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Metaheuristic FIR filter with game theory based compression technique- A reliable medical image compression technique for online applications ☆

Luo Li[a], Muneeswaran V.[b], Ramkumar S.[c], Emayavaramban G.[d], Gustavo Ramirez Gonzalez[e,*]

[a] Management School, Northwestern Polytechnical University, Xi'an 710129, Shaanxi, China
[b] Department of Electronics and Communication Engineering, Kalasalingam Academy of Research and Education, Anand Nagar, Krishnankoil, Srivilliputtur Post-626126, Virudhunagar District, Tamilnadu, India
[c] School of Computing, Kalasalingam Academy of Research and Education, Anand Nagar, Krishnankoil, Srivilliputtur Post-626126, Virudhunagar District, Tamilnadu, India
[d] Department of Electrical and Electronics Engineering, Karpagam Academy of Higher Education, Eachanari, Post-626126, Combatorer District, Tamilnadu, India
[e] Department of Telematics, De Cauca University, Colombia

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ABSTRACT

In image processing, there are many inventions results in processing the images effectively suitable for applications like change detection, SAR image analysis, Television i.e. for compressing videos for effective transmission etc. In Social network, exchange of bulk information needs an effective compression technique to compress, transmit, decompress and reconstruct the original quality of source information. Compression technique can reduce the storage deficiency, energy consumption. In this proposed methodology, an effective Finite Impulse Response filter designed with meta-heuristic techniques-a game theory-based approach provides a compromising data compression ratio for standard input images. Effective quality indicators such as compression ratio, Mean Square Error stands as proof for the implications of the anticipated technique in medical applications as it affords extraordinary results for compression of Ultrasound and MRI images, thus providing a pathway for a trans receiving data with minimum space required.

1. Introduction

Data compression is progression of dropping the size of data bits in information like audio, video, images and even the single valued data collected through sensors. The data compression is a tool in transmitting larger data with lesser transmitting cost by reducing the space required for representing a piece of information. This process eliminates the repetition of identical data bits in transmitting information. These all are achieved by using algorithm for application. The two crucial role of data compression is reducing storage space requirements and felicitating much faster communication. Compression process is mostly used in communication due to its efficacy in storing and transmitting data in fewer bits. There are variety of data compression techniques, but small number of algorithms are standardized. The data compression methods are broadly classified into two categories. They are lossy and lossless techniques. In lossy data compression technique, there occurs the loss in a data recovered after decompression. However, in lossless process the original information can be fully recovered without redundancy. The lossless process is not adaptable with the network which has a limited resource as they give better data recovery. In lossy process the evaluating the recovery error and degree of compression are the main things to consider in checking the quality of compression. In typical aggregation and compression techniques, cluster heads throw away surplus data and compress with lossy compression techniques. In this paper, we are going to discuss about different data compression techniques on images and their algorithms are valuated with metrics to find an efficient one.

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* Corresponding author.
E-mail addresses: shumababei7@163.com (L. Li), v.muneeswaran@klu.ac.in (M. V.), s.ramkumar@klu.ac.in (R. S.), emayavaramban.g@kahedu.edu.in (E. G.), gramirez@unicauca.edu.co (G.R. Gonzalez).

