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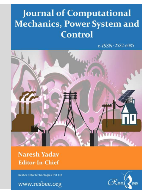

Compressed Sensing Reconstruction Model using Self-adaptive Salp Swarm Algorithm for Biosignals

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Abstract: Numerous applications require effectual data representation as well as reprocessing in signal processing. For effectual signal representation, the compression technique is exploited which is considered as the standard model. Nowadays, numerous novel approaches are adopted at the sensing level for compression. One of the growing domains is compressed sensing which is based on the revelation that is a minimum congregation of a linear projection of sparse signal's such as sufficient information for renovation. By means of Compressed Sensing, the signal sampling is allowed at a rate under the rate of Nyquist sampling when relies on the sparsity of the signal. Moreover, the original signal reconstruction from few compressive measurements is authentically used for the deviated reconstruction Compressed Sensing approaches. The main objective of this work is to propose a novel compressive sensing technique for signal reconstruction in biomedical data. Hence, using three phases the signal is compressed such as stable measurement matrix design, signal compression as well as reconstruction of the signal. Here, the compression phase involves a novel operational technique that comes first with three operations. Moreover, here, evaluation of Θ and normalization as well as signal transformation is performed. This work exploits the Haar wavelet matrix model to calculate the theta (Θ) value. Furthermore, this work assures the superiority of the developed model exploiting the optimization idea with the assessment process. By exploiting a novel optimization method named Self adaptive Salp Swarm Algorithm (SSA), is to optimally select the Haar wavelet function vector coefficient.

Keywords: Bio-Medical Data, Compression Sensing,HaarWavelet, Normalization, Signal.

Nomenclature

Abbreviations	Descriptions
WBAN	Wireless Body Area Network
MECG	Multi-Channel Electrocardiogram
CS	Compressed Sensing
RIP	Restricted Isometry Property
LSD-OMP	Least Support Denoising-Orthogonal Matching Pursuit
OSOS	Optimum Sparsity Order Selection
ADMM	Alternating Direction Method of Multipliers
BSBL	Bayesian learning
ECG	Electrocardiogram

1. Introduction

In numerous scenarios, for accurate diagnosis, it is very necessary to supervising the ECG signals for a long duration through multiple leads, hence the dimension of the data rises significantly [1]. For such high dimensional data, the processing, as well as storage, is neither competent nor sensible. Conversely, by means of the advancement of e-health technology, it is at present probable to supervise as well as to measure the cardiac signals online through wearable wireless sensors as well as transfer these signals to telehealth providers. Additionally, the large number of data transmissions is not effective. As a result, processing, acquisition, storage, integration, transmission as well as ECG signal retrieval plays a significant role in up-to-date applications. Hence, in an up-to-date health care system to minimize the cost as well as maximize the signal processing systems increases the compression of ECG is considered as a significant factor. To minimize the ECG signals dimension it is attractive when the precious diagnostic information preservation in recorded ECGs [2].

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In the signal processing method, the CS is considered as a rising which set up the sparse signals acquisition in a diminutive set of linear projections [3]. The measurement vector size is lesser than the original signal nevertheless it still comprises the needed information for precise recovery of signal. CS uses the structure of signal and signal acquisition enables at a sub-Nyquist rate, directly outputting the signal compressed form. As a result, the encoding of signal turns out to be reasonably easy as well as energy effectual in the CS model. In numerous resource-constrained applications, the CS features are exploited. Here, CS presents possible solutions to a few of the main confronts like computational complexity, the efficiency of energy as well as memory utilization, and so on. To minimize the energy utilization as well as system complexity, WBAN- set up mobile ECG telemonitoring is considered as the main application wherein CS is productively exploited. CS-based WBAN applications employ ECG signals inherent sparse nature neither in the time domain, nor wavelet domain for energy-effectual data minimization. Although existing wavelet-based ECG compression techniques possess advanced data compression ability to the CS-based techniques, their data encoding cost is considerably superior. Due to this, CS-based approaches are considered an effective substitute to wavelet-based techniques for WBAN applications. To extract the ECG signal spatial correlation, there are few more CS-based techniques are presented. For instance, the reconstruction signal of ECG formulation was together rephrased to attain the acceptable small reconstruction error as well as compression rate by replacing the conventional 11 norms by means o 11/12 norm [4].

