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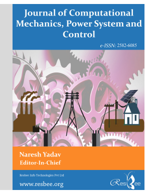

Cuckoo Search Algorithm based on Levy flight for the Bi-orthogonal Wavelet Filters on Compressed Sensing

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Abstract: In the medical research field, real-time health monitoring is turn out to be a significant issue in today's digital world. Body signals like EMG, ECG, EEG, so on are generated in the human body. This incessant monitoring produces an enormous number of data as well as therefore an effectual technique is necessary to contract the size of attaining huge data. To compress the data size the Compressed Sensing (CS) model is exploited. In numerous applications, this model is utmost used wherein the data size is large or to gather the data from a large number of samples at the Nyquist rate, the data acquisition is high cost. In this research, a new CS approach is used whereas the compression process performs in 3 states like Stable measurement matrix design, signal reconstruction as well as signal compression. Moreover, the compression process undergoes in particular working principle that is the Θ computation, signal transformation, and normalization. Evaluation of theta (Θ) value is proceeded exploiting a novel Improved bi-orthogonal wavelet filter is considered as the major contribution. In the scaling coefficients, the improvement is given wherein they are optimally tuned to process compression. Nevertheless, the tuning way is to be a huge issue and therefore this paper uses the meta-heuristic method scheme. The adopted optimization model called as Cuckoo Search Algorithm based on Levy flight (CSA-levy flight) is compared with the conventional models to reveal the performance based on error analysis.

Keywords: Compressed Sensing, Normalization, Nyquist Rate, Signal Reconstruction, Signal Compression, Signal Transformation.

Nomenclature

Abbreviations	Descriptions
CS	Compressed sensing
LB	Lower Bound
WSN	Wireless Sensor Nodes
ECG	electrocardiogram
RIP	Restricted Isometry Property
UB	Upper Bound
CSBS	CS- based spatiotemporal data fusion
NDOA	Neural Dynamics Optimization Algorithm
CS	Compressed sensing

1. Introduction

CS is a signal acquisition model that exceeds conventional restrictions of Nyquist sampling[1] This approach is enormously helpful in circumstances wherein data is big, or the acquisition process is too pricey to gather the number of illustrations at the Nyquist rate. In diverse domains, CS was simulated and the outcomes were effectual. Few researchers exhibit that CS hardware is efficiently deployed with minimum computational complexity. In ECG applications, CS approaches are deployed which is very effective in minimizing the utilization of WSN. A few instances are the CS-based ECG monitor as well as an encoder that is exhibited to utilize merely low power correspondingly while comparing with the baseline systems. In ECG applications, although CS showed is effective in minimizing the consumption of energy the reconstruction data quality still requires to be enhanced. In CS signal acquisition models in contrast with the basic signal acquisition merely some arbitrary samples are gathered using the input data projection onto an arbitrary matrix. Here, the number of samples is lesser than the signal length. If

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the data is sparse in the sensing domain or in any other transform domain CS theories state that the perfect reconstruction is probable although the sampling rate is below the Nyquist rate [6].

Actually, in the medical applications fields, CS is receiving enormous interest because of its ability to exceed the conventional restrictions in the sampling theory. In the bio-medicine field usually used as a signal are ECG and EEG, as they are indicators of the majority of dreadful diseases. Furthermore, the EEG utilization as a communication vector amid machines as well as a human is the new challenge in signal theory. In addition, the EEG signals recorded utilize an enormous number of data as well as where sampling, and signal transmission, is complicated in numerous applications hence, both EEG [7] and ECG signal monitoring is maximum significant. The conventional compression approaches are fine in data compression [10]. Nevertheless, , there is a need to obtain data at the Nyquist rate with noteworthy energy at minimum cost [8]. The up-and-coming CS model is used that is well-organized to solve attaining the data compression with a balanced saving in energy as a key to meet these constraints [11]. Even though, the original signal reconstruction subsequent to compression from sparse signal possessing little non-"0" elements is complex. However, some researchers attempt to present a solution to this inverse issue [3].

In CS, the problems associated with the reconstruction of the original signal are being resolved via Basis Pursuit De-Noising. These technqieus does no ensemble to time-critical reconstruction applications as they are additional complex as well as tedious. The convex optimization issues are being resolved by exploiting the FOCUSS. However, this is used for some restricted data. Therefore, it is important to have a best techniques for CS in ECG and EEG reconstruction with lower errors.