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2. Literature survey

In [1], data compression is employed in WSN for establishing privacy in the network. The authors considered the contextual privacy by preserving the contextual information as safe. The contextual information denotes the details regarding the time and place of the computed data. The motivation of the work is secreting the presence of a WSN from opponents by moderating the sensing ability of sensor nodes. This can be realized by reducing the transmission power of the sensor nodes. Hence the adversaries cannot discover the presence of the WSN. To alleviate the irregular energy dissipation characteristic, nodes which are unable to squander their energies on data transmission generates very few data to facilitate the nodes to deliver less data. The authors studied various data compression techniques to improve the lifetime of WSN where contextual privacy is introduced. In [2] adaptive data compression method is presented to reduce the blackout of sensor nodes which occurred because of greater energy absorption of the nodes beyond the harvested energy. The proposed technique intensifies the number of data receive at the sink by effectively exhausting garnered energy. In such technique, every sensor node compares the garnered energy and expended energy. When the differing energy surpass its loading capacity, it consumes the energy for data compression or for the enhancement of communication range. In [4], compressing neural networks are employed to frame data compression scheme for WSN, with the feature of error bound guarantee. This method exploits the spatial-temporal correlations existing among data to reduce data congestion and energy consumption. The adaptive rate of the distortion attribute equalizes the compressed data size and the error guaranteed. This type of compression technique releases the pressure on energy and bandwidth and thus gathers data below the allowable error boundaries. The experimentation proves that the proposed scheme provides less energy consumption and increased service life time. In Adaptive Lossless Data Compression (ALDC) the compression process is dynamically modified to a varying source. The data array to be compressed is separated into various blocks, and the optimal compression pattern is smeared for each block. The usage and methodologies of various optimization algorithm like genetic algorithm [3] and its modifications [4], Particle Swarm Optimization [5] and its modifications [6]. Wu et al. [7], presented a data compression and dimensionality reduction process for data fusion and aggregation process. These schemes decrease energy consumption and inhibit data congestion. The proposed in-network process can be adjusted to examine the temporal or spatial correlation with the help of an unsupervised neural network method. This process gets intrinsic data features from the earlier data samples to convert the raw measurements into a low dimensional representation. This mechanism also offers an error bound guarantee. Work presented jointly exploits compression processes to attain precision and competence in clustered networks. The value of mean-square deviation (MSD) is reduced in such a way that the cluster heads (CHs) can receive a virtuous estimate of the actual data from the nodes. By considering this estimation, a centralized Principal Component Analysis (PCA) technique is employed to accomplish the compression and recovery process for the predicted data on the CHs and the sink. The errors produced in these schemes are assessed theoretically and based on that, many algorithms are developed, and a cost-effective solution is obtained through the simulation results. In WSN, a sensor node collecting more data with higher sensing rate generally exploits more energy and drained quickly. Finally, their results were compared with existing system result to show the proposed system as efficient algorithm.

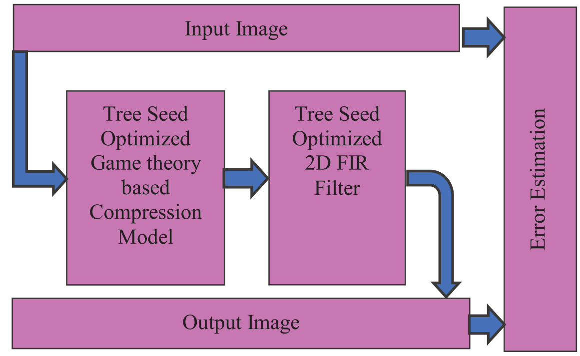

Fig. 1. General block diagram of proposed system.

3. Proposed meta-heuristic based game theory method for image compression.

Our proposed system uses an optimization algorithm in game theory based data compression method introduced by Liu et al. [8]. This system is to compress and encrypt the 2D image data.

The general block diagram of reconfigurable game theory-based data compression is shown in Fig. 1

Our proposed system mainly consists of three blocks they are

(i) Game theory-based compression
(ii) FIR filter
(iii) Error estimation

The above block diagram explains the process in data compression. The input 2D image will go through the game theory process. It consists of four processes under game theory model optimized with the Tree Seed Optimization algorithm like compression, transmission and reconstruction (decompression) to give a safer and efficient data to the end user. Then the decompressed image will be filtered by FIR filter optimized using Tree Seed Optimization algorithm to get the edge detected, Error free, noise free, redundancy less image. Finally, the reconstructed filtered image will be taken to find error estimation parameters with reference to the input image and then with that error estimation parameter values proposed method will compare with existing method to find the efficient one (Fig. 2).

3.1. Game theory model

Game theory model without optimization technique was clearly explained by Liu et al. [8]. The input image will go through four processes in this process. This method is the block-based game theory compression model, which each pixel of the image is considered as block. The first process is encryption. This encryption measure is to produce a privacy protection of image data to be compressed and transmitted to the destination. Here we use permutation encryption to permutate the images. This permutation process includes following steps.

3.1.1. Game theory-based compression model

Step 1 Divide the available input image into n blocks with the identical size (eg: 32 × 32).
Step 2 Encrypt the image by changing block and position of the pixels by generating the key using Key Derivative Function.
Step 3 The surreptitious and significant key seed will be directed to the encoder to decrypt the key.

