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PERFORMANCE ANALYSIS OF ORIGINAL PARTICLE SWARM OPTIMIZATION AND MODIFIED PSO TECHNIQUE FOR ROBUST CLASSIFICATION OF EPILEPSY RISK LEVEL FROM EEG SIGNALS

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Abstract

The aim of this work is to formulate a modified version of Particle swarm Optimization technique to enhance classification of epilepsy risk levels from EEG signals and to compare it with the Original PSO. Epilepsy is a serious brain disorder affecting many people around the globe. The Epileptic EEG signals from twenty patients are used in this work. For the dimensionality reduction purpose, the power spectral density values of EEG signals is determined. To these components the Original PSO is implemented. The Modified PSO is formulated by incorporating different functions to generate random number, and using aggregation factors to modify the velocity update equation. Eight bench mark functions namely Rectangular, Square, Cube, Scaling, Circle, Cylinder, sector and Cone are utilized. Based on parameters like Performance Index (PI), False alarm rate and Quality values (QV) the efficiency of both techniques is compared. With Scaling function PSO low PI value of 40.67% and Quality value of 14.60 are achieved. The performance got improved with Rectangular PSO with PI of 95.92% and QV of 22.43 when compared to value of 95.10 % and 22.17 with original PSO. With Square, Cube, Sector and Cone function PSO sensitivity of 100% is achieved in specific cases while with original PSO 97.57% is achieved.

Keywords: EEG Signals, Epilepsy, Power spectral density, Particle swarm Optimization, Modified PSO, Aggregation factor, Performance index, Quality value.

I. Introduction

Epilepsy is central nervous system disorder which involves hammering of normal activity of the brain [1] [2]. Among world total population one percent is affected by epilepsy. There is no total cure available for epilepsy till date [3].When epileptic seizure occurs, the patient losses control over body and mind. Most common symptoms are convulsions, loss of consciousness and starred spell [4]. The underlying cause for epileptic attack is loss of coordination in the neurons of brain [5]. They begin to fire rapidly and asynchronously which leads to recurrent and transient seizures. Out of hundred every one person experiences seizure in some time of his life, but mostly go unnoticed [6]. Epilepsy is broadly classified as focal, partial, generalized and unilateral seizures [7]. Each type has its own characteristic change in the brain waves. Electroencephalogram EEG is most frequently used diagnostic technique for brain wave analyses since its inception [8]. EEG waveforms exhibit different characteristics for each type of epilepsy [9]. It is minimal invasive with little discomfort to the patient. A group of scalp electrodes are placed over head to collect the brain signals. With the advent of computers it has become possible to monitor epileptic patients in real time. The further organization of the paper is as follows: Section II describes the procedures done to collect EEG recordings and dimensionality reduction done using power spectral estimation. Section III presents the analysis of PSO technique and Section IV includes Modified PSO for epilepsy detection. Section V describes result and discussions and finally section VI summaries our conclusion.

II. Materials and Methods

A. EEG Signals Acquisition

To analyze the performance of Particle Swarm Optimization in risk level classification of EEG signals, we have collected EEG signals from twenty epileptic patients who were under diagnosis and treatment in the Neurology Department of Sri Ramakrishna Hospital, Coimbatore. A paper record of sixteen channels EEG signals is acquired which is scanned using Umax 6696 scanner with a resolution of 600dpi. These EEG signals are contaminated with other biological signals and artifacts which are eliminated with the help of Neurologist . Brain waves are acquired continuously for thirty seconds which are sampled into epochs of two seconds with a sampling rate of 200Hz, since maximum frequency of EEG Signals is 50Hz. For each patient three epochs is collected, with each epoch having 16 Channel data values. These signals are enough to detect any epileptic activity. The general layout of the methodologies performed is stated below in Fig 1.

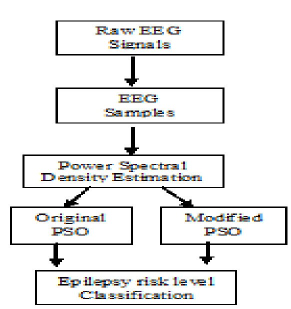

Fig 1. System Overview.