The main aim of this research is to develop a Compressed Sensing method is developed to compress EEG and ECG signals using three important stages using stable measurement matrix design, signal reconstruction as well as signal compression. Then, signal compression is performed using the stable measurement matrix that the signal transformation process, Θ computation, and normalization are attained. A novel Improved bi-orthogonal wavelet filter is used to evaluate the Θ value. A CSA-levy flight the optimization method is exploited to optimally tune the scaling coefficients. At last, the developed technique is evaluated with the conventional techniques.

2. Literature Review

In 2018, ZHENHUA GAN et al [1], proposed a wavelet denoising model based on the CS optimized using NDOA. It was rather resolved the denoising problems of noise pollution in microarray images. The NDOA-optimized wavelet denoising effectiveness on the basis of the CS gets improved work to orthogonal matching search and its enhanced approach in the Gaussian random observation matrix condition. In 2019, Mahmoud Mansouri Jam and Hamed Sadjedi [2], presented an approach to examining a matched wavelet with minimum wavelet filters length by exploiting spectral matching. In the designing approach, the conventional issue in spectral fashion was explained as well as the equivalent solution was presented. In the general approach, the issue present was the high computations in spectral phase matching which frequently generates errors in machine running, as a result, the phase matching approach turns out to be imperfect. Here, the errors, as well as computational costs that happen from such phase matching, were enhanced. Subsequently, thus enabling modeling of orthogonal wavelet transform filters with the least length a technique was presented. From the real world, the developed method has experimented with a signal. The neural signals compression in implantable microsystems was presented. In 2018, Lei Li et al [3], worked on a new CSBS approach to synthesize such high-spatiotemporal resolution images. Moreover, for CS reconstruction continuity constraints in the temporal domain were developed into the CSBS object function. Images were segmented into numerous minute patches as well as clustered into various groups through K-means to improved indicate the intrinsic features of the data. Dictionary training, high-resolution prediction, and measurement matrix identification were examined group-by-group. On the basis of the features learned from patch groups, transformational association amid spatial-temporal images had diverse resolutions was simply recognized. In 2017, Jingbo Wei et al [4], worked on the remote sensing image reconstruction from undersampled data that was needed using an onboard imaging system to reduce data volume as well as preserve the quality of the image. From low rank, group sparsity, singular-value thresholding, Nonlocal low-rank regularization as well as nonconvex surrogate functions derived have lately raised for image recovery. For remote sensing image reconstruction, to employ nonlocal low-rank compressed sensing, spectral and temporal redundancy was taken into consideration using the comparison of historical records else correlated bands.In 2020, Joaquín García-Sobrino et al [5], worked on the image segmentation, the performance image segmentation in data reconstructed subsequent to a near-lossless or lossy compression. Here, two compression standards, as well as two image segmentation approaches, were experimented on data from various instruments.

3. Functional Model of the Compressed Sensing

Let In be the input signal of continuous real-time and it is stated in eq. (1). $\{\psi_v\}_{v=1}^{G}$ represents $\Re^{G}$ represents any signal in the space equivalent to $G \times 1$ vector. The fundamental is taken into consideration as the orthonormal. Furthermore, the $G \times G$ basis matrix formulation undergoes by stacking vector $\{\psi_v\}$ as columns as well as it is shown as $\Psi := [\psi_1 | \psi_2 | .... | \psi_G]$. D_v indicates the weighting coefficient of column vector as well as it is depicted in Eq. (2), T represents the hermitian transpose operation. Moreover, D_v and In indicates an equal indication of the similar signal as well as they reside in the domain ψ_v as well as in time domain, respectively.

$$\mathrm{In} = \sum_{v=1}^{G} D_v \psi_v \text{ or } \mathrm{In} = \Psi . D \tag{1}$$

$$D_v = \langle \mathrm{In}, \psi_v \rangle = \psi_v^T \mathrm{In} \tag{2}$$

In three important processes, the input signal performs the Signal Compression, Stable Measurement Matrix, as well as Reconstruction. Fig. 1 demonstrates an architecture illustration of the developed signal reconstruction model.