In previous research, the probability of CS for minimum complexity as well as energy effectual data minimization in the WBAN-enabled ECG monitoring was quantified as well as established. Also, numerous models were considered for the CS-based reconstruction system as well as data acquisition. For the fetal ECG telemonitoring applications, a block sparse BSBL-based technique was used. Nowadays, few approaches using prior knowledge regarding ECG signals in the conventional reconstruction of CS techniques were exhibited with enhanced outcomes. In some studies, for the single-channel ECG signals, the telemonitoring systems referred are restricted. Nevertheless, by cardiologists for complete diagnosis, MECG signals are chosen [9], [10].

The main contribution of this research is to propose a novel approach based on the compressive signal for the reconstruction of signal in bio-medical data. The signal compression is performed by exploiting 3 stages namely compression of the signal, measurement of the stable, matrix as well as reconstruction of the signal. Furthermore, the compression of the signal phase is categorized into Θ evaluation, transformation as well as normalization. By exploiting the Haar wavelet matrix function value of Θ is estimated. Therefore, this work uses the other wavelets as well as Haar wavelets. Additionally, in this work, the Self-adaptive SSA model is proposed to select the Haar wavelet function coefficient optimally.

2. Literature Review

In 2018, TohidYousefiRezaii et al [1], developed a novel technique known as OSOS which computes the sparsity order by reducing the restoration error. Moreover, they had exhibited that the basis matrix on the basis of the increased Cosine kernel possesses high effectuality in compression with Gaussian basis matrices. The OSOS basics method was a robust model to scrutiny noise. The experimentation outcomes assure the effectiveness of the adopted technique regarding compression ratio.

In 2020, Javad Afshar Jahanshahi et al [2], exploited the Kronecker sparsifying bases to use the Spatio-temporal correlations of the MECG signals to enhance the compression of the signal broadcast by the sensors. Moreover, by means of low constraints, a compressed sensing-based technique was developed for effectual reconstruction as well as data acquisition. Particularly, an optimization formulation was developed, which comprises two constraints that were explained. Moreover, the sparsity constraint was developed via the 11 norm minimization. Subsequently, an effectual, as well as robust ADMM on the basis of technique, was proposed for the MECG signals reconstruction which resolves the ensuing optimization issue further efficiently.

In 2015, IsraaTawfic and SemaKayhan [3], presented two techniques using noise presence as well as absence, these techniques were LSD-OMP and LS-OMP. The techniques attain accurate support recovery without needing sparsity knowledge. An enhanced RIP was derived based on the circumstances with the optimal known outcomes. The analytical and observational were performed on the basis of the basic process for a diverse ECG signal.

In 2016, Anurag Singh and S. Dandapat [4], worked on a multi-channel CS model for MECG signals. Using the correlated information over the channels this paper concentrates on the flourishing MECG signals joint recovery by exploiting a minimum count of measurements. On the basis of a WMNM, a compressed sensing recovery approach was developed which uses the MECG signals joint sparsity in the recovery signals as well as wavelet domain from all the channels concurrently. To highlight the diagnostically significant MECG features, the developed WMNM approach pursues a weighting scheme.

In 2016, Anurag Singh and SamarendraDandapat [5], worked on a CS-based method for joint reconstruction/ compression of MECG signals. The MECG signals distribute spatially correlated cardiac information over channels that were used in a joint CS model for enhanced signal recovery. By using the MECG signals joint sparsity in the wavelet domain, the WMNM-based joint sparse recovery techniques were developed that was effectively make progress the signals from all the channels concurrently. By a multi-scale weighting technique, the developed models and use multi-scale signal information.

3. Developed Signal Reconstruction Model

Consider A as the continuous real input valued signal. $\Re^N$ indicates any signal representation regarding $N\times\mathbf{1}$ vector stated as $\{\psi_i\}_{i=1}^N$. Let us consider the orthonormal as basic. $\Psi := [\psi_1|\psi_2|.....|\psi_N]$ indicates the basis matrix formation $N\times N$ basis matrix, by stacking the vector $\{\psi_i\}$ as columns. The formulation of any signal is stated in eq. (1).

