Analysis of PSO and Hybrid PSO in Calculation of Epileptic Risk Level in EEG

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***Abstract*—The main aim of this paper is to compare and analyze the performance of the PSO algorithm and the hybrid PSO output in determining the epileptic risk level for the given Electroencephalogram signal inputs. Various parameters like energy, variance, peaks, sharp and spike waves, duration, events and covariance are calculated from the EEG signals. The two optimization technique has been used for classifying the risk level of the given inputs and the efficacy of the above two methods have been analyzed and compared using mean square error and quality value. 20 patients input are taken for analysis in both methods in calculation of risk level. Comparing to PSO output hybrid PSO method is efficient based on performance index and quality value.**

***Index Terms*— Electroencephalogram signals, Epileptic risk level, Particle swarm optimization (PSO), Hybrid PSO optimization, mean square error, quality value.**

I. INTRODUCTION

Electroencephalograms signal is the way of non-invasively observing human brain activity. It is recorded by hooking up electrodes in the scalp. Epilepsy occurs when there is a permanent change in brain tissues. About 50 million people in the world have epilepsy. The Classification of epilepsy risk levels, according to international standard is difficult because individual laboratory findings and symptoms are often inconclusive [1].EEG signals are used in the detection of epilepsy risk level. This paper gives the overview while calculating the epilepsy risk level using PSO and hybrid PSO algorithm for the given EEG input signals. Comparing both algorithm performance hybrid PSO gives the better performance in determining the risk level of the given EEG input signals. The performance of the both algorithm is measured and discussed on the basis of performance index and quality value. Twenty patient's recordings are taken as input for analysis, those who were under the evaluation and treatment in the neurological department of Sri Ramakrishna Hospital, Coimbatore, India. Using 10-20 international electrode placing method, 16 channel paper records has been recorded for analysis, selecting the artifacts free inputs for avoiding the false detection .Then the records are scanned by Umax 6696 scanner with resolution of 600 dpi [3]. Each epoch is of two seconds duration by scanning it to a image of 400x100 pixels and each epoch is sampled at a frequency of 200Hz. All twenty EEG records are used for both testing and training data. These EEG records had an average length of six seconds/channel and total length of 120 seconds/channel. A total of 960 epochs of 2 seconds duration are used.

II. PARAMETER ESTIMATION

The main aim of this paper is to calculate the epileptic risk level values for the given input using the signal parameters and PSO and hybrid PSO algorithms. Figure 1 shows the overall all risk level classifier system.

EEG inputs→ PSO and hybrid PSO analysis→Epilepsy risk level values

Fig 1: Overview of Risk Level Classification

The risk level output from PSO and hybrid PSO technique is accomplished as

1. From the input signals, four feature sand seven parameters are extracted using hard thresholding and soft thresholding of wavelet transform such as haar, DB2, DB4, Symets8.
2. Both algorithms are used in classification for epilepsy risk level at each channel from EEG signals and its parameters.
3. Both optimization technique results are calculated.
4. Performances of both techniques were analyzed.

The parameters of the risk level classification from EEG signal is calculated using,

1. The energy in each two-second epoch is given by[6]

$$E = \sum_{i=1}^{n} x_i^2 \qquad (1)$$

Where x_i is signal sample value and n is number of samples. The scaled energy is taken by dividing the energy term by 1000.

2. The variance is computed as σ given by[7]

$$\sigma^2 = \frac{\sum_{i=1}^{n}(x_i - \mu)^2}{n} \qquad (2)$$

Where $\mu = \frac{\sum_{i=1}^{n} x_i}{n}$ is the average amplitude of the epoch.

