedure using the holdout cross validation method to partition the dataset appropriately by parameter $p = 0.3$ we have used from 70% of dataset for training, 20% for test and 10% for validation check, also the number of hidden neurons is optimized with trial and error [3, 6]. Ultimately, the optimized classifier with the suitable process to train is considered for final signal classification. The results of MLP optimization and the details of dataset are represented in Table I.

C. Final Classification

After optimizing the MLP classifier, we have considered the Levenberg-Marquardt algorithm (LMA) to learn and 22 neurons in the hidden layer of net. So, to recognize the seizure attack with our optimal features the holdout cross validation is employed and 70% of dataset for training, 20% for test and 10% are used for validation check procedures. At last, by using our proposed algorithm to extract the features and feature optimization the optimized MLP classifier recognized the EEG signals into seizure and non-seizure classes with the rate accuracy of 90.0%, variance of error in 1.47×10^{-4} and mean values for Mean Square Error (MSE) of 0.0875. The final results of seizure detection in details for classifying with optimal features and without optimal features are represented in Table I.

VI. Conclusion

The combination of algebraic and statistical methods to evaluate the seizure attack is a convenient procedure. Our proposed SLMM algorithm to extract the features based on decomposing the pattern of EEG rhythms is a suitable basis for describing the seizure behavior. Moreover, the hybrid optimization algorithm using KNN and Scatter Search as the machine learning scenarios could analyze the attributes for selecting the optimal state with the appropriate performance of classification. Ultimately, the optimized MLP neural network classifier for recognizing the epileptic seizure attack has been applied and the disorder has been detected.

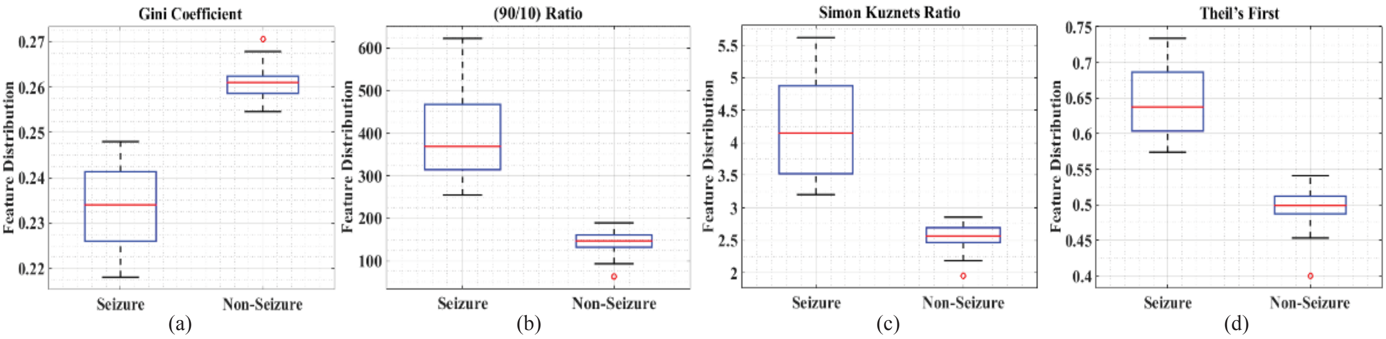

Fig. 3. The schema of (a), (b), (c) and (d) for optimal features distributions based on the IQR measure in sieuzre and non-seizure EEG signals.

TABLE I. FINAL RESULTS OF OUR ALGORITHM FOR EEG SEIZURE DETECTION.

Classification without Optimal Features				
Parameter	***Time of EEG Signal (min)***		***Accuracy rate (%)***	
	Seizure	*Non-Seizure*	*Correct*	*Wrong*
Training	*714 – (70%)*	*3654 – (70%)*	*87.1*	*12.9*
Test	*204 – (20%)*	*1044 – (20%)*	*73.3*	*26.7*
Validation	*102 – (10%)*	*522 – (10%)*	*66.7*	*33.3*
Total	*1020– (100%)*	*5220 – (100%)*	*82.0*	*18.0*
Accuracy Rate of the Optimal Features in KNN-Scatter Search (%)				
Features	**K=3**	**K=5**	**K=7**	**K=9**
Gini Coefficient	*46.67*	*30.00*	*33.30*	*36.66*
(90/10) Ratio	*36.67*	*46.66*	*40.00*	*56.67*
Kuznets Ratio	*26.60*	*23.33*	*16.66*	*13.33*
Theil's First	*16.66*	*20.00*	*20.00*	*46.67*
Classification with Optimal Features				
Learning Algorithm	**Levenberg-Marquardt**	**Bayesian Regulation**	**Scaled Conjugate Gradient**	**Resilient Method**
Training	*90.0%*	*82.9%*	*55.7%*	*75.7%*
Test	*93.3%*	*80.0%*	*46.7%*	*80.0%*
Validation	*86.7%*	*73.3%*	*66.7%*	*86.7%*
Total	*90.0%*	*81.0%*	*56.0%*	*78.0%*
Optimized Number of Hidden Neurons and Error				
MSE	*0.0712*	*0.1309*	*0.4074*	*0.1715*
Number	*22*	*5*	*45*	*34*
Final Results of Seizure Detection with Optimized MLP Classifier				
Detection Accuracy	**Results**	**Optimized Parameters**		**Results**
Mean of Accuracy	90%	**Hidden Neurons**		22
Mean of MSE	0.0875	**Learning Algorithm**		LMA
Variance of MSE	1.47×10^{-4}	**EEG Channel**		C3-P3

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