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

Moreover, S indicates the weighting coefficient, the column vector $N\times\mathbf{1}$ of, $S_i = \langle z,\psi_i\rangle = \psi_i^{Tx}A$ and Tx indicates the (hermitian) transpose operation. S and A indicates a similar signal's equivalent indication, with A in the time domain and S in the ψ_i domain. In three phases, the input signal is performed such as Compression of Signal, Stable Measurement Matrix, as well as Reconstruction of Signal. Fig 1 illustrates the block diagram of the developed model.

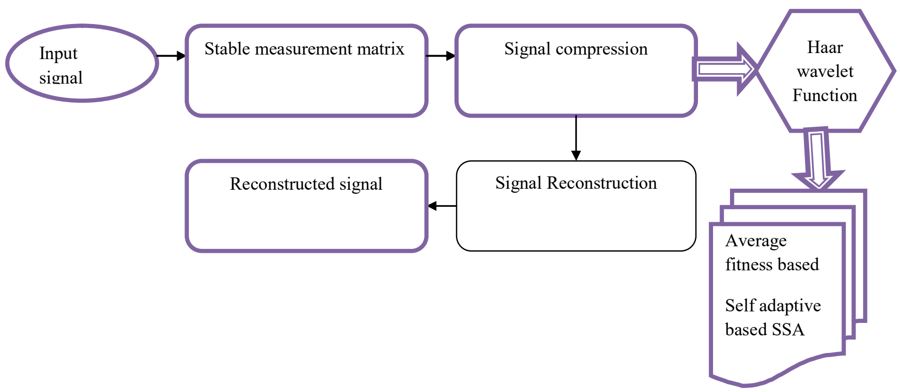


Fig. 1*Block diagram of the developed model*

At first, based on the Φ matrix, the measurement side of data acquisition systems is designed. The important objective model is the P measurement from whereas the length- N signal z is stably remodeled or consistently its S coefficient vector of sparse. Subsequently, the reconstruction process is not probable, if the measurement procedure affects the information in z. In general, the measurement procedure is explained by exploiting the matrices Ψ and Φ, as well as it is linear in nature. Eq. (2) states the non-linear algebra issue which is subjected to solve S with v, and basically, the solution performed ill-posed by smaller formulations which are unknown with $P < N$.

Although, M -sparsity safety is the initial priority. The linear integration of M columns of Θ is referred to as the equal measurement vector $S_i \neq 0$.

A linear formulations system $P\times M$ is created to solve those non- "0" entries if the recognized priority M entries of S are non- "0". Furthermore, P that is the count of formulation exceeds anything else equivalent to M that is the count of unknown. The adequate and necessary circumstances were performed to assure the good conditioning of $P\times M$. Using this, eq. (2) states for *vec* any vector which shares the same nonzero entries M, the stable inverse is sported and is for *vec* any vector that shares the same non-"0" entries for some $\in > 0$. By matrix Θ, it is stated as the definite M -sparse vectors length must be preserved.

$$1 - \in \leq \frac{\|\Theta vec\|_2}{\|vec\|_2} \leq 1 + \in \tag{2}$$

Almost, M nonzero entries location S is unknown. For both M -sparse and compressible signals the stable inverse has an adequate circumstance is for Θ to assure (3) for a random vec $3M$ -sparse vector and it is called as Restricted Isometry Property. The substitute method which exploited

To enhance stability, another technique that employed cause assure of measurement matrix Φ indicates incoherent in sense that vector $\{\phi_j\}$ using sparsifying basis, without the sparsifying basis is shown using the $\{\psi_i\}$ vector and conversely.

Using the Fourier uncertainty law, coherence is produced. $\{\psi_i\}$ and $\{\phi_j\}$ are performs the role by Fourier sinusoids as well as delta spikes. In order to circumvent aforesaid problems in CS, the random matrix Φ is chosen. Using the Gaussian Φ , 2 engrossing and practical properties are exploited.