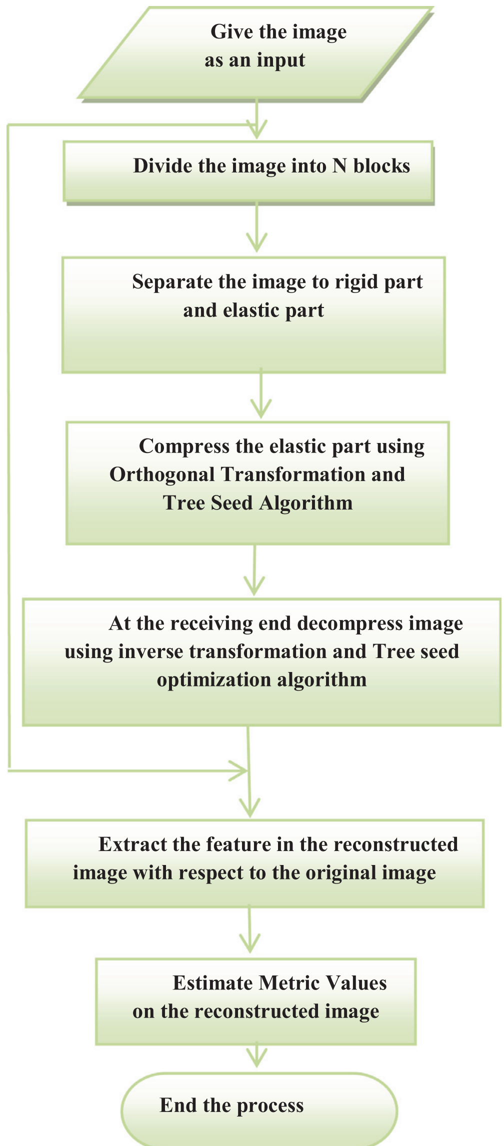

Fig. 2. Flowchart of the proposed system.

Encrypted blocks are then compressed using game theory compression algorithm. In this technique, every block will be considered as players N. These players will compete to capitalize on the non-cognitive eminence of the image adjacent to compression ratio. The player must use the strategy to regulate number of bits to characterize the trampled image beneath the constraint to increase the reconstructed picture quality. The total bit stream should not be more than $B \times R$. This can be write as

$$\sum_{i=1}^{N} b_i \leq B \times R, \tag{1}$$

Then the steps for compression are explained below:

Step 1 The scrambled block will be ideally classified into two fragments: firm and adaptable part. Individual translated block can be preserved as a vector extent of N and $\alpha \times N$ pixels are carefully chosen randomly. These pixels are held in reserve; therefore, it's is denoted as firm. While the adaptable part will be compressed and held redundant.

Step 2 Compress the elastic part of the image using orthogonal transformation with the orthogonal matrix H. The transformation coefficient is given by $O_1, O_2 \ldots O_{(1-\alpha)\ \times N}$.

$$\left[O_1, O_2 \ldots O_{(1-\alpha)\ \times N}\right] = \left[e_1, e_2, e_3, \ldots e_{(1-\alpha)} \cdot N\right] \times H, \tag{2}$$

Then the compressed image will go through reconstruction process.

Step 1 Separate the rigid and elastic pixels and denote the elastic pixels as $e'_1, e'_2, \ldots e'_{(1-\alpha)} \cdot N$.

Step 2 Calculate the coefficients

$$\left[O_1, O_2 \ldots O_{(1-\alpha)\times N}\right] = \left[e'_1, e'_2, \ldots e'_{(1-\alpha)} \cdot N\right] \times H$$

Then the process of inverse orthogonal transformation is adopted

$$\left[e''_1, e''_2, \ldots, e''_{(1-\alpha)N}\right] = \left[O''_1, O''_2, \ldots, O''_{(1-\alpha)N}\right]. H^{-1}, \tag{7}$$

The number of players 'N' and the parameter 'α' was found iteratively using the Tree Seed optimization algorithm [9]. The usage of Tree Seed algorithm becomes highly appreciable in the case of constrained optimization [10], neural network optimization [11] and image processing applications [12,13]. The TSA algorithm is illustrated below:

Step 1 The primary position of tree is placed utilizing the equation

$$T_{i,j} = L_j + r_{i,j}\left(H_j - L_j\right)$$

where L_j and H_j are the lowest and highest range of search space and $r_{i,j}$ is a random variable

