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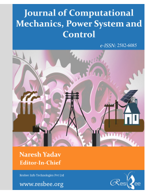

Compressed Sensing Reconstruction Approach using Self Adaptive Butterfly Optimization Algorithm for Bio-Signals

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Abstract: Various applications require competent reprocessing and data representation in signal processing. To efficiently represent the signal the compression is represented as a standard technique. Nowadays, numerous novel approaches are adopted for compression at the sensing level. Compressed Sensing (CS) is represented as a growing domain that is based on revelation, and it gathers a sparse signal linear projection such as sufficient information for reconstruction. Using the CS, signal sampling is performed at a rate under the Nyquist sampling rate when relying on signals sparsity. In addition, original signal reconstruction from a few compressive measurements could be authentically used by CS deviated reconstruction approaches. The major objective of this work is to use a novel CS approach to reconstruct signals in biomedical data. Therefore, by performing three phases the signal can be compressed such as measurement matrix design, signal reconstruction, and signal compression. Here, the compression phase involves a novel working technique that follows three operations such as the transformation of signal, Θ evaluation and normalization. In this work, the Haar wavelet function is exploited for the evaluation of the theta. Furthermore, this work assures the superiority of the developed model by using the optimization process with the estimation process. The Haar wavelet function vector coefficient is optimally chosen by exploiting a novel optimization approach named Self Adaptive Butterfly Optimization Algorithm (BOA) algorithm. At last, the adopted model performance is evaluated with the conventional techniques and the outcomes reveal the betterment of the proposed model.

Keywords: Compression, Haar Wavelet Function, Normalization, Nyquist Sampling Rate, Reconstruction, Signal Processing.

Nomenclature

Abbreviations	Descriptions
IoT	Internet of Things
MCU	Microcontroller Unit
BS	Base Station
EEG	electroencephalographic
CS	Compressive sensing
QoS	Quality of Service
WBSNs	Wireless Body Sensor Networks
CSBS	CS- based spatiotemporal data fusion
ASIC	Application-Specific Integrated Circuit
PMU	Power Management Unit
RF	Radio Frequency
AIC	Analog-to-Information Converter

1. Introduction

In current days, numerous studies are conducted for IoT development on the basis of the associated health fields [1]. Aforesaid fields are authorized using various wearable battery-driven sensors which gather as well as record diverse important signs for an extensive period. By exploiting the minimum power communication protocols the gathered data is transferred to a close by the gateway. Subsequently, the gateway presents the data to the host cloud. Several data analysis, as well as signal processing methods, is carried out to present computer-aided medical assistance at the cloud level. Nevertheless, these fields' performance is bottlenecked mostly by the restricted wearable sensors lifetime. Hence, searching data compression approaches can minimize the amount of data transmission from sensors to gateway; therefore extending the lifetime of the sensor. Moreover, the theory of CS has been revealed to be a

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reliable compression approach that present the optimal trade-off among the quality of reconstruction as well as minimum-power utilization evaluated with the existing compression techniques like segmentation else transform coding as well as labeling approaches [2].

The CS rose as a technique that can present whole signal information if there is a diminutive set of signal coefficients obtainable. Hence, this technique observed numerous applications, and one among those in the biomedical reconstruction of the signal. It is significant that to highlight the adequate amount of examples to recover the signals in the CS case which is lesser than the one stated in the Nyquist-Shannon theorem. For signal compression as well as acquisition, the CS model is shown which an energy effectual model appropriate is for WBSN based embedded biomedical monitors. The main contribution of CS is to indicate the information substance of the input signal by exploiting small digital words regarding the Nyquist rate sampling. From a set of distributed sensors as well as compressed, the embedded signals are obtained with minimum energy utilization to change the communication restraints such as energy as well as bandwidth among the BS as well as sensors, generally via the gateways [3].

Although, in numerous areas namely medical data, the CS increases in development, but it has few restrictions or confronts. The conventional CS compressed the data before the transmissions as well as therefore the resources are exhausted because of the large number of data samples are avoided during the compression. The digital CS has few restrictions so the compression approach might often be hard and therefore it requires an important computational power as well as memory. The conventional CS possesses the main disadvantage on the processing execution as well as the transmission of the data in signal compression/reconstruction. Additionally, terms of the sparse solution errors in the ECG modeling which are produced using the Cosine kernel as well as Gaussian functions are compensated using the CS technique. The conventional CS approach that is modeled on the biomedical hardware is completely concentrated on signal reconstruction effectually using either approach that efficiently identifies the dictionary learning else the sparsest coefficient [5].