B. Power Spectral density

Each channel of an epoch got 400 sampled values, this leads to increase in dimension of data set which will hamper the risk level classification. We have extracted power spectral values of EEG signals which are further dimensionally reduced. Power spectral value shows how the power of a signal varies with change in frequency [10]. Let x(t) be the EEG signal, the Fourier transform of Signal X(ω) is given by

$$X(w) = \int_{-\infty}^{+\infty} x(t) e^{-jwt} dt \qquad (1)$$

The square of the magnitude of X(ω) gives the power spectral values. We have implemented rectangular window for this purpose. Only the maximum spectral density is further used for study thus reducing the high dimensionality curse [11].

III. Practical Swarm Optimization

With inspiration from bird flocking and fish schooling concept, James Kennedy and Russell Eberhert developed a new optimization technique called Particle Swarm optimization in 1995 [12]. It is well suited for non linear functions and very much related to Evolutionary Computation and Swarm theory [13]. The population is called as swarm and individual are Particles, which have similar kind of characteristic and behavior [14].The Particle exchange velocity and position updates while exploring the search space. The equation to update velocity and position is given below [15].

$$V_i (k+1) = w * V_i + C_1 * r_1 * (pbest_i - X_i (k)) + C_2 * r_2 * (gBest_i - X_i (k)) \qquad (2)$$

$$X_i (k+1) = X_i (k) + V_i (k+1) \qquad (3)$$

where $V_i(k+1)$ and $V_i(k)$ represents velocity of i^{th} particle at iteration k+1 and k, $X_i(k+1)$ and $X_i(k)$ represents position of i^{th} particle at iteration k+1 and k, w is inertial weight, pbest is the personal best position of particle, gbest is the global best position achieved by any particle in the swarm, C_1 and C_2 are self and social recognition coefficients, r_1 and r_2 are random numbers in the range 0 to 1. The overall Original PSO algorithm is explained below [16].

1. Initialize Swarm with particles having velocity and position randomly.
2. Fix the target value or maximum number of iterations.
3. Find the personal best position of each particle pBest.
4. If new pbest is better than previous one update pBest value to new one.
5. Find the global best position available in the swarm.
6. If new gbest is better than previous one, update gBest value to new one.
7. Update the velocity and position of each particle in swarm using (2) and (3)

8. Check for stopping condition else go to step 3 until desired target or maximum iteration is achieved.

The Original PSO is applied to the spectral values. The constants C_1 and C_2 are kept 2. The r_1 and r_2 are randomly generated independent of each other. The Modified version of PSO is explained in the next section. In section V the comparison between Original PSO and Modified PSO is done.

IV. Modified PSO

In the original PSO algorithm both the constants r_1 and r_2 are randomly generated. They are independent of each other with a range of [0, 1]. These numbers accelerate toward pbest and gbest [17]. To study the effect of different methods of random number generation in the performance of Particle Swarm Optimization, we have developed some benchmark functions to generate random numbers. In these cases r_1 and r_2 are not independent rather they are related by a function[18]. Some of them are Square, Circle Cone etc. Each of these function produce unique combination of random number pairs. The functions used are tabulated below.

Table I. Different Functions Used In Modified PSO.

Serial No.	Function	Formulation
1	Rectangular	$r_1 = 2r_2$
2	Square	$r_1 = r_2$^^{2}
3	Cube	$r_1 = r_2$^^{3}
4	Scaling	$r_1 = r_2/2$
5	Circle	$r_1 = \prod * r_2$^^{2}
6	Cylinder	$r_1 = \prod * r_2$^^{3}
7	Sector	$r_1 = 1/3 * \prod * r_2$^^{2}
8	Cone	$r_1 = 1/3 * \prod * r_2$^^{3}

These functions are incorporated into Original PSO algorithm. For each epoch these different functions are used to calculate the random numbers. The algorithm follows the same steps as original PSO for pbest and gbest determination. The velocity update equation is altered by incorporating aggregation factors [19]. Each component of velocity update equation is multiplied by a factor which controls the effect of previous velocity, position, pBest and gBest values on the new velocity. These factors range from 0 to 1 and named as a1, a2 and a3. Thus the modified velocity equation is given below.

$$V_i\,(k+1) = a1 * w * V_i + a2 * C_1 * r_1 * (pbest_i - X_i(k)) + a3 * C_2 * r_2 * (gBest - X_i(k)) \quad (4)$$

We have taken four cases for each factor; each case has got unique aggregation factor combination. The cases are tabulated below in table II.

Table II. Aggregation Factor Value for Each Case.