At first, the full N spikes are used to demonstrate each row of Φ with the basis $\Psi = 1$ of delta spikes with maximum probability possesses Φ incoherent. By exploiting the measure arguments concentration, the $P \times N$ id Gaussian matrix $\Theta = \Phi I = \Phi$ must possess the RIP with maximum probability, if $P \geq con M \log(N/M)$ with con a few constant. Therefore, the M -sparse, length- N , as well as compressible is recuperated.

4. Signal Compression Scheme for Developed Technique

The signal compression process starts after the completion of measurement matrix evaluation. By means of three stages, the signal compression is performed and that are explained as below:

a) Signal Transformation

The transformation of signal carries on as a result of the measurement matrix. By additional widespread data acquisition technique as a compressed [6] indication without moving through the mediator stage of carrying N samples, this signal is directly condensed. Presume one of the general linear measurement procedures that compute $P \times N$ inner products amid A and a collecting of vectors $\{\phi_j\}_{j=1}^{p}$ as in $v_j = \langle A, \phi_j \rangle$. Within the $P \times 1$ vector v , stacking measurement v_j and measurement vector ϕ_j^{Tx} as rows within a $P \times N$ matrix Φ as well as replaced in eq. (1), and it is indicated in eq. (3).

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

b) Θ evaluation

Subsequently, Φ indicates random Gaussian measurements which is general in the logic which Θ possesses RIP with utmost probability for each probable and it is stated in eq. (4).

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

Wherein Θ is indicated as $P \times N$ matrix. Here, by exploiting the Haar wavelet function the Ψ evaluation is carried out which is described. Further, the major objective of this paper is to choose the best vector coefficient in the Haar wavelet function. It is primarily concentrated due to the entire performance responsibility rate based upon the function. Using the novel optimization technique named AF- GWO algorithm, the best-chosen vector coefficient V is used.

c) Process of Signal Normalization

After the completion of the optimal chosen explains the optimal vector coefficient, spontaneously Θ turns out to be the best Θ^* thus the process turns into high class. Using Θ^* , the normalization procedure ensued. Actually, normalization represents scaling in signals at the same level. Here, based on eq. (5), the normalization is given, whereas v indicates compressed signal.

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

5. Haar wavelet for Ψ process

For the Hilbert space, the Haar wavelet's [7] orthogonal basis $\{g_n(t)\}$ $X_2[0,1]$ stated in eq. (6) and (7).

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

Wherein

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

Each Haar wavelet g_n earns the aid $(2^{-c}l, 2^{-c}(l+1))$, therefore in the interval [0, 1], it is "0". Furthermore, while there is a raise in n the Haar wavelet turns out to be more localized. Therefore, using $\{g_n(t)\}$ the local basis is created. As stated in eq. (8), in the Haar series any function $f(t) \in X_2(0,1)$ is elongated. Moreover, using eq. (9), the Haar coefficient $co_i, i = 0,1,2,....,$ is exhibited. As stated in eq. (10), it is computed; therefore the integral square error ε is minimized. The Haar wavelet orthogonal property is shown in eq. (11).

$$f(t) = \sum_{i=0}^{\infty} co_i g_i(t), \; n = 2^c + l, \; c \ge 0, \; 0 \le l \le 2^c \quad (8)$$

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

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

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

The infinite terms of counts are included in eq. (7) and the summation might be concluded subsequent to q terms, if $f(t)$ is piecewise constant or approximate to piecewise constant as well as it is stated in eq. (12).

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

Moreover, $q = 2^c$, Tp indicates the transportation id, $\hat{f}(t)$ indicates truncated sum. Haar function vector $F_q(t)$ and Haar coefficient vector V_q indicated in eq. (13) and (14) correspondingly. The gathered points are considered in eq. (15), and eq. (16) defines the m-square Haar matrix $\Phi_{q\times q}$. Therefore, $\hat{f}_q$ is stated in Eq. (17). As the $\Phi_{q\times q}$ m-square Haar matrix is an invertible matrix, the Haar coefficient vector V_q^{Tp} is stated in eq. (18).

$$F_q(t) \triangleq [g_0(t), g_1(t), ..., g_{q-1}(t)]^{Tp} \quad (13)$$

$$V_q \triangleq [co_0, co_1, ..., co_{q-1}]^{Tp} \quad (14)$$

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

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

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

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

6. Working Model of Developed Technique for Signal Reconsuction Phase

Subsequent to the normalization procedure completion, the compressed signal experiences the reconstruction procedure, as well as the after-effect outcome signal, is attained. The reconstruction process is described as below:

Using RIP, the theoretical certainty is indulged that a M -sparse or compressible signal are explained totally by P measurement in v, whilst the recovery procedure is not defined. The random measurement metric Φ is considered by the signal reconstruction, the measurement v, and sparsifying basis Ψ, and performed the length- regeneration N signal z else subsequent it's S coefficient of the sparse vector. In eq. (2), due to $P < N$ there might be numerous infinite S' which convenes $\Theta S' = v$ and relies on the $(N-P)$-dimensional hyperplane $\Gamma := \Lambda(\Theta) + S$ associated with the null space $\Lambda(\Theta)$ of Θ transformed into the true sparse solution S. In the null space, this is due to any vector l, if $\Theta S = v$ subsequently $\Theta(S+l) = v$. Therefore, the most important objective is to ascertain S and it represents the coefficient of the sparse vector of signal in the transformed null space.

Analyze L_r vector norm S by $\left(\|S\|_r\right)^r = \sum_{i=1}^{N} |S_i|^r$. When $r = 0$ L_0 norm is obtained this calculates the number of S non-zero entries. Hence, M -sparse vectors have L_0 norm M.

Reconstruction of least L_2 norm: the minimum square is employed in this traditional model to resolve inverse issues, that is vector is chosen in the converted null space Γ with least L_2 norm energy and it is stated in Eq. (19).

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

In addition, an appropriate closed-form solution is there $\hat{S} = \Theta^{Tr}(\Theta\Theta^{Tr})^{-1} v$. When the vector S is M -sparse L_2 was not determined. A non-sparse $\hat{S}$ is discovered rather than a great deal of ringing.

Minimum L_0 norm reconstruction: In eq. (4), due to the signal sparsity bon-refection by L_2 norm, in eq. (20), a logical substitute to search the sparsest vector in the translated null space Γ is performed.

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

Moreover, by this optimization, the M -sparse signal precisely with utmost probability will be recovered which is exhibited with $P = M + 1$ iid Gaussian measurements. Unfortunately, to resolve regarding numerically unstable as well as an NP-complete issue in eq. (5). This issue requires an absolute listen of whole $\binom{M}{N}$ probability integrations to locate the nonzero entities in S.

Reconstruction of least L_1 norm: From $P \geq cM\log(N/M)$ iid Gaussian measurements the compressive sensing is stated. The M -sparse vector and the nearly approximate compressible vectors are reconstructed stably with high achievability through the L_1 optimization and it is stated in eq. (21).

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

Here, this is stated as the convex optimization problem that reduces to a linear program therefore the basis following, when the computational complexity is stated as $O(N)^3$.The random measurements are involved by the CS data acquisition system to summarize based on Φ and pursued using the reconstruction of linear programming to attain z. At last, the reconstruction of the signal $\hat{R}$ is attained.

(a) Objective model

In this paper, the main contribution lies in the minimization of error at the time of the training stage. It is used by computing the error amid the original signal A as well as reconstructed signal $\hat{R}$ and it is stated in eq. (22). In reality, the error must be least and therefore obtains superior outcomes.

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

b) Proposed Self-adaptive SSA

In this paper, a novel SSA method is proposed and it is called Self-adaptive SSA [8]. Initially, this approach begins by arbitrary parameter initialization within a definite range based on the issue and it is stated in eq. (22).

$$x_{i,j} = x_{min,j} + U(0,1) \times \left(x_{min,j} - x_{max,j}\right) \tag{23}$$

wherein, $x_{i,j}$ represents the i^{th} solution for the j^{th} dimension, $U(0,1)$ indicates a uniform arbitrary number in the range of [0,1], $x_{max,j}$ and $x_{min,j}$ indicates upper as well as lower bounds of the issue in the test i relies upon the range [1, 2, 3....n], j as [1, 2, 3....D].

The proposed approach comprises enhancement in the exploitation as well as exploration operations in the SSA approach.