3. Covariance of Duration. The variation of the average duration is defined by [6]

$$CD = \frac{\sum_{i=1}^{p}(D - T_i)^2}{pD^2} \qquad (3)$$

The following parameters are extracted using wavelet transforms

4. The total number of positive and negative peaks exceeding a threshold is found.
5. Spikes are detected when the zero crossing duration of predominantly high amplitude peaks in the EEG waveform lies between 20 and 70 ms and sharp waves are detected when the duration lies between 70 and 200ms.
6. The total numbers of spike and sharp waves in an epoch are recorded as events.
7. The average duration is given by

$$D = \frac{\sum_{i=1}^{p} t_i}{p} \qquad (4)$$

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Where, t_i is one peak to peak duration and p is the number of such durations.

The Wavelet transform is an effective tool for feature extraction because it allows for the analysis of inputs at various levels of resolution [3]. It acts as a sort of mathematical microscope through which different parts of the signals are examined by adjusting the focus [8]. The wavelet transform (WT) of a function f (t) is an integral transform defined by [9],

$$wf(a,b) = \int_{-\infty}^{\infty} f(t)\, \psi^{*}_{a,b}(t)\, dt \qquad (5)$$

Where ψ^* (t) denotes the complex conjugate of the wavelet function ψ (t). The transform yields a time–scale representation similar to the time frequency representation of the short- time Fourier Transform (STFT). The set of the analyzing function the wavelet family is deduced from a mother wavelet ψ (t) by [10],

$$\psi^{*}_{a,b}(t) = \frac{1}{\sqrt{2}}\psi\left(\frac{t-b}{a}\right) \qquad (6)$$

Where a and b are the dilation (scale) and translation parameters respectively. The mother wavelet is a short oscillation with zero mean. The discrete wavelet transforms (DWT) results from discretized scale and translation parameters e.g. $a=2^j$ and $b = n.\ 2^j$ where j & n are integer numbers. There have been several investigations into additive noise suppression in signals using wavelet transforms. Johnstone and Donoho's [10] principal work is on Thresholding the DWT of a signal and then reconstructing it. The method relies on the fact noise commonly manifests itself as smaller values, and wavelet transforms provides a scale based decomposition. Thus, most of the noise tends to be represented by wavelet coefficients at the finer scales. Discarding these coefficients would result in a natural filtering out of noise on the basis of scale [11]. Because the coefficients at such scales also tend to be the primary carriers of edge information, by setting the wavelet coefficients to zero if their values are below a threshold. These coefficients are mostly those corresponding to noise. The edge related coefficients, on the other hand, are usually above the threshold. In this study, at first the effect of simple Haar wavelet is undertaken. Haar wavelet function is defined as [12]

$$\psi(t) = \begin{cases} 1; 0 \le t < 1/2 \\ -1; \frac{1}{2} \le t < 1 \\ 0 : otherwise \end{cases} \qquad (7)$$

A. Signal Estimation

Wavelet Thresholding is a signal estimation technique that exploits the capabilities of wavelet transform for signal denoising or smoothing. It depends on the choice of a threshold parameter which determines to great extent the efficacy of denoising. Here energy is taken as the threshold function. Typical threshold operators for denoising include hard threshold, soft threshold, and affine (firm) threshold. Hard threshold is defined as [8]

$$\rho_T(x) = \begin{cases} x, if\,|x| > T \\ 0, if\,|x| \le T \end{cases} \qquad (8)$$

Where T is the threshold level.

Soft Thresholding (wavelet shrinkage) is given by

$$\rho_T(x) = \begin{cases} x - T, if\,(x \ge T) \\ x + T, if\,(x \le T) \\ 0, if\,|x| < -T \end{cases} \qquad (9)$$

Haar, Db2, Db4 and Sym8 wavelets with Hard Thresholding and four types of soft Thresholding methods such as Heursure, Minimaxi, Rigrsure and Sqtwolog are used to extract the parameters from EEG signals. With the help of expert's knowledge and our experiences with the references [5],[7], we have identified the following parametric ranges for five linguistic risk levels (very low, low, medium, high and very high) in the clinical description for the patients which is shown in table I.