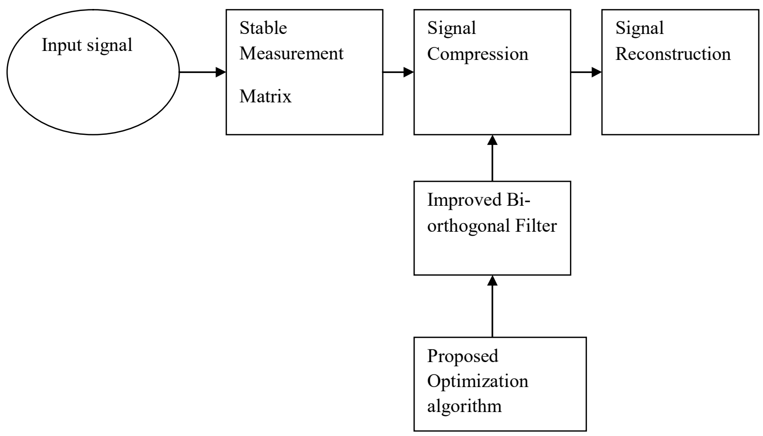

Fig.1. *Block diagram of the developed CS model*

a) Stable measurement matrix: At first, based on the Φ represents the "stable measurement matrix, data acquisition system measurement side" is designed. The major contribution of this is to measure W from that length-G signal In is remodeled in a stable way or consistently its sparse coefficient vector S in the basis of Ψ. In this scenario, if the measurement procedure shatters up information that is present in In, subsequently original signal reconstruction is not probable. Generally, the measurement procedure is linear in nature, they are stated regarding Φ and Ψ. On the basis of eq. (3), to solve the D is stated as v which is a linear algebra issue, as well as solutions, are performed ill-posed.

$$c = \Phi . \mathrm{In} = \Phi \Psi D = \Theta D \tag{3}$$

Nevertheless, the K – sparsity safety is the initial priority. In this scenario, the measurement vector v is merely linear integration of K-columns of $\Theta : \Phi\Psi$ in that resultant equivalent $D_v \neq 0$. Furthermore, if non-zero entries are represented as K- entries of D, subsequently $W \times K$ can be stated as a linear equations system to solve these nonzero entries of D, while $K \geq W$. In addition, high-quality conditioning of $W \times K$ is assured with the help of adequate and essential circumstances. For any vector vec, the stable inverse is sported which shares equal nonzero K – entries similar to D with this well-conditioned system and the eq. (4) indicates the mathematical formulation, wherein in a few scenarios the value of $\in > 0$. Conversely, by matrix Θ length of these particular K-sparse vectors is required to be preserved. Generally, K nonzero entry localization belongs to D is unknown in prior. Subsequently, eq. (4) should be fulfilled to obtain a stable inverse state for K-sparse and compressible signals for Θ in random vector (vec) equivalent to $3K$-sparse and it is basically indicated as RIP. Furthermore, the measurement matrix Φ is incoherent as well as it is assured by a substitute method regarding stability. This method on stability can be attained based on the Ψ in "sparsifying basis with sense vector" $\{\phi_u\}$ as well as without sparsifying vector $\{\psi_v\}$ and vice-versa. Moreover, $\{\phi_u\}$ and $\{\psi_v\}$ role is to play by the delta spikes and using the Fourier sinusoids. Using the Fourier uncertainty principle all of an abrupt incoherence is produced.

$$1-\in\leq\frac{\|\Theta vec\|_2}{\|vec\|_2}\leq 1+\in \quad (4)$$

Furthermore, the matrix Φ is chosen as an arbitrary to resolve the problems associated with compressive sensing. These are referred to as the two attractive and functional properties in Gaussian Φ. Initial Φ is incoherent with $\Psi=1$ of delta spikes with maximum probability, as G spikes indicate every row of Φ. By means of the attentiveness of measured influence $W\times G$ i.i.d Gaussian matrix $\Theta=\Phi I=\Phi$ having RIP with maximum probability is shown, while the condition $W\geq c_{con}K\log(G/K)$ is fulfilled. The variable c_{con} is a least constant and from $W\geq c_{con}K\log(G/K)<<G$, K -sparse, length- G, as well as compressible is recovered.

b) Signal compression scheme: Subsequent to measurement matrix evaluation, the signal compression procedure starts. In the adopted technique, signal compression occurs in three important stages, namely signal transformation, calculation of Θ as well as normalization.

