Fast channel selection method using modified camel travelling behavior algorithm

Zaineb M. Alhakeem[1], Ramzy S. Ali[2]
[1]Department of Communication Engineering, Iraq University College, Basrah, Iraq
[2]Department of Electrical Engineering, Universitas of Basrah, Basrah, Iraq

Article Info	ABSTRACT
	Brain computer interface (BCI) is a protocol to communicate between the human brain and a device or application using brain signals. These signals translated to useful commands by using features extraction and classification. The most widely used features is the power of alpha and beta rhythms. This type of features gives only 70% of classification accuracy without any extra processing using fixed channels to read the signals. Because the distribution of the power in the brain is not a standard for all people, each one has his own brain power map. A selection algorithm is used to find the best channels that could generate higher power than the fixed ones. Modified camel travelling behavior algorithm is used to select the channels that used to extract the power of alpha and beta bands of motor imagery signals. This algorithm is faster to find the best set of channels, and obtain classification accuracy more than 95% using support vector machine classifier. *This is an open access article under the [CC BY-SA](#) license.*
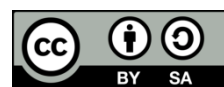
Corresponding Author:

Zaineb M. Alhakeem
Department of Communication Engineering, Iraq University College
Basrah, Iraq
Email: zaineb.alhakeem@iuc.edu.iq

1. INTRODUCTION

Brain computer interface (BCI) is a communication protocol between a device and the human brain that will convert the brain signals to useful commands. The BCI systems consists of multiple steps starting from data recording, extracting features, selecting features, ending with classify the features [1], [2]. There are many applications of using electroencephalogram (EEG) signals such as in rehabilitation, communication between a disabled person and other applications [3]–[5]. BCI systems still to this moment have problems and limitations, the researchers try to propose solutions to generalize this type of systems. The optimizations algorithms could introduce some solutions in features selection, parameters selection and features extraction methods. Roy *et al*. [6] used genetic algorithm (GA) to find the optimal path of the robotic arm to reach the destination. Fatourechi *et al*. [7] used the hybrid genetic algorithm to select the optimum window size of EEG data. In [8], [9] used GA to select the best extracted features set among 36 to create a features vector that will be used to classify motor imagery (MI) signals. Yang *et al*. [10] used the same algorithm but with electroocography ECoG signal. Gonzalez *et al*. [11] used particle swarm optimization (PSO) to select the channels that will be used to extract the features of P300 component. Kee *et al*. [12] used multi-objective GA to select channels for both signals P300 and MI. Ma *et al*. [13] used PSO in selecting parameters of support vector machine (SVM) classifier to improve the accuracy of MI signal. Liu *et al.* [14] selects the features in multiclass classification using firefly algorithm, they extract features using common spatial pattern method (CSP) and the local characteristics-scale decomposition method (LCD). They test their proposed method in a maze game. Yacoub *et al.* [9] used GA to select the more relevant samples in sliding window in to time domain.

Noori *et al.* [15] used GA to select features from functional near-infrared spectroscopy (fNIRS) signals. Nakisa *et al.* [16] used all the evolutionary algorithms to select the features of EEG signals to recognize emotion of a human begin. Kumar [17] used GA to select the filter order and frequency range to the band-pass filter of preprocessing step of EEG signal.

2. RESEARCH METHOD

The steps of any BCI system are: a) data recording, b) preprocessing methods, c) features extraction, d) features selection, and e) classification process. Some steps are not very necessary in all models such as preprocessing and features selection, that depends on the quality of the data and number of features respectively. The following sections discusses the used data set, features extraction method, features selection method and the classifier.

2.1. Dataset

Thirteen signals recorded from eight healthy people using two different recording devices, which they are g.tec and Neuroscan using five or six recording channels, only five for all the subject that used in this work. The used channels labels are: C3, C4, Cz, Cp3, and Cp4. All the signals have the sampling rate 256 Hz except SubB has sampling rate equals to 250 Hz. These signals are recorded by Dr. Cichocki's Lab. All of them are recording motor imagery signals of left and right hands. Table 1 shows the details information of each signal. Some subject recorded multiple session in different days. The subject is sitting in front of a computer screen about one meter distance. On the screen an arrow appeared to notify the subject which hand movement should be imagined. A break of two seconds prior to each imagination task. All the subject are informed to avoid blinking and other unwanted movements during the recording sessions [18].