Table I: Parameter Ranges for Various Risk Levels

Risk levels / Normalized Parameters	Normal	Low	Medium	High	Very high
Energy	0-1	0.7-3.60	2.9-8.20	7.6-11	9.2-30
Variance	0-0.3	.15-0.45	.4-2.2	1.6-4.3	3.8-10
		1-4	3-8	6-16	
Peaks	0-2	1-5	4-10	7-16	12-20
Events	0-2	1-5	4-8	7-11	15-28
Sharp waves	0-2	0.15-0.45	0.4-2.2	1.8-4.6	10-12
Average Duration	0-0.3	0.025-0.1	0.09-0.4	0.28-0.64	3.6-10
Covariance	0-0.05				0.54-1

III. PSO [PARTICLE SWARM OPTIMIZATION]

In particle swarm optimization, all individuals in the swarm have the same behaviours and characteristics. It is assumed that information on the position and performance of particles can be exchanged during social interaction among particles in the neighborhood. Importantly, the particle swarm optimization relies on social interaction among particles through exchanging detailed information on position and performance. However, in the physical world, this type of complex communication is not always possible. The particle swarm optimization algorithm was introduced by Kennedy and Eberhart in 1995 [4]. The algorithm consists of a swarm of particles flying through the search space. Each individual *i* in the swarm contains parameters for position x and velocity v. The position of each particle represents a potential solution to the optimization problem. The dynamics of the swarm are governed by a set of rules that modify the velocity of each particle according to the experience of the particle and that of its neighbors depending on the social network structure within the swarm as shown in equation 10. By adding a velocity vector to the current position, the position of each particle is modified. As the particles move around the space, different fitness values are given to the particles at different locations according to how the current positions of particles satisfy the objective. At each iteration, each particle keeps track of its personal best position, pbest. Depending on the social network structure of the swarm, the global best position, gbest, and/or the local best position, lbest is used to influence the swarm dynamic. After a number of iterations, the particles will eventually cluster around the area where fittest solutions are.

The swarm behavior in conventional particle swarm optimization is influenced by the number of particles, neighborhood size, inertia weight, maximum velocity, and acceleration calculation to modify the velocity. The larger the number of particles in the swarm, the more likely the swarm will converge on the global optimum, because the social information exchange is increased. (This is dependent on different neighborhood types and the neighborhood size.) The performance of a PSO algorithm can be improved through other system parameters. The influence of the current velocity on the new velocity can be controlled by an inertia weight. A large inertia weight compels large exploration through the search space; a smaller inertia weight causes reduced exploration. The influence of the particle's experience and that of its neighbor is governed by the acceleration calculation. The further away the particle is from the best position from its own experience and its neighbor, the larger a change in velocity that is made in order to return to that best position. The acceleration limits the trajectory of the particle oscillation. The smaller the acceleration, the smoother the trajectory of the particle is. However, too small an acceleration may lead to slow convergence, whereas too large an acceleration drives the particles towards infinity. The new velocity is limited by the given maximum velocity to prevent particles from moving too fast in the space. The dynamics of the swarm are governed by a set of rules that modify the velocity of each particle according to the experience of the particle and that of its neighbors depending on the social network structure within the swarm as shown in equation 15. The performance index using PSO is shown in table I. Performance index is given as,

$$PI = \frac{PC-MC-FA}{PC} \times 100 \tag{10}$$

Where,

PC-Perfect Classification-agrees the risk level output.

MC-Missed Classification –assumes high risk level as low risk level

FA-False Alarm-assumes low risk level as high risk level.

Table II: Performance Index for Wavelet Hard Thresholding in PSO Method

Wavelet Transforms With Hard Thresholding	Perfect Classif ication	Missed Classi fication	False Alarm	Perfor mance Index
Haar	61.45	15.625	22.91	37.58
Db2	61.18	16.14	22.65	36.44
DB4	64.57	12.49	22.91	44.72
Sym8	63.52	11.44	23.95	44.81

After a number of iterations, the particles will eventually cluster around the area where fittest solutions are. The swarm behavior in conventional particle swarm optimization is influenced by the number of particles, neighborhood size, inertia weight, maximum velocity, and acceleration calculation to modify the velocity. The performance of a PSO algorithm can be improved through other system parameters [11].The influence of the current velocity on the new velocity can be controlled by an inertia weight. The acceleration limits the trajectory of the particle oscillation. The new velocity is limited by the given maximum velocity to prevent particles from moving too fast in the space.