In this algorithm, the initial phase solution space exploits the formulation from the general CS and GWO approaches. Here, aforesaid approaches are effective in the operation of exploration as well as therefore formulation enhancement will offer the effectual results. The novel enhanced formulation is stated as follows:

$$x_1 = x_i - A_1\left(C_1 \cdot x_{new} - x_i^t\right)$$

$$x_3 = x_i - A_3\left(C_3 \cdot x_{new} - x_i^t\right) \tag{24}$$

$$x_{new}^{t+1} = \frac{x_1 + x_2 + x_3}{3} \tag{25}$$

$$x_{new}^{t+1} = x_{new}^t + \alpha \times L(\lambda)\left(x_{best} - x_{new}^t\right) \tag{26}$$

wherein x_{new} indicates the new solution produced for any d dimensional from the randomized population within the search space issue and, from $A = 2a.r_1 - a$ and $C_2 \cdot r_2$ and the A_1, A_2, A_3 and C_1, C_2, C_3 are derived. Here a decreases linearly within the range of [0, 2]. Moreover $L(\lambda)$ as well as α and indicates Lévy distributed random numbers and fundamental uniformly distributed, r_1 and r_2 indicates arbitrary numbers distributed uniformly within [0, 1]. Based on eq. (26), Lévy flight based step size is produced,

$$L(\lambda) \sim \frac{\lambda\Gamma(\lambda)\sin(\pi\lambda/2)}{\pi}\frac{1}{s^{1+\lambda}}\left(s >> s_0 >> 0\right) \tag{27}$$

wherein $s = \frac{U}{|V|^{1/\lambda}}$; $V \sim N(0,1)$ $U \sim N\left(0, \sigma^2\right)$; $\sigma^2 = \left\{\frac{\Gamma(1+\lambda)}{\lambda\Gamma[(1+\lambda)/2]} \cdot \frac{\sin(\pi\lambda/2)}{2^{(\lambda-1)/2}}\right.$. In addition, $\Gamma(\lambda)$ represents a gamma function, and the λ value equivalent to 1.5. From standard Gaussian distribution, the λ parameter is attained possess mean 0 and variance, σ^2. Eq. (24) and (25) uses both the CS as well as GWO operations in association with each other. The selection stage of the developed approach is to perform the greedy selection to ascertain if the newly produced solutions are superior to the preceding optimal solution. For a widespread minimization procedure possessing $F\left(x_i^t\right)$ indicates the fitness for x_i^t solution, the selection procedure is stated as eq. (28).

$$x_{new}^{t+1} = \begin{cases} x_{new} & \text{if } F(x_{new}) < F\left(x_i^t\right) \\ x_i^t & \text{otherwise} \end{cases} \tag{28}$$

Other than this, one more significant disadvantage of conventional SSA is unbalanced exploitation as well as exploration operation and it is stated by the controlling parameters c_1.

$$c_1 = c_{max} + (c_{min} - c_{max}) \times \log_{10}\left(a + \frac{10t}{t_{max}}\right) \tag{29}$$

On the basis of logarithmic adaptive inertia weight the eq. (29) is stated and exploits logarithmic minimizing the arbitrary number compare with the few particular constant value. Moreover a indicates any arbitrary number in the range of [0, 1], c indicates the inertia weight parameter and, t_{max} and t are the maximum and the current number of iterations. Moreover, the basic formulation for the similar is population reduction is minimization is stated in eq. (30).

$$n(g+1) = \text{round}\left[\left(\frac{n_{min} - n_{max}}{FEs_{max}}\right).FEs_{max} + n_{max}\right] \tag{30}$$