Table 1. The information of the data set

Subject	Duration (sec)	Number of trails
SubA_6chan_LR_s1	3	130
SubA_6chan_LR_s2	4	134
SubB_6chan_LR	3	162
SubC_6chan_LR_s1	3	170
SubC_6chan_LR_s2	5	158
SubC_6chan_LR_s3	3	48
SubC_6chan_LR_s4	3	120
SubC_6chan_LR_s5	4	90
SubD_5Chan_LR	4	80
SubE_5Chan_LR	4	48
SubF_6Chan_LR	4	80
SubG_6Chan_LR	3	120
SubH_6Chan_LR	3	150
Average	3.54	111.15

2.2. Features extraction

There are many features extraction methods in literature the simplest one is extracting the power of both alpha and beta rhythms. These rhythms are well known rhythms in MI signals are alpha (8−12) Hz and beta (14−30) Hz. These rhythms are extracted using time-frequency method, discrete wavelet transform (DWT) with (db2). DWT is a suitable tool to extract features from nonstationary signals such as EEG signal [4]. Alpha and beta rhythms are extracted from the details of the fifth and fourth level of the DWT of the original signal as shown in Figure 1. The power of these signals is calculated by squaring the samples then averaging each segment of the signal. Tables and Figures are presented center, as shown below and cited in the manuscript.

2.3. Selection algorithms

Meta-heuristic algorithms give a good solution to select parameters in many applications. In this work the modified CA is used to select the best channels to find the feature from five channels. As the Authors proofed that it is fast and reliable algorithm in low dimensions applications [19]. The following sections discuss some metaheuristic algorithms that used in this paper.

2.4. Genetic algorithm

Genetic algorithm is a well-known algorithm that based on the natural selection with genetics inspired operators. Each chromosome consists of genes (bit) 0 or 1 in binary genetic algorithm. The GA involved three operations: selection, crossover and mutation see Figure 2. This algorithm has six parameters should be tuned [20].
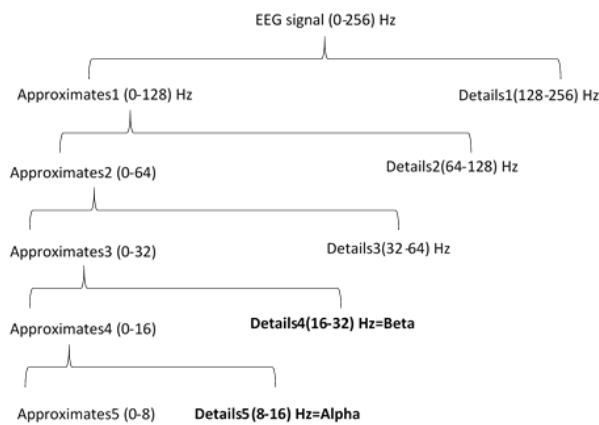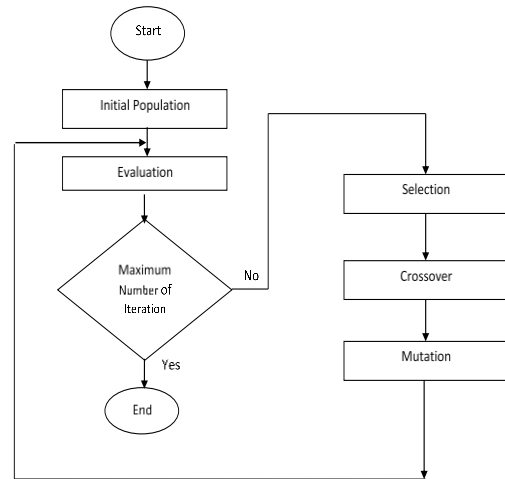
Figure 1. DWT levels of EEG signal

Figure 2. Flow chart of genetic algorithm

2.5. Crow search algorithm (CSA) [21]

Askazadah proposed a search algorithm that based on the behavior of the crows. Crows have large size brain make them able to remember faces, the places of food after long time, can use tools and can communicate with each other. This algorithm use population of crows to explore the search area. Only two parameters should be tuned (awareness and flight length). At each iteration best solution is found and used directly to find the best hiding place (best position) see Figure 3, the position update is (1).
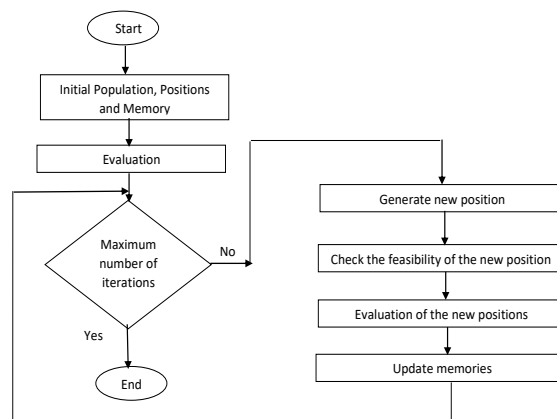