The major contribution of this work is to present a novel approach on the basis of compressed sensing for the reconstruction of signals in biomedical information. The signal compression is performed by exploiting three stages namely, signal compression, reconstruction of the signal, and stable Measurement matrix. Furthermore, the signal compression phase is subcategorized into Θ evaluation, transformation and normalization. The Haar wavelet matrix function is exploited to estimate Θ . In addition, to choose the coefficient of optimal vector in the Haar wavelet function, the optimization model is exploited. Therefore, the adopted self-adaptive BOA technique is exploited for optimal selection.

2. Literature Review

In 2020, C.H. Pimentel-Romero et al [1], presented a serious study regarding the advancement of a few CS adaptations to recognize the advantages as well as constraints of each of them in the sensing phase. Moreover, a novel model was presented (Nearly Orthogonal Rakeness-based CS), which aspires to surmount restricts of CS adaptations enfolded in this paper. After the intensive numerical experimentations on EEG signals and synthetic signals, the adopted model performs better than the conventional techniques regarding the compression ability needed to attain a target QoS.

In 2018, LEI LI et al [2], worked on a new CSBS based data fusion technique to synthesize such high-spatiotemporal resolution images. A minimum-spatial resolution remote sensing image was performed as a sampling of the maximum-spatial resolution image with CSBS. In the spatial domain of images, the down-sampling was designed as a matrix of CS measurement in CSBS. In addition, continuity constraints were developed into the CSBS object function to reconstruct the CS in the temporal domain. In order to improve the data intrinsic features, images were segmented into numerous little patches and clustered into numerous groups through K-means. Dictionary training, identification of measurement matrix, as well as prediction of high-resolution were performed group-by-group.

In 2020, Dr. P.T. Kalaivaani and Dr. Raja Krishnamoorthy [3], worked on an ASIC of WBSNs, which was exploited to cover in as a get-together for medical employment. The adopted WBSN consists of novel modeled sensor interface that were integrated by contact ports, passive RF receiver, low-power MCU, a PMU, wireless transistor control, and minimum power harvesting capacity comprise.

In 2016, Daniele Bortolotti et al [4], worked on the WBSN to attain as well as process biomedical signals, for example, ECG, transfer them to the WBSN gateway. Even though they exhibit diverse autonomy needs (weeks vs. days) both gatewaysa , as well as the bio-sensing node, was battery-powered devices. The rakeness-based CS was exhibited to perform better conventional CS and attains a superior compression for a similar quality level, thus reducing the costs of transmission in the node. Nevertheless, numerous studies focused on node efficiency, avoiding the energy cost of the CS decoder. Here, the cost of energy, as well as real-time reconstruction feasibility on the gateway, was evaluated, by taking into consideration of diverse signal reconstruction approaches.

In 2016, Fabio Pareschi et al [5], reported the model and execution of an AIC based on the CS. In CMOS technology, the system was comprehended and aims the biosignals acquisition with Nyquist frequency equipped. In order to increase the performance as well as minimize the hardware complexity, co-model hardware coupled with the reconstruction as well as acquisition approaches.

3. Proposed Signal Reconstruction Model

Consider the continuous real-valued input signal as A. In $\Re^N$ any signal representation regarding $N \times 1$ vector is $\{\psi_i\}_{i=1}^{N}$. Let us represent an essential as orthonormal. $\Psi := [\psi_1|\psi_2|.....|\psi_N]$ represent the $N \times N$ basis matrix formation, by stacking vectors $\{\psi_i\}$ as columns. The formulation of any signal is represented in eq. (1), wherein, S represents the column vector $N \times 1$ of weighting coefficient, $S_i = \langle z, \psi_i \rangle = \psi_i^{Tx} A$ and Tx represents the hermitian transpose operation. S and A represents the similar signal's equal illustration, with A in the time domain as well as S in the ψ_i domain.

$$A = \sum_{i=1}^{N} S_i \psi_i \text{ or } A = \Psi S \quad (1)$$

The input signal undergoes 2 phases such as stable measurement matrix, signal compression as well as signal reconstruction. Fig 1 illustrates an schematic diagram of the adopted signal reconstruction model.