Serial No.	Case	Values		
		a1	***a2***	***a3***
1	I	0.6	0.2	0.2
2	II	0.6	0.3	0.1
3	III	0.5	0.3	0.2
4	IV	0.5	0.4	0.1

Hence there are total 32 combinations. These combinations are applied to the spectral values and the result has been obtained. Finally comparison is done with the Original PSO based on some performance criteria.

V. Results and Discussion

The performance of modified PSO and Original is compared with the help of two parameters, Quality value and Performance Index [20]. Other measures evaluated are false alarm, missed classification, Perfect classification, time delay and Average detection. With modified PSO having rectangular function (Case II) has got the highest performance index value of 95.92 % while scaling function (Case I) low value of 40.67%. With Square, Cube, Sector and Cone function PSO sensitivity of 100% is achieved in specific cases while with original PSO 97.57% is achieved.

The formulae to calculate above parameters are described in (5), (6), (7) and (8).

$$PI = \frac{PC - MC - FA}{PC} \times 100 \qquad (5)$$

$$Se = \frac{PC}{PC + FA} \times 100 \qquad (6)$$

$$Sp = \frac{PC}{PC + MC} \times 100 \qquad (7)$$

$$Average\ \ Detection = \frac{Sp + Se}{2} \times 100 \qquad (8)$$

Where FA = False alarm, MC = Missed Classification, PI = Performance Index, PC = Perfect Classification, Se =sensitivity, Sp= specificity [2].

Another important parameter which reflects overall quality of the classifiers is Quality value [6][7]. Four factors namely missed classification, false alarm, time delay and perfect classification determines the quality value of a classifier.

$$Q_v = \frac{C}{(R_{fa} + 0.2) * (T_{dly} * P_{dct} * 6 * P_{msd})} \qquad (9)$$

Where, C is scaling constant which is set to 10 as this scales the value of Qv obtained into a range which is readable.

P_{dct} - the percentage of perfect classification

P_{msd} - the percentage of perfect risk level missed

R_{fa} - the number of false alarm per set,

T_{dly} - the average delay of the onset classification in seconds.

The Rectangular PSO with case II values achieve a good and highest QV value of 22.43 while Original PSO got value of 22.17. This shows the overall quality is increased. The Table III gives the performance comparison of Original PSO and Modified PSO Techniques

Table **III. Performance Comparison of Original PSO and Modified PSO Techniques.**

CLASSIFIER		**PC (%)**	**MC (%)**	**FA (%)**	**PI (%)**	**Se (%)**	**Sp (%)**	**Average Detection (%)**	**Time Delay (Second)**	**QV**
Original PSO		95.41	2.29	2.244	95.10	97.57	97.78	97.71	2.05	22.17
Function		**MODIFIED PSO**								
Rectangular	***Case I***	95.83	1.58	2.55	95.65	98.40	97.43	97.92	2.02	22.21
	Case II	96.11	1.53	2.36	95.92	98.47	97.64	98.06	2.02	22.43
	Case III	96.17	1.17	2.76	94.41	98.60	97.35	98.09	1.99	21.89
	Case IV	95.76	1.53	2.48	95.78	98.47	97.52	97.99	2.01	22.33
	Case I	77.61	0	22.49	68.17	100	77.61	88.68	1.55	16.08