Figure 3. Flow chart of crow search algorithm

$$x^{i,iter+1} = \begin{cases} x^{i,iter} + r_i \times fl^{i,iter} \times (m^{j,iter} - x^{i,iter}) \\ a\ random\ position \qquad O.W. \end{cases} \tag{1}$$

The memory update is (2):

$$m^{i,iter+1} = \begin{cases} x^{i,iter} \\ m^{i,iter} \quad O.W. \end{cases} if \quad f(x^{i,iter+1}) better\ than\ f(x^{i,iter}) \tag{2}$$

2.6. Modified camel travelling behavior algorithm (modified CA) [19]

The camel is an animal have the ability to stay without food or water for a longtime in the hot weather. As it is known, the camel travels in group known as caravan. The modified CA based on the behavior of the camel in searching for food and water. The camels distributed randomly when one of the group found a good spot of food, this camel communicate with the others, and the method of communication depends on the visibility of this animal. Visibility and the temperature are parameters affect the camel behavior so they are included into the algorithm. Let us assume that the size of the caravan is N, and the environment dimension is D. The camel in location i given in the (3).

$$x_d^{i,iter} = (xmax - xmin) \times Random\ value + xmin \tag{3}$$

$xmin$ and $xmax$ are the minimum and maximum limits of the location they are belongs to the period [0,1]. The effect of the temperature is given by the (4).

$$E_d^{i,iter} = 1 - \frac{T_d^{i,iter} - Tmin}{Tmax - Tmin} \tag{4}$$

Where:

$$T_d^{i,iter} = (Tmax - Tmin) \times Random\ value + Tmin \tag{5}$$

Depending on the visibility value the updating of the location is either as the flowing equation or as the previous one.

$$x_d^{i,iter} = x_d^{i,iter-1} + E_d^{i,iter}(x_d^{best} - x_d^{i,iter-1}) \tag{6}$$

The flowchart of this algorithm is shown in Figure 4.

2.7. Classification method

SVM is one of the fast, simple classifiers that is used widely in EEG features classification [22]. This method maximized the distance between two hyperplanes that separate the regions of two classes. There are different types of kernels functions: linear and nonlinear depending on the distribution of the features' points linearly separable and non-separable [4], [23], [24] see Figure 5.

2.8. The proposed method

In our previous work we used GA and CSA to select the best channel to extract power features of EEG signal with a condition to decrease the processing time [25]. Usually in selecting channels and features there is a problem a raised with the random generation of the binary variable, which is generating zero variable in one part of the meta-heuristic algorithm or multiple parts of it. We already solved this problem in our work but the algorithm that we used sill not so fast.
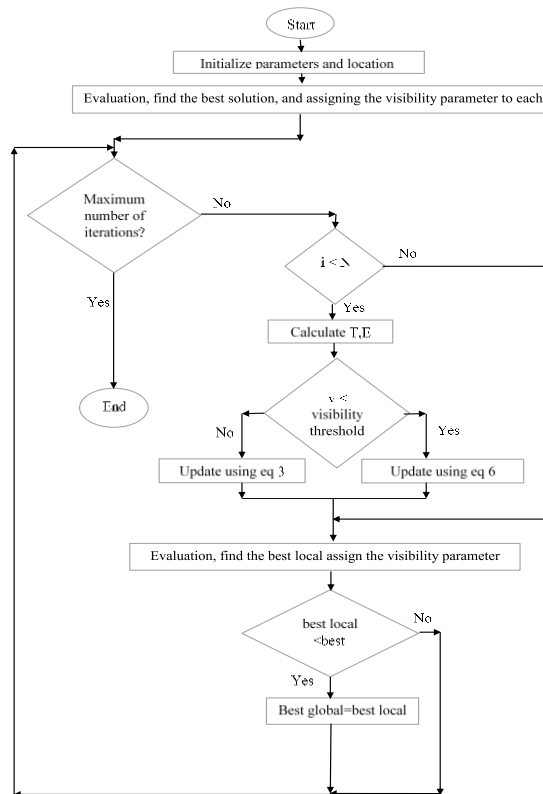

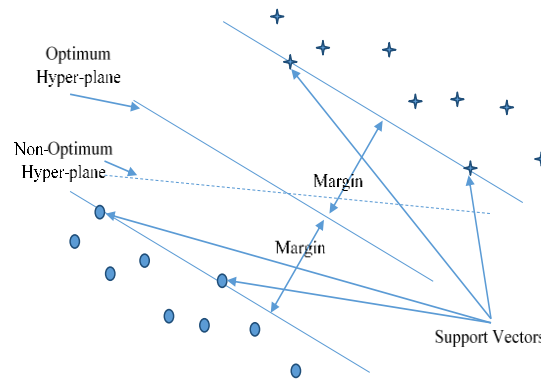Figure 4. Camel travelling behavior algorithm (modified CA) flow chart

Figure 5. Support vector machine

In this work modified CA is used to find the best channels to extract the power of alpha and beta rhythms. This algorithm is suffer from the probability of generating zero value solution in binary selection that will stop the iterations of the algorithm. To solve this problem a complement of the solution is used to get out of this situation. BCI applications based on finding features to be transmitted to a useful commands, to find the features there must be always a signal to be used to extract these features. When a zero solution generated in metaheuristic algorithms this means there is no channel selected to extract the features which is not a realistic situation.