3.1 Stable Measurement Matrix

At first, the data acquisition systems measurement side is designed which is based on the Φ matrix. The P measurement is the important contribution from wherein length- N signal z is stably reconstructed otherwise constantly its S sparse coefficient vector. In z, the reconstruction is not performed probably while the measurement procedure affects the information. In general, the process of measurement is stated in linear nature by exploiting the matrices Ψ as well as Φ. Based on eq. (2), the non-linear algebra issue is stated by resolving S with υ as well as the solution basically performed unclear using the simpler formulations which are unidentified with P<N.

Although, M -sparsity security is the initial priority. The linear integration of M columns of Θ is referred to as measurement vector v which is equal to $S_i \neq 0$. A linear formulation system $P \times M$ is created to solve the non-zero entries. Furthermore, P represents the count of formulations that exceed or are equivalent to M that is the amount of unknown. To ensure the good conditions of $P \times M$ adequate and essential conditions were performed. Therefore, eq. (2) represents the stable inverse which is activated for vec any vector which distributes the sane non-zero entries M for some $\in > 0$. It is described as a particular length M -sparse vector by matrix Θ must be conserved.

$$1 - \in \leq \frac{\|\Theta vec\|_2}{\|vec\|_2} \leq 1 + \in \quad (2)$$

Almost, the M nonzero entries position in S is unknown. For both M -sparse as well as compressible signals the stable inverse pretenses and adequate circumstance are for Θ to induce (3) for a random vec 3M -sparse vector and it is stated as RIP.

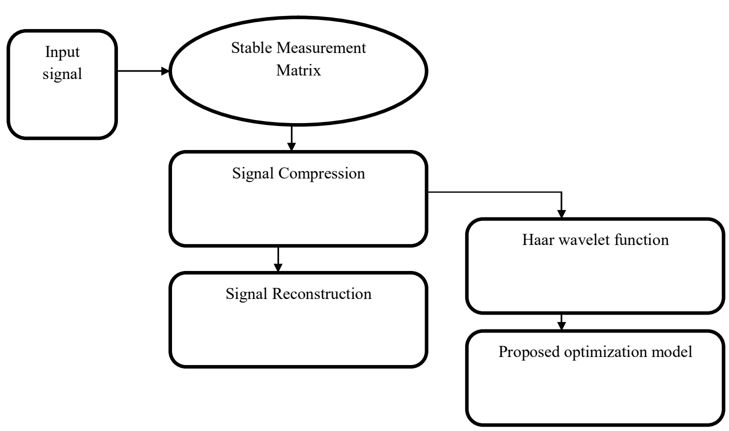


Fig.1. *Schematic diagram of the adopted signal reconstruction model*

Another technique that is exploited to assure the measurement matrix Φ is incoherent to enhance the stability in the sense which vector $\{\phi_j\}$ with and without sparsifying basis is shown as $\{\psi_i\}$ vector conversely. Using the Fourier uncertainty law, coherence is produced instantly. $\{\phi_j\}$Is performed by the delta spikes as well as the $\{\psi_i\}$ is performed by the Fourier sinusoids.

The arbitrary matrix Φ is chosen to evade these problems in CS. Here, two attractive, as well as helpful properties, are imposed using the Gaussian Φ. At first, on basis of $\Psi = 1$ of delta spikes with maximum probability possesses Φ incoherent, due to complete N spikes is obtained to demonstrate each row of Φ. The $P \times N$ iid Gaussian matrix $\Theta = \Phi I = \Phi$ must possess the RIP with high probability exploiting the measure arguments concentration, if $P \geq conM\log(N/M)$ with *con* a few constant. Therefore, the M - sparse and length- N, compressible is recuperate.