IV. CONVENTIONAL PSO ALGORITHM

PSO learned from the scenario and used it to solve the optimization problems. In PSO, each single solution is a "bird" in the search space. We call it "particle". All of particles have fitness values which are evaluated by the fitness function to be optimized, and have velocities which direct the flying of the particles. Consider N number of particles where each particle represents a potential solution. Particles are then flown through the hyperspace, where the position of each particle is changed according to its own experience and that of its neighbors. In the original formulation of PSO [14], each particle is defined as a potential solution to the problem in a D-dimensional space. The particle *i* is represented in a D-dimensional space as

$$Xi = (xi1, xi2, xi3, \ldots,xiD) \tag{11}$$

and each particle maintains a memory of its previous best position. The best previous position of the *ith* particle can be represented *as*

$$Pi = (pi1, pi2, pi3, \ldots,piD \tag{12}$$

And the velocity for the ith particle is represented as

$$Vi = (vi1,vi2,vi3,\ldots,viD) \tag{13}$$

The particle position with the highest fitness value for the entire run is called the global best. The global best particle among all the particles in the population is represented by

$$Pg = (pg1, pg2, pg3, \ldots,pgD) \tag{14}$$

At each iteration the velocity vector of every particle is adjusted based on its best solution and the best solution of its neighbors. The position of the velocity adjustment made by the particle's previous best position is called the cognition component and the position of the velocity adjustments using the global best is called the social component.

$$V_i(k+l)=wV_i(k)+c_1r_1(k)*(P_i(k)-X_i(k)+c_2r_2(k)*(s_i(k)*(s_i(k)-X_i(k)) \tag{15}$$

$$xid (t +1) = xid (t) + vid (t) \tag{16}$$

Where w is the inertia weight, η1 and η2 are positive acceleration constants. The velocity vector drives the optimization process and reflects socially exchanged information [13]. Table III shows the conventional PSO results of sym 8 wavelet of hard thresholding.

Table III: Analysis of Conventional PSO in Hard Thresholding

Parameters	Conventional PSO Optimization sym8 wavelet and hard thresholding
Risk Level classification rate (%)	78.94368
Weighted delay(s)	2.47
False Alarm rate\set	0.27
Performance index%	69.48055
Quality value	18.5

V. HYBRID PSO OPTIMIZATION

Because Hybrid PSO is the modified form of the general PSO which is used to calculate risk levels of the input given. The Particle swarm optimization is the common method to get the optimized output for the given input. It works on the principle of birds flocking.

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The three important factors of the PSO depend on position, velocity and fitness. It calculates the two best position as pbest and gbest. Pbest is the local best position and gbest is the global best position. To train the inputs LM algorithm is used. The general PSO suffers in the problem of local minima. To get the better optimized result we are using the modified PSO. The hybrid PSO algorithm is discussed below,

The position of particle i is represented as

$$X_i = (x_{i1,} x_{i2} \ldots x_{iD}) \quad (17)$$

Each particle also maintains a memory of its previous best position, represented as

$$P_i = (p_{i1,} p_{i2} \ldots p_{iD}) \quad (18)$$

A particle in a swarm is moving; hence, it has a velocity, which can be represented as

$$V_i = (v_{i1,} v_{i2} \ldots v_{iD}) \quad (19)$$

Each particle knows its best value so far (pbest) and its position. Moreover, each particle knows the best value so far in the group (gbest) among pbests. This information is analogy of knowledge of how the other particles around them have performed. Each particle tries to modify its position using the following information:

- the distance between the current position and pbest
- the distance between the current position and gbest

This modification can be represented by the concept of velocity. Velocity of each agent can be modified by the following equation in inertia weight approach.