When there is no signal used to extract features the system will stop. To prevent this shutdown in the system an easy solution could be used, which is repeat the loop to generate other solution until non zero solution is generated. This solution take time as we proofed in our previous work [25]. Other solution is used in this situation, which is taking the complement of the solution, this works even with applications need more than one bit to be active to keep working see Figure 6, Figure 7, and Figure 8.

The training phase consisted of reading the data, apply the selection algorithm, extract features from the signals of the selected channels then test the classification accuracy. The set of channels that obtain the best classification accuracy is saved to be used in the training phase see Figure 9(a). The testing phases of the system consist of applying the testing data to the best channels set that found in the trining phase, extract the features from this signals and classify them see Figure 9(b).

3. RESULTS AND ANALYSIS

The proposed solution is tested using three metaheuristic algorithms: GA, CSA and modified CA using Matlab 2018a, personal computer of Core i7, 8 GB DDR3 memory and the dataset of thirteen different signals. A comparison among three selection algorithms (GA, CSA and modified CA) is made, all algorithms used the proposed solution. These results are compared with features extraction using all the available channels. Table 2 shows the comparison results modified CA is the superior one with about 99% of classification accuracy. Almost all the samples are recognized to the correct classes. To find the effect of adding the complement of the solution in the selection algorithms on the processing time a comparison is made and the results are shown in Table 3. The processing time is taken as the average of 30 runs of each algorithm and the time is measured in hours. It is found out that in our previous work CSA is better than GA in processing time only. CSA with the no zero condition is faster than GA with the same accuracy of classification. Now the modified CA is better in both classification accuracy and processing time. Table 4 shows a comparison according to the size of features vector that number of selected channels using modified CA is less that all the used other algorithm. The number of channels is an integer number but we take the average of 30 runs.

Table 2. A comparison according to classification accuracy among different selection algorithms methods and all the five channels

Subject	Power of all channels	GA-no zero	Ref [25]	CA-no zero
Average of sub A 2LR	72.05	70.9336	70.30214	99.5893
SubB_6Chan_2LR	78.4	83.06584	82.90123	100
Average of sub C 2LR	53.83824	67.13233	66.74403	98.8722
SubD_5Chan_2LR	55	70.125	68.70833	100
SubE_5Chan_2LR	93.8	90.34722	90.27778	99.5833
SubF_6Chan_2LR	60	78.04167	77.29167	100
SubG_6Chan_2LR	66.7	59.30556	58.55556	99.0556
SubH_6Chan_2LR	52.7	54.86667	53.73333	100
Average accuracy	66.56103	71.72724	71.06426	99.63755
Standard deviation	13.430249	11.82024	12.12835	0.426494

Decrease number of selected channels will decrease the size of features vector that will be fed to the classifier, this will decrease the processing time. After 30 runs of all the algorithms modified CA is the superior among the other algorithms. Figure 10 to Figure 12 and Table 5 show a full comparison among the three meta heuristic algorithms according to three comparison parameters, processing time, classification accuracy and number of channels.

Table 3. A comparison according to the time consumed in processing 30 runs

Subject	GA-no zero	Ref [25]	Modified CA-no zero
Average of sub A	12.98198	10.2177	7.98
SubB_6Chan_LR	15.39609	12.74286	7.671389
Average of sub C	11.27761	9.204347	7.457722
SubD_5Chan_LR	9.583662	6.705311	5.47
SubE_5Chan_LR	5.524507	4.275156	3.541389
SubF_6Chan_LR	9.276981	9.112548	5.474444
SubG_6Chan_LR	11.50763	10.02671	7.274722
SubH_6Chan_LR	18.56046	15.51766	9.596667
Average	11.76362	9.725287	6.808292
Standard deviation	3.725589	3.210562	1.759795

Table 4. A comparison among different meta-heuristic algorithm according to the number of channels