3.2 Signal Compression Scheme for the Adopted Technique

The signal compression process starts if the measurement matrix evaluation is performed. Moreover, the compression of the signal is performed in three stages and that are stated as below:

A. Signal Transformation

The transformation of the signal continues by preceding the measurement matrix. The signal is condensed directly by widespread data acquisition technique as a compressed [6] indication without moving through the mediator stage of carrying N samples.

Suppose that the majority general process of linear measurement that computes $P \times N$ inner products amid A and a vectors congregation $\{\phi_j\}_{j=1}^{p}$ as in $v_j = \langle A, \phi_j \rangle$. Within the measurement, vector ϕ_j^{Tx} stacking the measurement v_j and within a $P \times N$ matrix Φ, $P \times 1$ vector v as rows and replaced in Eq. (1) and it is stated in Eq. (3).

$$v = \Phi A = \Phi \psi S = \Theta S \tag{3}$$

B. Θ Evaluation

As a result, Φ represents the arbitrary Gaussian measurements, which is very common in the logic and Θ possesses RIP with maximum probability for each probable and eq. (4) states the Θ value.

$$\Theta := \Phi\Psi \tag{4}$$

Wherein Θ represents the $P \times N$ matrix. Here, Ψ evaluation is performed by exploiting the Haar wavelet function. Further, choosing the best vector coefficients in the Haar wavelet function is considered the most important objective of this paper. It is highly concentrated due to the whole responsibility of the performance rate based on the function. By using the novel optimization approach, the vector coefficient V is optimally chosen.

C. Signal Normalization Process

If the optimal vector coefficient is defined by the optimal selection, then impulsive Θ turns into the optimal Θ^* thus the process turns out to be refined. By means of Θ^* the normalization process is followed. Reality, Normalization represents the scaling and the signals in the same level. Here, based on the equation stated in Eq. (5), the normalization is subjected, wherein v represents the compressed signal.

$$norm = p^{-1}(\Theta^*)v \tag{5}$$

3.3 Haar Wavelet Function for Processing of Ψ

The eq. (6) and (7) represent the Haar wavelets [7] orthogonal basis $\{g_n(t)\}$ for the Hilbert space $X_2[0,1]$. Each Haar wavelet g_n obtains the assistance $(2^{-c}l, 2^{-c}(l+1))$, therefore in the interval [0, 1], it is "0". Furthermore, the Haar wavelet turns out to be highly localized while there is a raise in n. Therefore, by $\{g_n(t)\}$ the local basis is produced.

As per eq. (8), any function $f(t) \in X_2(0,1)$ can be expanded in the Haar series. Moreover, eq. (9) represents the coefficient of Haar $co_i, i = 0,1,2,....,$. It is computed with the intention that integral square error ε is minimized as well as it is stated in Eq. (10). The Haar wavelet orthogonal property is exhibited in eq. (11).

$$g_n(t) = g_1(2^c t - l), n = 2^c + l, c \geq 0, 0 \leq l \leq 2^c \tag{6}$$

Wherein

$$g_0(t) = 1, 0 \leq t < 1, g_1(t) = \begin{cases} 1, & 0 \leq t < 0.5 \\ -1, & 0.5 \leq t < 1 \end{cases} \tag{7}$$

$$f(t)=\sum_{i=0}^{\infty} co_i g_i(t),\ n=2^c+1,\ c\geq 0,\ 0\leq 1\leq 2^c \tag{8}$$

$$co_i=2^c\int_0^1 f(t)g_i(t)dt \tag{9}$$

$$\varepsilon=\int_0^1\left[f(t)-\sum_{i=0}^{q-1} co_i g_i(t)\right]^2 dt, q=2^c, c\in\{0\}\cup N \tag{10}$$

$$\int_0^1 g_1(t)g_i(t)dt=\begin{cases}2^{-c}, b=1\\ 0, \quad b\neq 1\end{cases} \tag{11}$$