$$V_i(k+l)=C+wV_i(k)+c_1r_1(k)*(P_i(k)-X_i(k)+c_2r_2(k)*(s_i(k)*(s_i(k)-X_i(k)) \quad (20)$$

Where w is called as the inertia factor which controls the influence of previous velocity on the new velocity, C is the concatenation factor, r1 and r2 are the random numbers, which are used to maintain the diversity of the population, and are uniformly distributed in the interval [0,1]. c1 is a positive constant, called as coefficient of the self-recognition component; c2 is a positive constant, called as coefficient of the social component. From equation (13), a particle decides where to move next, considering its own experience, which is the memory of its best past position, and the experience of its most successful particle in the swarm. Table IV shows the overall performance of the hybrid PSO algorithm in hard thresholding in sym8 wavelet transform.

Table IV: Performance of Hybrid PSO in Hard Thresholding

Parameters	Hybrid PSO Optimization haar wavelet and hard thresholding
Risk Level classification rate (%)	83.5
Weighted delay(s)	2.48
False Alarm rate\set	0.30
Performance index%	80.8
Quality value	19.2

VI. RESULTS AND DISCUSSION

The performance of the hybrid PSO and PSO is also analyzed using the performance index calculation. The network is trained using LM algorithm to minimize the square output error. The simulations were realized by employing Neural Simulator 4.0 of Matlab v.7.0 [19]. As the number of patterns in each database for training is limited, the technique of S-fold cross validation is employed to partition the data [16]. The two optimization technique efficiency is measured using the parameters like performance index, quality value, etc. Table V and table VI shows the performance index rate of the code converter output of hard and soft thresholding for different wavelet transforms. Table V shows the performance index for different wavelets.

Table V: Performance of PSO and Hybrid PSO in Performance Index in Hard Thresholding

Hard Thresholding	Performance Index	
	PSO	Hybrid PSO
Haar	67.84335	78.992
DB2	71.4487	80.522
DB4	74.379	85.706
Sym8	69.48055	81.374

Table VI: Performance of PSO and Hybrid PSO in Error Calculation in Soft Thresholding

Soft Thresholding	Performance Index	
	PSO	Hybrid PSO
Haar wavelet		
Heursure	70.44235	84.75
Minimaxi	70.015	84.46
Rigrsure	76.31	83.65
Sqtwolog	65.67	83.05
DB2 Wavelet		
Heursure	70.081	86.053
Minimaxi	74.8345	83.877
Rigrsure	77.042	84.614
Sqtwolog	61.716	79.7
DB4 Wavelet		
Heursure	74.27	82.754
Minimaxi	74.753	83.6865
Rigrsure	68.486	88.998
Sqtwolog	63.34855	82.804
Sym8 Wavelet		
Heursure	74.9085	87.5405
Minimaxi	70.82655	82.674
Rigrsure	69.688	85.896
Sqtwolog	66.26185	79.4815

In Order to compare different classifier we need a measure that reflects the overall quality of the classifier. Their quality is determined by three factors.

(i)Classification rate

(ii) Classification delay

(iii)False Alarm rate

The quality value QV is defined as [4],

$$Q_v = \frac{C}{(R_{fa}+0.2)*(T_{dly}*P_{dct}+6*P_{msd})} \quad (21)$$

Where, C is the scaling constant R_{fa} is the number of false alarm per set; T_{dly} is the average delay of the on set classification in seconds, P_{dct} is the percentage of perfect classification, and P_{msd} is the percentage of perfect risk level missed.A constant C is empirically set to 10 because this scale is the value of QV to an easy reading range. The higher value of QV, the better the classifier among the different classifier, the classifier with the highest QV should be the best. Table 4 and table 5 shows the Comparison of the PSO and hybrid PSO neural networks optimization techniques.

It is observed from that hybrid PSO classifier is performing well with the highest Performance Index and Quality Values. The Hybrid PSO with hard Thresholding is a higher threshold response method with least weighted delay of 2.35 seconds. Even though the neural networks are performing well in terms of parameters but the training over head for hybrid PSO performance is higher and is favored for long term analysis.