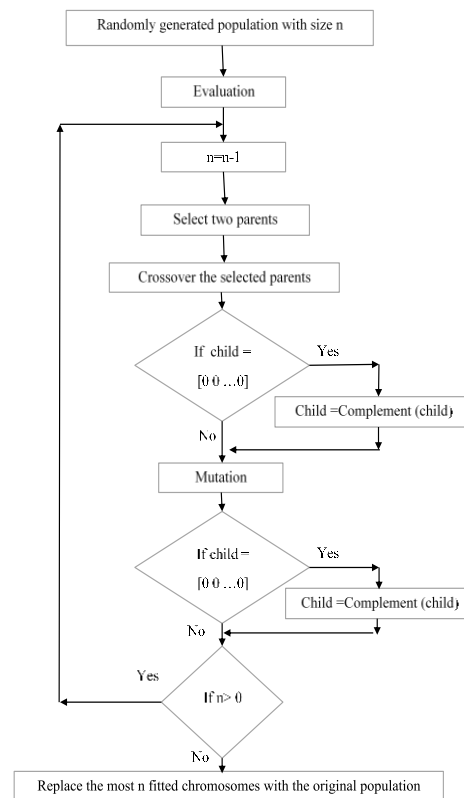| Subject	GA-no zero	CSA-no zero	Modified CA-no zero
Average of sub A 2LR	3.55	3.63	3.03
SubB_6Chan_2LR	3.4	3.4	3.2
Average of sub C 2LR	2.77	2.59	2.7
SubD_5Chan_2LR	5	5	2.7
SubE_5Chan_2LR	3.6	3	2.56
SubF_6Chan_2LR	4.7	4.6	2.6
SubG_6Chan_2LR	2	2	2.7
SubH_6Chan_2LR	4.8	4.7	2.86
The average number of channels	3.7275	3.615	2.79375

Figure 6. GA with no-zero condition

Table 5. A comparison among different meta-heuristic algorithm according to number of channels and accuracy of classification

| Subject	GA-no zero		CSA-no zero		Modified CA-no zero	
	No. channels	Accuracy	No. channels	Accuracy	No. channels	Accuracy
Average of sub A	3.55	70.9336	3.63	70.30214	3.03	99.5893
SubB_6Chan_LR	3.4	83.06584	3.4	82.90123	3.2	100
Average of sub C	2.77	67.13233	2.59	66.74403	2.7	98.8722
SubD_5Chan_LR	5	70.125	5	68.70833	2.7	100
SubE_5Chan_LR	3.6	90.34722	3	90.27778	2.56	99.5833
SubF_6Chan_LR	4.7	78.04167	4.6	77.29167	2.6	100
SubG_6Chan_LR	2	59.30556	2	58.55556	2.7	99.0556
SubH_6Chan_LR	4.8	54.86667	4.7	53.73333	2.86	100
Average	3.7275	71.72724	3.615	71.06426	2.79375	99.63755
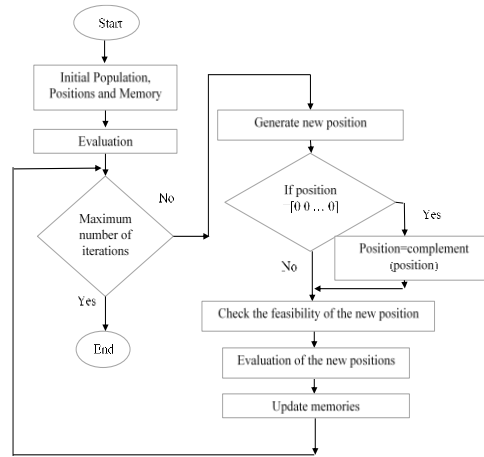
Figure 7. CSA with no-zero condition
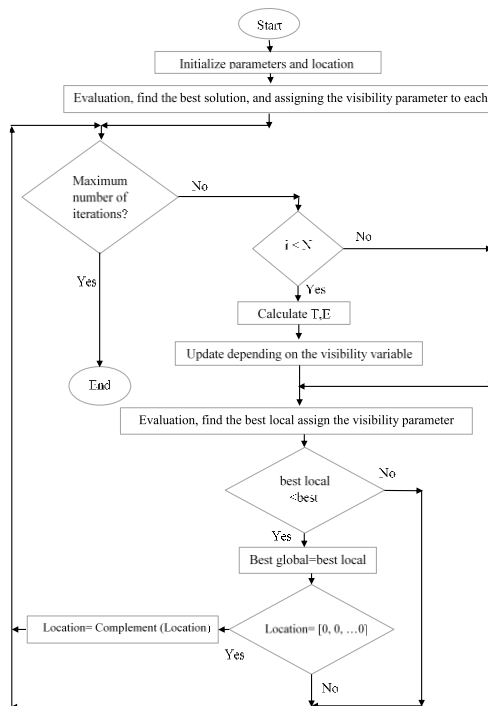