The infinite terms of numbers are involved by the eq. (7) series. The summation might be halted subsequent to q terms, if $f(t)$ is piecewise constant or estimated to piecewise constant and it is stated in Eq. (12), where $q=2^c$, the transportation id indicated as Tp, the truncated summation is represented as $\hat{f}(t)$. Eq. (13) defines the Haar coefficient vector V_q and Eq. (14) defines the Haar function vector $F_q(t)$, correspondingly. By taking into consideration of the collocation points which are stated in Eq. (15), the eq. (16) defines the m-square Haar matrix $\Phi_{q\times q}$. As a result, $\hat{f}_q$ as stated in Eq. (17), $\Phi_{q\times q}$ represents the m-square Haar matrix, which is an invertible matrix, and Haar coefficient vector V_q^{Tp} is represented in eq. (18)

$$f(t)\approx\sum_{i=0}^{q-1} co_i g_i(t)=V_q^{Tp}F_q(t)=\hat{f}(t) \tag{12}$$

$$V_q \triangleq [co_0, co_1, \ldots\ldots, co_{q-1}]^{Tp} \tag{13}$$

$$F_q(t)\triangleq[g_0(t), g_1(t), \ldots\ldots, g_{q-1}(t)]^{Tp} \tag{14}$$

$$t_b=\frac{(2b-1)}{2q}, b=1,2,\ldots\ldots, q \tag{15}$$

$$\Phi_{q\times q}\triangleq\left[F_q\left(\frac{1}{2q}\right)\ F_q\left(\frac{3}{2q}\right)\ \ldots\ldots\ F_q\left(\frac{2q-1}{2q}\right)\right] \tag{16}$$

$$\hat{F}_q=\left[\hat{f}\left(\frac{1}{2q}\right)\ \hat{f}\left(\frac{3}{2q}\right)\ \ldots\ldots\ \hat{f}\left(\frac{2q-1}{2q}\right)\right]=V_q^{Tp}\Phi_{q\times q} \tag{17}$$

$$V_q^{Tp}=\hat{f}_q\Phi_{q\times q}^{-1} \tag{18}$$

4. Reconstruction of Signal stage using Adopted technique

Subsequent to the normalization process completion, compressed signal experiences the reconstruction procedure, as well as ensuing output signals, is attained. The reconstruction process is stated as below:

Using RIP, the theoretical guarantee is presented that is a compressible signal else M -sparse is stated completely by P measurement in v, yet the process of recovery is not described. In eq. (2), due to $P<N$ there might be numerous infinite S' which convenes $\Theta S'=v$ and it relies on $(N-P)$-dimensional hyperplane $\Gamma:=\Lambda(\Theta)+S$ associated with the null space $\Lambda(\Theta)$ of Θ transformed into true sparse solution S. This is because of any vector l in null space, if $\Theta S=v$ subsequently $\Theta(S+l)=v$. Therefore, the major contribution is to ascertain S, which represents the signal sparse coefficient vector in converted null space [9].

By $(\|S\|_r)^r=\sum_{i=1}^{N}|S_i|^r$ recognizing the L_r norm of the vector S. The L_0 norm is attained while $r=0$, that computes the amount of S non-zero entries, hence, M -sparse vector pretenses L_0 norm M.

Minimum L_2 ***norm reconstruction:*** In the traditional technique the least square is exploited to resolve the inverse issue that is the vector is chosen in transformed null space Γ with minimum L_2 norm energy as well as is stated in Eq. (19). In addition, it suitable closed-form solution is there $\hat{S}=\Theta^{Tr}(\Theta\Theta^{Tr})^{-1}v$. The L_2 minimization was not ascertained when the vector S is M -sparse. A non-sparse $\hat{S}$ is seen as a substitute with an abundance of ringing.

$$\hat{S} = \arg\min \|S'\|_2 \text{ such that } \Theta S' = v \tag{19}$$

Minimum L_0 ***norm reconstruction:*** Due to the signal sparsity bon-refection using L_2 norm in Eq. (4), and the eq. (20) represents a logical alternate solution to search the sparsest vector in translated null space Γ is performed. Moreover, using the optimization it is exhibited with $P = M + 1$ iid Gaussian measurements, the M-sparse signal precisely with maximum probability is improved. Unfortunately, to resolve the numerically unstable as well as an NP-complete issue, the Eq. (5) is hard. This issue requires complete details of whole $\binom{M}{N}$ probability integrations to locate the non-zero entities in S.