Square	***Case II***	77.43	0	21.86	67.96	100	77.43	88.79	1.73	16.30
	Case III	93.08	0.28	5.21	94.11	99.72	93.36	96.98	1.91	20.98
	Case IV	94.10	0.35	4.23	95.57	99.65	95.76	97.71	1.93	21.57
Cube	***Case I***	73.92	0	23.50	64.93	100	73.92	87.95	1.52	15.88
	Case II	75.42	0	24.58	62.48	100	75.42	87.71	1.51	15.24
	Case III	93.68	0.14	6.39	93.95	99.38	94.03	96.37	1.88	20.54
	Case IV	95.56	0.97	3.54	95.33	99.03	96.53	97.78	1.91	21.43
Scaling	***Case I***	62.66	0	36.01	40.67	100	62.66	93.68	1.28	14.60
	Case II	74.79	0	25.20	61.82	100	74.79	87.47	1.49	15.37
	Case III	76.36	0	23.64	65.38	100	76.36	88.18	1.53	16.12
	Case IV	84.44	0.62	13.98	81.43	99.38	85.06	92.53	1.74	17.70
Circle	***Case I***	95.56	1.31	3.38	95.31	98.41	96.88	97.78	1.99	21.96
	Case II	95.14	1.38	3.10	95.31	98.68	96.88	97.78	1.99	21.91
	Case III	95.90	1.52	2.55	95.73	98.54	97.36	97.95	2.01	22.18
	Case IV	95.97	0.56	3.54	95.80	99.44	96.46	97.99	1.95	21.86
Cylinder	***Case I***	95.49	0.69	3.68	95.41	99.31	96.32	97.81	1.95	21.72
	Case II	95.42	0.90	3.54	95.34	98.96	96.46	97.50	1.97	21.74
	Case III	95.83	0.28	3.89	95.64	99.72	95.95	97.92	1.94	21.73
	Case IV	95.76	1.67	2.57	95.57	98.33	97.42	97.88	2.02	22.13
Sector	***Case I***	77.61	0	22.39	67.22	100	77.61	88.80	1.55	16.37
	Case II	73.89	0	26.11	57.41	100	73.89	86.95	1.48	16.42
	Case III	95.83	1.74	2.43	95.65	98.26	97.57	97.92	2.02	22.22
	Case IV	95.90	1.74	2.36	95.72	98.26	97.64	97.92	2.02	22.27
Cone	***Case I***	75.14	0	24.86	62.23	100	75.14	87.57	1.50	16.12
	Case II	73.89	0	26.11	57.41	100	73.89	85.70	1.48	16.42
	Case III	95.70	1.39	6.25	95.48	98.61	97.01	97.85	1.99	22.01
	Case IV	95.69	1.53	2.71	95.49	98.47	97.22	97.85	2.00	22.02

The Comparison plots are given below. Figure 2 shows the Perfect Classification, Missed Classification, false alarm and performance index values for Modified PSO with different functions and Original PSO.

Figure 3 shows Perfect Classification, Specificity and Sensitivity measure comparison. Figure 4 shows the Quality value and time delay plot of each classifier.

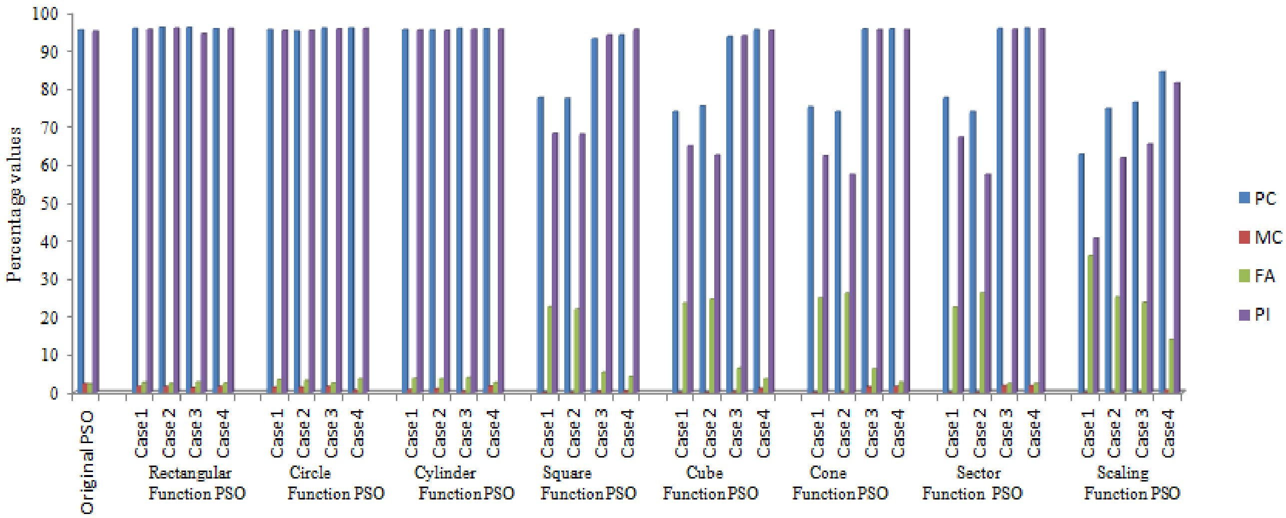

Fig 2: Perfect Classification, Missed Classification, False Alarm and Performance index Values for Original and Modified PSO.