Figure 8. Camel travelling algorithm with no-zero condition
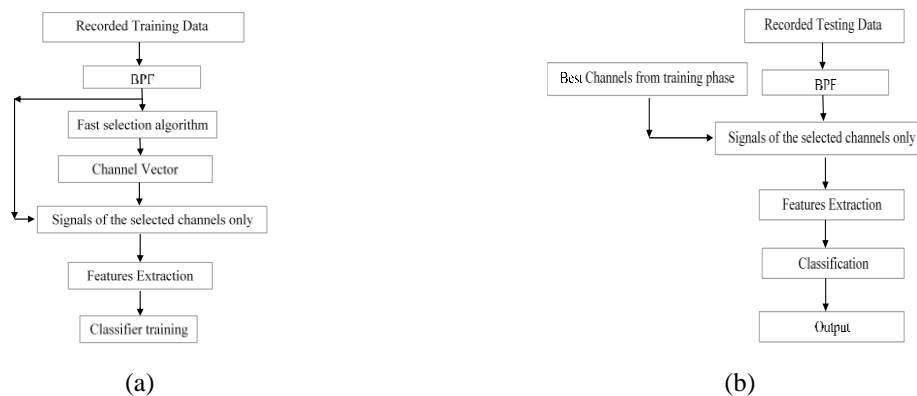

(a)　　　　　　　　　　　　　　　　　　(b)

Figure 9. Training and testing phases of fast selection method: (a) training phase using fast selection algorithm and (b) testing phase using fast selection algorithm selection
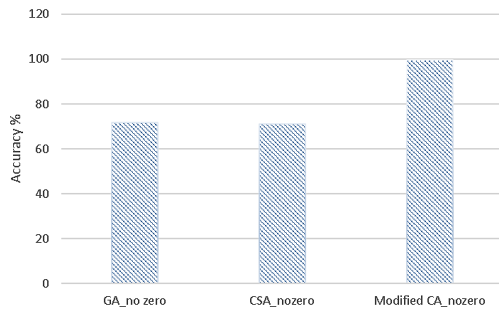
Fast channel selection method using modified camel travelling behavior algorithm (Zaineb M. Alhakeem)

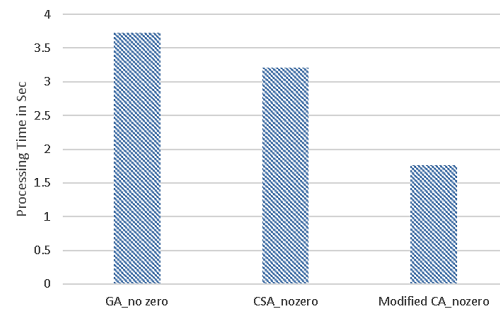Figure 10. A full comparison according to the accuracy of the classifier

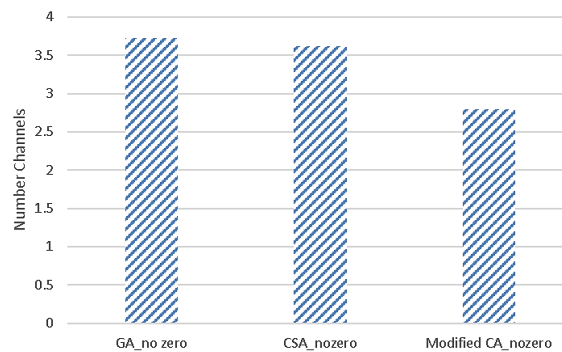Figure 11. A full comparison according to the time of processing

Figure 12. A full comparison according to the number of channels

4. CONCLUSION

BCI one of the applications that do not accept the absence of the signal even for short time. Always there should be a signal, so features could be extracted and classified. In features selection or channels selection, binary variables are used. Meta heuristic algorithms depends on random generation of variables. Always there is a chance to generate a zero variable. This type of variable is not accepted in BCI systems. In this paper a solution is proposed for this problem. This solution depends on taking the complement of the variable to prevent system shutdown because of the unacceptable variable. The complement is used to make the solution is valid for other application that need more than one bit of the binary variable to operate. The proposed solution is applied on three metaheuristic algorithms which are (GA, CSA and modified CA). The testing results shows that modified CA with no zero variable solution is faster, give shorter variables with highest classification accuracy. In this paper SVM with linear kernel is used as classifier, which is give more than 95% of classification accuracy.