$$\hat{S} = \arg\min \|S'\|_0 \text{ such that } \Theta S' = v \tag{20}$$

Minimum L_1 ***norm reconstruction:*** The CS is given as from $P \geq cM \log(N/M)$ iid Gaussian measurements. Using L_1 optimization, the M-sparse vector, as well as intimately approximate compressible vectors, are renovated stably with great option and it is indicated in eq. (21). Here the computational complexity is represented as $O(N)^3$. The CS data acquisition system includes arbitrary measurements to summarize based on Φ is pursued using the reconstruction of linear programming to attain z. At last, the reconstructed signal $\hat{R}$ is attained.

$$\hat{S} = \arg\min \|S'\|_1 \text{ such that } \Theta S' = v \tag{21}$$

4.1Objective Model

The major contribution of this paper lies in the objective of minimization of error throughout the training stage. It is used by computing the error between the original signal A as well as the reconstructed signal $\hat{R}$ and it is exhibited in Eq. (22). In reality, the error must be least and thus obtain enhanced outcomes.

$$obj = \min(A - \hat{R}) \tag{22}$$

4.2 Proposed Self adaptive BOA algorithm

Following artificial experiences [8], the first sensory modality coefficient c and the first power exponent coefficient of the fragrance coefficients are chosen in the conventional BOA [10]. Numerous simulations are requiring previous to the preliminary c and the preliminary a is chosen. The arbitrary count r very much affects the searching effectiveness in the search phase. While r is chosen too high, too great arbitrary parameter creates that BOA has large randomization, hence, it is simple to jump from one area to one more area that subjects to minimum searching accurateness and minimum searching effectiveness.

In BOA, to attain superior optimization outcomes an enhanced BOA model is developed which is based on the self-adaptive approach, as well as the adopted approach called self-adaptive BOA. In order to eradicate the stochastic behavior as well as fragrance coefficients blindness in BOA, the novel fragrance coefficient adds a self-adaption model.

Eq. (23) is used to update the new fragrance coefficient.

$$f^{new} = u \times \left(1 - \frac{t}{T}\right) \tag{23}$$

wherein T represents maximum iteration and t represents the current iteration. u follows the conventional normal distribution by exploiting the computation model to generate a more balanced distribution of fragrance.

The perfect optimization procedure involves the maximum searching capability of early on stage as well as great precision the capability of later phase.

The novel location updating formulation in the global search stage can be stated as below.

$$x_i^{t+1} = g^* + \left(x_i^t - g^*\right) \times f^{new} \tag{24}$$

wherein g^* *indicates* the optimal location in the searching space.

The proposed model exploits the average value of the optimal location as well as the worst location in each iteration to update the next location of each butterfly for the local search phase that can minimize the blindness of arbitrarily choosing two butterflies. The new location updating formulation in local search stage can be stated as below:

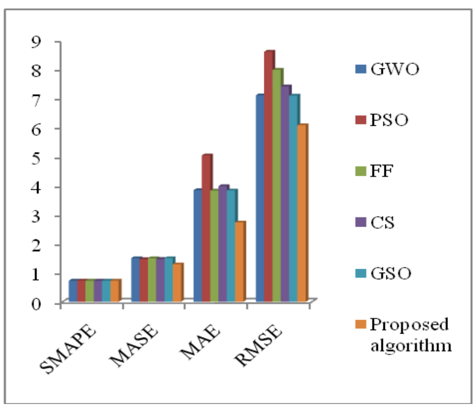
$$x_i^{t+1} = \frac{1}{2} g^* \times \left(g^* + w^*\right) \times f^{new} \tag{25}$$

wherein w^* represents the worst location in searching space.