Step 2 The seed value is updated using any one of the two relations

$$S_{i,j} = T_{i,j} + \alpha_{i,j}\left(B_j - T_{r,j}\right)$$

or

$$S_{i,j} = T_{i,j} + \alpha_{i,j}\left(T_{i,j} - T_{r,j}\right)$$

where $T_{i,j}$ is tree location, $T_{r,j}$ is random tree and B_j is best tree position and $\alpha_{i,j}$ is the random variable. The two update rule are used accordingly with comparison with ST and $\alpha_{i,j}$

Step 3 The best values are selected using

$$B = min\left\{f\left(T_{i,j}\right)\right\}; i = 1, 2, 3, \ldots, p, j = 1, 2, 3, \ldots, n$$

3.1.2. FIR filter

The FIR filter is used to filter the finally reconstructed image to give error free image. The error may be due to capturing the image through image sensor or while it's going through the different processes many crucial information might get lost.The FIR filter consists of three steps first consist of converting the input image in spatial domain to frequency domain using Fast Fourier Transform. Then the signal get process by the filters and the filtered signal will go through inverse FFT to translate the frequency domain filtered signal to spatial domain pixel matrix of images. The filter coefficients of FIR filter are optimized using the procedure adopted in [14,15]. This process illustrated in block diagram represented as Fig. 3.

4. Error estimation and performance metrics

The error estimation part is to calculate various metrics related to the image with respect to the input image to find the optimized compression algorithm. This metric will be calculated on the output filtered image of the proposed system and on the output images of the existing system. The various metrics used on the output images were explained below.

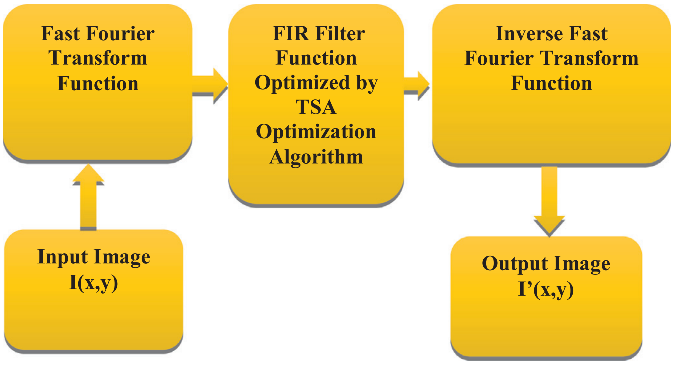

Fig. 3. Block diagram of FIR Filter process.

Fig. 4. Standard Jupiter image of JPEG algorithm.

4.1. Compression ratio

As the name implies, compression ratio cast-off the capability of the proposed compression algorithm by comparing the memory occupied by the compressed image to that of the inventive image. Greater value of compression ratio indicates the efficacy of the compression with the indicative better.

$$CR\left(i, \hat{i}\right) = \left(\frac{z\left(\hat{i}\right)}{z(i)}\right) \times 100, \tag{14}$$

where $z(\hat{i})$ and $z(i)$ represents the numbers of bits used to represent the communicated/compressed and the inventive data, respectively.

4.2. MSE and RMSE

The MSE characterizes the collective squared error among the flattened and the inventive image.

$$MSE = \frac{\sum_{M,N} [I_1(m,n) - I_2(m,n)]^2}{M * N}, \tag{15}$$

M and N are the number of rows and columns in the input images.

Fig. 5. Compressed output image of 3D-DCT compression.

RMSE is used to compare differences between two images of before compression and after compression.

$$\text{RMSE} = \text{square root (MSE)}, \tag{16}$$

4.3. PSNR ratio

PSNR is demarcated as the relation of noise over an original image and a coded/decoded image, PSNR is usually articulated in terms of logarithmic decibel (dB) scale.

$$PSNR = 10\log_{10}\left(\frac{R^2}{MSE}\right), \tag{17}$$

4.4. Bits per pixel

BPP is an absolute measure and represents the average number of bits needed to encode each image pixel information (e.g. color).

$$bpp = \frac{S_{comp}}{N_{pixels}}, \tag{18}$$

where S_{comp} denotes the size of compressed image and N_{pixels} denotes number of pixels. The resultant values obtained from calculating metrics on output images were tabulated and compared in result and discussion part [19].

5. Results and discussion

By using, the different compression methods explained above. The images of data set 1 and dataset 2 are compressed, transmitted and decompressed to find efficient technique among the existing and proposed methods. The methods are compared effectively with its capacity, computational time and performance metrics in determining the quality of compression.