REFERENCES

[1] P. Diez, "Smart Wheelchairs and Brain-computer Interfaces: Chapter 1-Introduction," *Mobile Assistive* Technologies, Academic Press, 2018, pp. 1-21, doi: 10.1016/B978-0-12-812892-3.00001-7.
[2] L. F. N. -Alonso and J. G. -Gil, "Brain Computer Interfaces, a Review," *Sensors,* vol. 12, no. 2 pp. 1211-1279, 2012, doi: 10.3390/s120201211.
[3] Z. M. Alhakeem and R. S. Ali, "Session to Session Transfer Learning Method Using Independent Component Analysis with Regularized Common Spatial Patterns for EEG-MI Signals," *Iraqi Journal for Electrical and Electronic Engineering*, vol. 15, no. 1, pp. 13–27, 2019, doi: 10.37917/ijeee.15.1.2.
[4] Z. M. Alhakeem, R. S. Ali, and R. A. A. -Alhameed, "Wheelchair Free Hands Navigation Using Robust DWT_AR Features Extraction Method With Muscle Brain Signals," in *IEEE Access*, vol. 8, pp. 64266-64277, 2020, doi: 10.1109/ACCESS.2020.2984538.
[5] O. George, R. Smith, P. Madiraju, N. Yahyasoltani, and S. I. Ahamed, "Motor Imagery: A Review of Existing Techniques, Challenges and Potentials," *2021 IEEE 45th Annual Computers, Software, and Applications Conference (COMPSAC)*, 2021, pp. 1893-1899, doi: 10.1109/COMPSAC51774.2021.00286.
[6] R. Roy, M. Mahadevappa, and C. S. Kumar, "Trajectory path planning of EEG controlled robotic Arm using GA," *Procedia Computer Science*, vol. 84, pp. 147–151, 2016, doi: 10.1016/j.procs.2016.04.080.
[7] M. Fatourechi, A. Bashashati, R. K. Ward, and G. E. Birch, "A hybrid genetic algorithm approach for improving the performance of the LF-ASD brain computer interface," *Proceedings. (ICASSP '05). IEEE International Conference on Acoustics, Speech, and Signal Processing*, 2005, vol. 5, pp. v/345-v/348, doi: 10.1109/ICASSP.2005.1416311.

[8] R. Corralejo, R. Hornero, and D. Álvarez, "Feature selection using a genetic algorithm in a motor imagery-based Brain Computer Interface," *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2011, pp. 7703-7706, doi: 10.1109/IEMBS.2011.6091898.

[9] C. Yaacoub, G. Mhanna, and S. Rihana, "A Genetic-Based Feature Selection Approach in the Identification of Left/Right Hand Motor Imagery for a Brain-Computer Interface," *Brain Sciences*, vol. 7, no. 1, 2017, doi: 10.3390/brainsci7010012.

[10] J. Yang, H. Singh, E. L. Hines, F. Schlagheckend, D. D. Iliescu, M. S. Leeson, and N. G. Stocks, "Channel selection and classification of electroencephalogram signals: An artificial neural network and genetic algorithm-based approach," *Artificial Intelligence in Medicine*, vol. 55, no. 2, pp. 117–126, 2012, doi: 10.1016/j.artmed.2012.02.001.

[11] A. Gonzalez, I. Nambu, H. Hokari, and Y. Wada, "EEG Channel Selection Using Particle Swarm Optimization for the Classification of Auditory Event-Related Potentials," *Scientific World Journal*, 2014, doi: 10.1155/2014/350270.

[12] C. -Y. Kee, S. G. Ponnambalam, and C. -K. Loo, "Multi-objective genetic algorithm as channel selection method for P300 and motor imagery data set," *Neurocomputing*, vol. 161, pp. 120-131, 2015, doi: 10.1016/j.neucom.2015.02.057.

[13] Y. Ma, X. Ding, Q. She, Z. Luo, T. Potter, and Y. Zhang, "Classification of Motor Imagery EEG Signals with Support Vector Machines and Particle Swarm Optimization", *Computational and Mathematical Methods in Medicine*, 2016, doi: 10.1155/2016/4941235.

[14] A. Liu, K. Chen, Q. Liu, Q. Ai, Y. Xie, and A. Chen, "Feature Selection for Motor Imagery EEG Classification Based on Firefly Algorithm and Learning Automata," *Sensors*, vol. 17, no. 11, 2017, doi: 10.3390/s17112576.

[15] F. M. Noori, N. Naseer, N. K. Qureshi, H. Nazeer, and R. A. Khan, "Optimal feature selection from fNIRS signals using genetic algorithms for BCI," *Neuroscience Letters*, vol. 647, 2017, pp. 61-66, doi: 10.1016/j.neulet.2017.03.013.