Table VII: Performance of PSO And Hybrid PSO in Quality Value Calculation in Hard Thresholding

Hard Thresholding	Quality value	
	PSO	Hybrid PSO
Haar	17.8525	19.213
DB2	18.2905	19.8935
DB4	19.2315	19.945
Sym8	18.574	19.7935

Table VIII: Performance of PSO And Hybrid PSO in Quality Value Calculation in Soft Thresholding

Soft Thresholding	Quality Value	
	PSO	Hybrid PSO
Haar wavelet		
Heursure	18.227	19.4735
Minimaxi	18.2955	19.552
Rigrsure	19.885	19.951
Sqtwolog	17.401	19.329
DB2 Wavelet		
Heursure	18.7675	20.677
Minimaxi	18.96	20.0315
Rigrsure	19.0625	19.8155
Sqtwolog	16.8745	18.531
DB4 Wavelet		
Heursure	19.735	19.467
Minimaxi	18.922	19.3995
Rigrsure	17.828	20.943
Sqtwolog	16.8805	19.5685
Sym8 Wavelet		
Heursure	19.61	20.7305
Minimaxi	18.2545	19.348
Rigrsure	18.6555	19.576
Sqtwolog	17.2635	18.8548

Table VII and table VIII shows the Quality Value of hybrid PSO optimization under Different Wavelet Transforms of hard and soft Thresholding for twenty patients. It is identified that Haar wavelet transform hard Thresholding and sqtwolog of soft thresholding will be a better choice in terms of quality values. Table 5 depicts the Quality Value of hybrid PSO optimization yechnique under Different Soft Thresholding and Wavelet Transforms for twenty patients. Thus hybrid PSO gives better result than the PSO in risk level calculation.

VII. CONCLUSION

This paper compares and analyzes the performance of the PSO and hybrid PSO in epileptic risk level calculation from EEG inputs. It compares both the algorithm in terms of performance index and quality value. On comparison than the PSO and hybrid PSO, hybrid PSO gives better result, the performance index is approximately 90 less than in PSO which is 79 and quality value is about 20 in hybrid PSO and 17 in PSO. So the hybrid PSO gives better result.