5.1. Dataset 1

The dataset 1 consists of synthetic aperture radar image of the planet Jupiter. In the dataset 1 images, we used compressed

Fig. 6. Compressed output image of SR-DWT compression.

Fig. 7. Compressed output image of proposed method.

JPEG image to be compare with compression performed by 3D-DCT (3 dimensional-DCT), SR-DWT (Sub band replacement –DWT), K-means and proposed method. Fig. 4 shows the standard Jupiter image of JPEG algorithm. Figs. 5–7 shows the compressed output image using 3D-DCT SR-DWT compression and compressed output image of proposed method respectively. The better the compressing, the lower the image size. There comes an additional disadvantage of noise, high computational time, degradation of information. So there have to additional features to overcome this issue to get efficient compression. In the output images of compression methods shown above we can't find any improvement in compression with our naked eye. To find an efficient algorithm performance metrics for each output images were evaluated and compared.

Fig. 8. Input medical images used for evaluating the efficiency of the proposed method.

Fig. 9. Compressed output medical images obtained using the proposed method.

Table 1
Comparison of performance metrics for various compression methods.

Methods	Parameters	256 × 256
JPEG	Time (s)	5.981
	CR	21.09
	PSNR (dB)	39.95
	MSE (dB)	7.31
	RMSE (dB)	4.66
3D-DCT	Time (s)	6.93
	CR	16.10
	PSNR (dB)	49.29
	MSE (dB)	0.76
	RMSE (dB)	−0.93
SR-DWT	Time (s)	5.081
	CR	49.57
	PSNR (dB)	35.64
	MSE (dB)	12.68
	RMSE (dB)	6.32
Proposed	Time (s)	2.216
	CR	8.91
	PSNR (dB)	65.33
	MSE (dB)	1.32
	RMSE (dB)	1.812

Table 2
Comparison of performance metrics for medical Images using various compression methods.

Type	Parameters/ Methods	PSNR (dB)	MSE (dB)	CR	BPP
Lossy technique	DCT	67.80	0.62	6.91	0.11
	DWT	62.87	0.31	5.90	1.04
	Fractal	67.97	0.22	1.83	1.42
Lossless technique	DPCM	43.81	0.72	0.63	0.50
	Huffman	29.37	0.81	6.59	1.38
	SPHIT	35.64	0.73	2.83	0.58
	Proposed method	68.02	0.09	7.42	0.71

The proposed method is also applied for compressing the medical images. The modality chosen for evaluating the proposed methodology are Ultrasound Abdominal Images in Brightness mode configuration and Magnetic Resonance Images of Knee and Cartilage. The experimental input medical image to be used for evaluation of the proposed method is shown in Fig. 8. Fig 8(a) represents a anterior view of a human gallbladder in which the shading effects are found beyond the gallbladder, any compression scheme designed for medical applications must not disturb the intrinsic details found/present in the image as it has huge clinical implications. Fig. 8(b) shows a enlarged human gallbladder with a presence of calcification in it lower part and Fig. 8(c) represents the gallbladder in an folded stage. On application of data compression techniques, the intrinsic details were not disturbed, which supports the fact that frequency components in the images such as edges and boundaries are not destructed during the process of compression (Table 1).

Thus, the proposed methodology can be used as state-of-the-art method for compressing medical images that aids in faster transmission and reception of medical data without destruction thus enhancing the segmentation process that proceeds further [12,16]. Output images for the corresponding input images in Fig. 9(a-c) is shown in Fig. 9 and the performance evaluation metrics that are used in assessment are reflected in Table 2. The proposed method can also be used in compression of one-dimensional signals [17,18].

6. Conclusion

Comparing various method of data compression, the proposed system shows high compression ratio values and low peak signal to noise ratio and mean square error than obsolete lossy and lossless compression algorithms. Our proposed system is a lossless algorithm and in the second process of proposed algorithm, the filters has used to improve the quality of the images by eliminating errors, noises, reducing redundancy and recovering every information in the original image. Thus, with result of comparison, Reconfigurable FIR filter-based Game theory Data compression is proved as an efficient one.

References

[1] S. Kim, et al., Increasing network lifetime using data compression in wireless sensor networks with energy harvesting, Int. J. Distrib. Sensor Netw. 13 (1) (2017) 1550147716689682.

[2] J.M. Yi, E.J. Oh, D.K. Noh, I. Yoon, Energy-aware data compression and transmission range control for energy-harvesting wireless sensor networks, Int. J. Distrib. Sensor Netw. 13 (4) (2017).