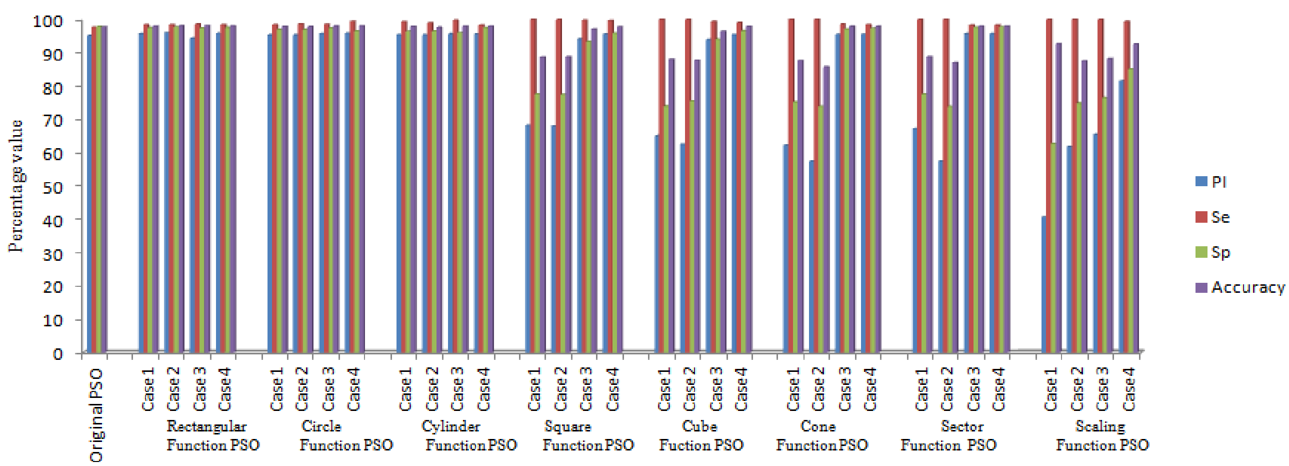

Fig 3: Performance index, Sensitivity, Specificity and Average Detection Values for Original and Modified PSO.

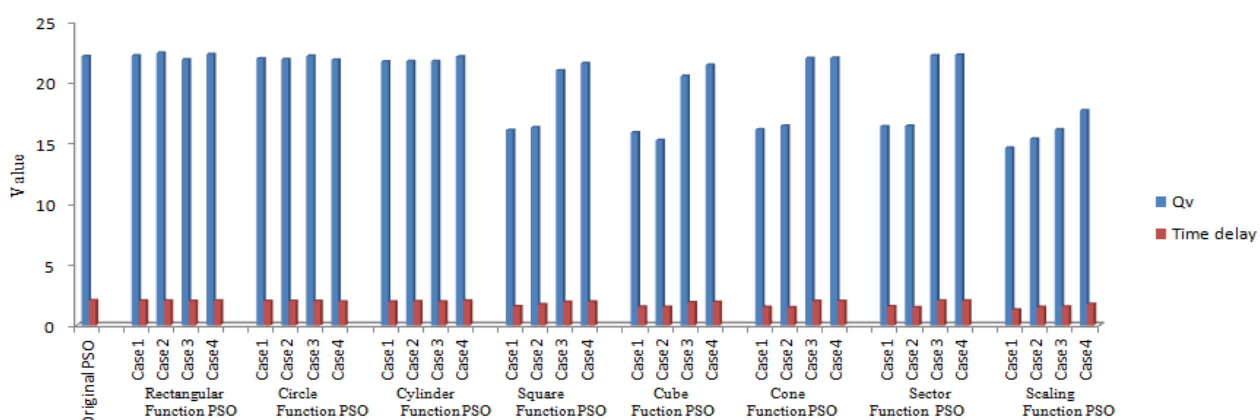

Fig 4: Quality value and Time delay Values for Original and Modified PSO.

VI. Conclusion

The main aim of this work is to formulate an algorithm using particle swarm optimization technique for epilepsy risk level classification from EEG signals. The original PSO algorithm is modified by implementing different functions for random number generation to enhance its performance. The goal is to achieve high Performance Index, Quality value and low false alarm rate and missed classification rate. The EEG signals acquired from patients are sampled and digitized. The feature extraction is done using power spectral density estimation which acts as means for dimensionality reduction. To these spectral values Original PSO and modified PSO with different functions and aggregation factors is applied. We found that Rectangular PSO with aggregation factors a1=0.6, a2=0.3, a3=0.1 has attained high performance index and Quality value of 95.92 % and 22.43. Hence there is improvement in the robustness of Original PSO which got value of 22.17. Scaling function PSO performs least in epilepsy risk level detection.

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