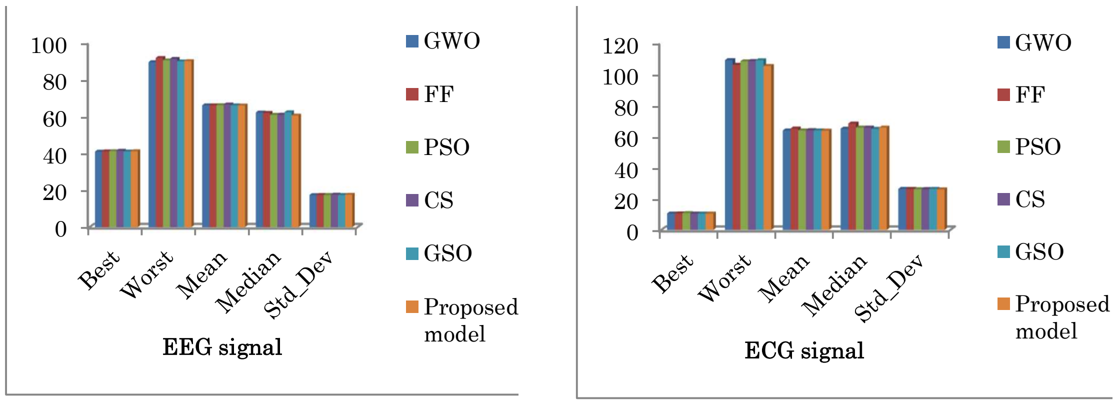
Wherein, FEs_{max} indicates the utmost number of iterations n_{max} and n_{min} indicates the utmost and minimum population sizes. The aforesaid points are integrated to model the novel self-adaptive SSA approach.

7. Experimental Procedure

In this section, the experimental procedure of the proposed and conventional models is described. Here, both these approaches were implemented using ECG as well as EEG signals as input.

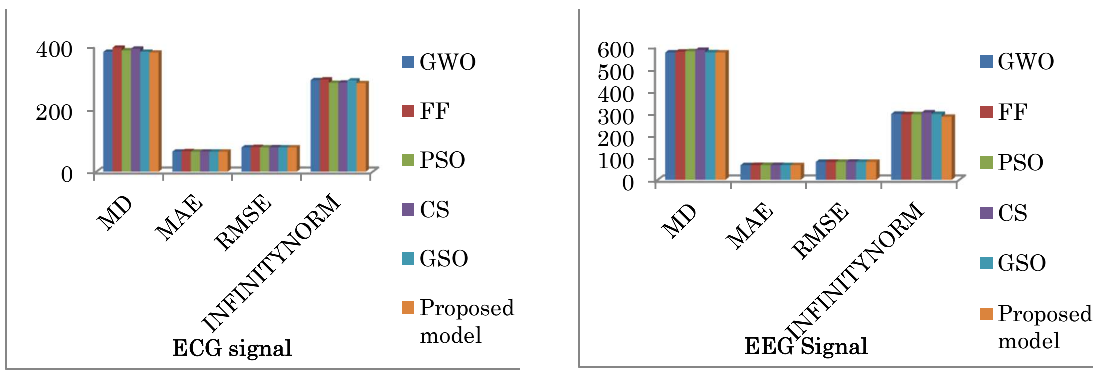
In fig 2, the developed technique performance analysis is done with the existing techniques regarding statistical performance. Here, the best, mean, worst, median, as well as standard deviation, are exploited. Moreover, the statistical analysis is carried regarding the EEG signals as well as ECG signals. The overall analysis of the developed technique presents superiority while comparing with the conventional techniques.

In fig 3, the performance analysis regarding error is performed concerning the metrics such as MD, MAE, RMSE, and proposed model. Here, the proposed technique presents a minimum error while comparing with the conventional models.



(a) (b)

Fig. 2*Statistical analysis of developed as well as existing techniques (a) EEG signal (b) ECG signal*



(a) (b)

Fig.3*Error performance of proposed and existing techniques for (a) EEG signal (b) ECG signal*

8. Conclusion

CS has emerged as a promising model to identify numerous challenges due to its of its energy-efficient data minimization process. A novel compressive sensing approach was developed in this work for the signal reconstruction which is available in bio-medical data. In three phases, signal compression was carried out such as compression of the signal, stable measurement matrix as well as reconstruction of the signal. Furthermore, the compression of the signal was operated based on three classifications such as normalization, Θ evaluation as well as transformation. Here, the theta evaluation was performed on the basis of the Haar wavelet matrix function. Moreover, this work included the optimization model with the estimation process that was known as the objective model. Accordingly, a novel optimization approach Self-adaptive SSA was exploited in order to choose the Haar wavelet function optimally. Finally, the developed technique performance was evaluated with the conventional techniques and the outcomes analysis was performed. The overall analysis revealed that the performance of the developed model was better than traditional models.

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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