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REFERENCES

1. Dr.R.Harikumar,T.Vijayakumar,(2011)"Comprehensive Analysis of Hierarchical Aggregation Functions Decision Trees, SVD, K-means Clustering, PCA and Rule Based AI Optimization in the Classification of Fuzzy based Epilepsy Risk Levels from EEG Signals "ISSN 2150-7988 Volume 3.
2. Tanyawat Sanguanchue, Kietikul Jearanaitanakij (2012) "Hybrid Algorithm for training feed-forward neural network using PSO-Information gain with back propagation algorithm." IEEE 978-1-4673-2025.
3. Dr.R.Harikumar,Dr.C.Palanisamy(2011) "Performance Analysis of Fuzzy Techniques Hierarchical Aggregation Functions Decision Trees and Support Vector Machine (SVM)for the Classification of Epilepsy Risk Levels from EEG Signals" IEEE ERIPNO.:ER/0904480/M/01/1193.
4. Alison A Dingle et al (1993) 'A Multistage System to Detect Epileptic form Activity in the EEG', IEEE Transactions on Biomedical Engineering, 40(12):1260-1268.
5. J.Kennedy and R.Eberhart, Particle Swarm Optimization, Proc. IEEE International Conf. on Neural Networks, Perth , Vol. 4, pp 1942-1948,1995.
6. C.R. Hema, M.P.Paulraj, R. Nagarajan,S. Yaacob, A.H. Adom, "Application of Particle Swarm Optimization for EEG Signal Classification" BMFSA(2008-13-1-11) .
7. R. Eberhart and Y. Shi, "Evolving Artificial Neural Networks," Proceedings of the 1998 International Conference on Neural Networks and Brain, pp. PL5 - PL13, 1998.
8. J. Salerno, "Using the particle swarm optimization technique to train a recurrent neural model," IEEE International Conference on Tools with Artificial Intelligence, pp. 45-49, 1997.
9. M. Omran, A. Salman, and A. P. Engelbrecht, "Image classification using particle swarm optimization," *Proceedings of the 4th Asia-Pacific Conference onSimulated Evolution and Learning 2002 (SEAL 2002)*, pp.370-374, 2002.
10. C. A. Coello, E. H. Luna, and A. H. Aguirre, "Use of particle swarm optimization to design combinational logic circuits," *Lecture Notes in Computer Science(LNCS)*, No.2606, pp. 398-409, 2003.
11. S. Ujjin and P. J. Bentley, "Particle swarm optimization recommender system," *Proceedings of the IEEE Swarm Intelligence Symposium 2003 (SIS 2003)*, pp. 124-131, 2003.
12. R. Eberhart and Y. Shi, "Evolving Artificial Neural Networks," *Proceedings of the 1998 International Conference on Neural Networks and Brain*, pp. PL5 - PL13,1998.
13. J. Salerno, "Using the particle swarm optimization technique to train a recurrent neural model," *IEEE International Conference on Tools with Artificial Intelligence*, pp. 45-49, 1997.
14. R. Mendes, P. Cortez, M. Rocha, and J. Neves, "Particle swarms for feedforward neural network training,"*Proceedings of the 2002 International Joint Conference onNeural Networks (IJCNN 2002)*, pp. 1895-1899, 2002.
15. Kennedy, J. and Mendes, R. Population structure and particle swarm performance. In In Proceedings of the IEEE Congress on Evolutionary Computation, pages 1671–1676, Hawaii, USA, 2002.
16. Omran, M. Particle Swarm Optimization Methods for Pattern Recognition and Image Processing.PhD thesis, Department of Computer Science, University of Pretoria, South Africa, 2005.
17. Schwefel, H. Evolution and Optimum Seeking.Wiley, New York, 1995.
18. Shi, Y. and Eberhart, R. Parameter selection in particle swarm optimization. In In: Proceedings of Evolutionary Programming 98, pages 591–600,1998.
19. Shi, Y. and Eberhart, R. C. A modified particle swarm optimiser. In IEEE International Conference on Evolutionary Computation, Anchorage,Alaska, 1998.
20. Arthur C Gayton (1996), 'Text Book of Medical Physiology',

Prism Books Pvt. Ltd., Bangalore, 9th Edition.
21. Michael Meissner, Michael Schmuker and Gisbert Schneider" optimized Particle Swarm Optimization (OPSO) and its application to artificial neural network training" BMC Bioinformatics, **7**:125 doi:10.1186/1471-2105-7-125,2006.
22. A. Nowak, J. Szamrej, and B. Latane. From private attitude to public opinion: A dynamic theory of social impact. *Psychological Review*, 97(3):362-376, 1990.
23. R. Poli. Analysis of the publications on the applications of particle swarm optimisation. *Journal of Artificial Evolution and Applications*, Article ID 685175, 10 pages, 2008.
24. Shermeh ,Ata E. Zadeh Ghaderi, Reza" An intelligent system for classification of the communication formats using PSO" ISSN: 0350-5596,2008.
25. Principe, "Brain Machine Interfaces: Mind over Matter", 2005.
26. http://www.ece.ufl.edu/publications/Archives/int henews/2005 /brainmachine.html
27. M. Teplan, "Fundamentals of EEG Measurement", Measurement Science Review,Vol. 2, Section 2, 2002.
28. N.J Huan and R. Palaniappan, "Classification of Mental Tasks using Fixed and Adaptive Autoregressive Models of EEG Signals" IEEE EMBS Conference, pp 507 – 510, 2004.
29. Z. A Keirn and J. I. Aunon, "A New Mode of Communication between Man and hisSurroundings" IEEE Transactions on Biomedical Engineering, Vol. 37.no. 12. pp 1209-1214, 19.

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