[3] D.E. Goldberg, Genetic Algorithms in Search, Optimization and Machine learning, Addison-Wesley, New York, 1998.

[4] J. Yen, J.C. Liao, B. Lee, D. Randolph, A hybrid approach to modeling metabolic systems using a genetic algorithm and simplex method, IEEE Trans. Syst. Man Cybern. Part B 28 (1998) 173–191.

[5] R.C. Eberhart, J. Kennedy, A new optimizer using particle swarm theory, in: Proceedings of the Sixth International Symposium on Micro Machine and Human Science, Nagoya, Japan, 1995, pp. 39–43; J. Kennedy, R.C. Eberhart, Particle swarm optimization, in: Proc. IEEE Int'l Conf. Neural Networks, Piscataway, NJ, USA, 1995, pp. 1942–1948.

[6] S.F. Fan, E. Zahara, Hybrid simplex search and particle swarm optimization for unconstrained optimization problems, Eur. J. Oper. Res 181 (2007) 527–548.

[7] M. Wu, L. Tan, N. Xiong, Data Prediction, Compression, and Recovery in Clustered Wireless Sensor Networks for Environmental Monitoring Applications, Elsevier Inc, 2015.

[8] S. Liu, A. Paul, G. Zhang, G. Jeon, A game theory-based block image compression method in encryption domain, J. Supercomput. 71 (9) (2015) 3353–3372.

[9] M.S. Kiran, TSA: tree-seed algorithm for continuous optimization, Expert Syst. Appl. 42 (19) (2015) 6686–6698.

[10] M.S. Kıran, An implementation of tree-seed algorithm (TSA) for constrained optimization, in: Intelligent and Evolutionary Systems, Springer, Cham, 2016, pp. 189–197.

[11] V. Muneeswaran, M.P. Rajasekaran, Performance evaluation of radial basis function networks based on tree seed algorithm, in: 2016 International Conference on Circuit, Power and Computing Technologies (ICCPCT), IEEE, 2016, March, pp. 1–4.

[12] V. Muneeswaran, M.P. Rajasekaran, Gallbladder shape estimation using tree-seed optimization tuned radial basis function network for assessment of acute cholecystitis, in: Intelligent Engineering Informatics, Singapore, Springer, 2018, pp. 229–239.

[13] V. Muneeswaran, M.P. Rajasekaran, Local contrast regularized contrast limited adaptive histogram equalization using tree seed algorithm—an aid for mammogram images enhancement, in: Smart Intelligent Computing and Applications, Singapore, Springer, 2019, pp. 693–701.

[14] V. Muneeswaran, M.P. Rajasekaran, Analysis of particle swarm optimization based 2D FIR filter for reduction of additive and multiplicative noise in images, in: International Conference on Theoretical Computer Science and Discrete Mathematics, Cham, Springer, 2016, December, pp. 165–174.

[15] V. Muneeswaran, M.P. Rajasekaran, Beltrami-regularized denoising filter based on tree seed optimization algorithm: an ultrasound image application, in: International Conference on Information and Communication Technology for Intelligent Systems, Cham, Springer, 2017, March, pp. 449–457.

[16] V. Muneeswaran, M.P. Rajasekaran, Automatic segmentation of gallbladder using bio-inspired algorithm based on a spider web construction model, J. Supercomput. (2018) 1–26.

[17] Li Junwei, S. Ramkumar, G. Emayavaramban, D. Franklin vinod, M. Thilagaraj, V. Muneeswaran, M. Pallikonda Rajasekaran, V. Venkatraman, A.F. Hussein, Brain computer interface for neurodegenerative person using electroencephalogram, IEEE Access 7 (1) (2019) 2439–2452.

[18] G. Jialu, S. Ramkumar, G. Emayavaramban, M. Thilagaraj, V. Muneeswaran, M. Pallikonda Rajasekaran, A.F. Hussein, "Offline analysis for designing electrooculogram based human computer interface control for paralyzed patients", IEEE Access, Vol. 6(1), pp. 79151–79161.

[19] U.R. Achary, Y. Hagiwara, S.N. Deshpande, S. Suren, J.E.W. Koh, N. Arunkumar, E.J. Ciaccio, C.M. Lim, Characterization of focal EEG signals: a review, Future Gener. Comput. Syst. 91 (2019) 290–299.