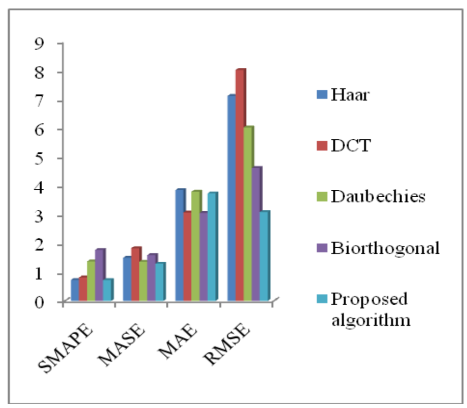
5. Result and Discussion

In this section, the experimental analysis of the adopted model was demonstrated. Here, the ECG, as well as EEG signals, were exploited as the input that was gathered from "https://physionet.org/physiobank/database/edb/, https://physionet.org/physiobank/database/aami-ec13/, https://physionet.org/physiobank/database/motion-artifact/, https://physionet.org/physiobank/database/mssvepdb/dataset1/ on October 2018". Here, the adopted self adaptive BOA model performance was evaluated over existing techniques regarding the error performance. Moreover, the performance analysis was carried out in two phases regarding the wavelet function as well as optimization approaches. For statistical analysis were Haar, Daubechies, DCT, as well as Biorthogonal, wavelet functions were exploited. The performance evaluation on error analysis was used in the metrics like "Symmetric Mean Absolute Percentage Error (SMAPE), Mean Absolute Scaled Error (MASE), Mean Absolute Error (MAE), Root-Mean-Square Error (RMSE). Here, the proposed model was compared with the conventional models such as Grey Wolf Optimization (GWO), Particle Swarm Optimization (PSO), Firefly (FF), Crow Search (CS) and Group Search Optimization (GSO) algorithms.

The performance analysis of error for EEG as well as ECG signal in optimization algorithms and different wavelets for the adopted and existing techniques is demonstrated in fig 2 and 3. In Fig 2, the proposed model is 22% superior to GWO, 12% superior to PSO, 25% superior to FF, 18% superior to CS, and 292% superior to GOA with respect to the SMAPE. In Fig 3, the proposed model is 13% superior to GWO, 18% superior to PSO, 15% superior to FF, and 19% superior to CS for MASE. The overall analysis exhibits that the error is minimum while comparing with the conventional wavelets.

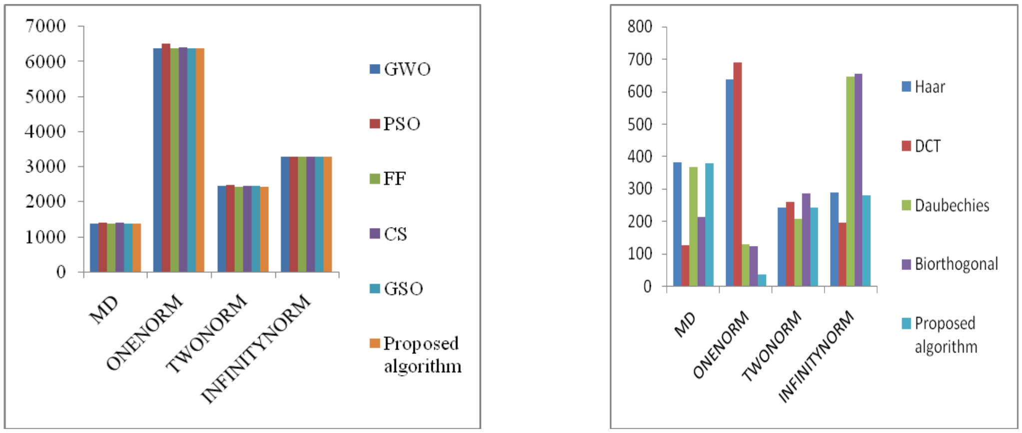


(a)



(b)

Fig.2. *Performance analysis for proposed and conventional models (a) EEG signal (b) ECG signal for SMAPE, MASE, MAE and RMSE*



(a) (b)

Fig.3. *Performance analysis (a) EEG signal (b) ECG signal for MD, One norm, two norms, and infinity norm*

6. Conclusion

A novel compressive sensing approach was presented in this work for the reconstruction of the signal that was in bio-medical data. The signal compression was carried out in three stages like stable measurement, Signal compression, and reconstruction of the signal. Furthermore, compression of the signal was performed in three classifications such as $\Theta_{evaluation}$, transformation, as well as normalization. Here, for the theta evaluation, the Haar Wavelet Matrix function was exploited. In this work, the optimization model was employed with the evaluation process that was the main objective model. Therefore, a novel optimization approach was exploited named self-adaptive BOA to choose optimally the Haar wavelet function vector coefficient. Finally, the adopted technique performance was evaluated with the conventional techniques and the analysis of the outcomes was performed.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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