[16] B. Nakisa, M. N. Rastgoo, D. Tjondronegoro, and V. Chandran, "Evolutionary Computation Algorithms for Feature Selection of EEG-based Emotion Recognition using Mobile Sensors," *Expert Systems with Applications*, vol. 93, pp. 143-155, 2018, doi: 10.1016/j.eswa.2017.09.062.

[17] S. Kumar and A. Sharma, "A new parameter tuning approach for enhanced motor imagery EEG signal classification," *Medical & Biological Engineering & Computing*, vol. 56, pp. 1861–1874, 2018, doi: 10.1007/s11517-018-1821-4.

[18] Z. M. Alhakeem, H. Hakim, and O. A. Hassan, "Motor Imagery Electroencephalogram Datasets, Where and How to Find Them: A Review", *Iraq university college journal of engineering and applied sciences* (IUCJEAS), vol. 1, no. 2, 2021. [Online]. Available: https://magazine.iuc.edu.iq/wp-content/uploads/2021/12/dr.zainab.pdf

[19] R. S. Ali, F. M. Alnahwi, and A. S. Abdullah, "A modified camel travelling behaviour algorithm for engineering applications," *Australian Journal of Electrical and Electronics Engineering*, vol. 16, no. 3, 176-186, 2019, doi: 10.1080/1448837X.2019.1640010.

[20] M. Melanie, "An Introduction to Genetic Algorithms", *Massachusetts Institute of Technology*, Cambridge, Massachusetts, London, England: Massachusetts Institute of Technology, 1996. Online. [Available]: https://www.boente.eti.br/fuzzy/ebook-fuzzy-mitchell.pdf

[21] A. Askarzadeh, "A novel metaheuristic method for solving constrained engineering optimization problems: Crow search algorithm," *Computers & Structures*, vol. 169, pp.1–12, 2016, doi: 10.1016/j.compstruc.2016.03.001.

[22] N. Alamdari, A. Haider, R. Arefin, A. K. Verma, K. Tavakolian, and R. F. -Rezai, "A review of methods and applications of brain computer interface systems," *2016 IEEE International Conference on Electro Information Technology (EIT)*, 2016, pp. 0345-0350, doi: 10.1109/EIT.2016.7535263.

[23] A. Athanasiou, *et al.*, "Towards Rehabilitation Robotics: Off-the-Shelf BCI Control of Anthropomorphic Robotic Arms," *BioMed Research International*, 2017, doi: 10.1155/2017/5708937.

[24] S. Sanei and J. A. Chambers, *EEG Signal Processing*, Chichester, England: John Wiley & Sons Ltd, 2007. Online. [Available]: https://faculty.washington.edu/seattle/brain-physics/textbooks/sanei.pdf

[25] Z. M. Alhakeem and R. S. Ali, "Fast Channel Selection Method Using Crow Search Algorithm," *ICICT '19: Proceedings of the International Conference on Information and Communication Technology*, 2019, pp. 210–214, doi: 10.1145/3321289.3321309.

BIOGRAPHIES OF AUTHORS

Zaineb M. Alhakeem 🆔 🔍 SC 🔄 was born in Basrah, Iraq in 1983. She received the B.Sc. and M.Sc. degrees in Computer engineering from the University of Basrah, in 2005 and 2008 respectively. She is also had her PhD degree within the Electrical Engineering Department, College of Engineering in 2020, University of Basrah, Basrah, Iraq. Her teaching interests covering wide areas of modules across the department of Computer Engineering and Communication Engineering, Iraq University College, include Neural Networks, Distributed systems, Control Systems, Modelling and simulation, Microprocessor and Microcontrollers and Programming Languages. Her research interests include Biomedical Engineering, Digital signal processing, Artificial inrelegent and renewable energy. Dr. Alhakeem is a Member in the IEEE. She can be contacted at email: zaineb.alhakeem@iuc.edu.iq.

Ramzy S. Ali 🆔 🔍 SC 🔄 received the B.Sc and M.Sc degrees in Electrical Engineering and Control and Computers Engineering from the University of Basrah, Basrah, Iraq in 1985 and 1989 respectively. He also received his PhD degree in the field of Control and Systems from the Saint-Petersburg State Polytechnic University, Russia in 2003. He is currently a Professor at the University of Basrah. His teaching interests covering wide areas of modules across the department of Electrical Engineering, University of Basrah, include Intelligent Control Systems, Robust Control Systems, Microprocessor and Microcontrollers and Industrial Automation. He currently serves as a co-editor of the Basrah Journal for Engineering Sciences. His research interests include Intelligent Control of Robotics, Computational Intelligence, Chaos and Nonlinear dynamics, Renewable electrical energy systems, and PLC applications in industrial and engineering education. Dr. Ramzy is a Senior Member of the IEEE. He can be contacted at email: rsalwaily@ieee.org.