i) Signal transformation: It is the first step of signal compression; it happens subsequent to the measurement matrix. In [27], signal condensation happens directly with the aid of additional common data acquisition methods without moving through the go-between phase of carrying G samples. Let a general linear measurement procedure in that the inner products of $W\times G$ is calculated amid input images *In* and the meeting of vectors $\{\phi_u\}_{u=1}^{W}$ as in $v_u=\langle In,\phi_u\rangle$. ϕ_j^{Tx} rows measurement vector within in $W\times G$ matrix Φ, the stacking measurement of vector v indicate v_u within the matrix $W\times 1$. Furthermore, eq. (5) is reformulated by replacing eq. (1) based on aforesaid measurements.

$$v=\Phi In=\Phi\psi D=\Theta D \quad (5)$$

ii) Θ Evaluation: The matrix computation Φ represents an arbitrary Gaussian measurement which is referred to as universal in nature. Then, for each probable, Θ possesses RIP with maximum probability. Eq. (6) represents the mathematical formula associated with the evaluation of Θ, wherein the Θ value value is indicated as a $P\times N$ matrix.

$$\Theta:=\Phi\Psi \quad (6)$$

The main aim of this paper is to contribute to the evaluation of Ψ value by exploiting the improved bi-orthogonal wavelet filter. Here, it lies to tune the best spatial coefficients in the bi-orthogonal filter. This work develops a novel hybrid approach namely, CSA-levy flight that noticeably tends peak level performance for the optimal tuning.

iii) Signal Normalization process: If the Ψ evaluation turns out to be optimized with optimal scalar coefficient. Subsequently, Θ repeatedly is represented as optimal Θ^*. The signal scaling in indistinguishable level is indicated as the normalization process and the normalization happens based on eq. (7), in that v is represented as the compressed signal.

$$Norm=W^{-1}(\Theta^*)v \quad (7)$$

4. Signal Reconstruction and Bi-orthogonal Wavelet Transform for Processing of Ψ

The main significant factor is the bi-orthogonal filter generation which must be estimated in an accurate way.

4.1 Adopted Bi-orthogonal Filter Generation

The adopted model exploits 4 bi-orthogonal wavelets such as bior 3.1, 3.3, 3.5, and 3.7 wavelet, correspondingly. In reality, wavelets (Wa) are arranged based on number of eradicating moments of DF (No_{DF}) as well as number of diminishing movements of RF (No_{RF}). Hence, in the wavelet number 3.1, number 3 in integer part indicates No_{RF} as well as number 1 in decimal part shows No_{DF}.

In default wavelet, bior 3.1 possess "4 RF $(\hat{r}_0,\hat{r}_1,\hat{r}_2,\hat{r}_3)$ values as well as 4 DF $(\hat{y}_0,\hat{y}_1,\hat{y}_2,\hat{y}_3)$. Like this, wavelet bior 3.3 has 4 DF $(\hat{y}_0,\hat{y}_1,\hat{y}_2,\hat{y}_3)$ and 8 DF $(\hat{r}_0,\hat{r}_1,\hat{r}_2,\hat{r}_3,\hat{r}_4,\hat{r}_5,\hat{r}_6,\hat{r}_7)$, wavelet bior 3.5 has 4 DF $(\hat{y}_0,\hat{y}_1,\hat{y}_2,\hat{y}_3)$ and 12 RF $(\hat{r}_0,\hat{r}_1,\hat{r}_2,\hat{r}_3,\hat{r}_4,\hat{r}_5,\hat{r}_6,\hat{r}_7,\hat{r}_8,\hat{r}_9,\hat{r}_{10},\hat{r}_{11})$, and wavelet bior 3.7 has 4RF $(\hat{y}_0,\hat{y}_1,\hat{y}_2,\hat{y}_3)$ and 16 DF $(\hat{r}_0,\hat{r}_1,\hat{r}_2,\hat{r}_3,\hat{r}_4,\hat{r}_5,\hat{r}_6,\hat{r}_7,\hat{r}_8,\hat{r}_9,\hat{r}_{10},\hat{r}_{11},\hat{r}_{12},\hat{r}_{13},\hat{r}_{14},\hat{r}_{15})$ values in default". Nevertheless, using a novel hybrid approach in the developed model the values are fine-tuned instead of exploiting the default values. Significantly, the optimal tuned on the basis of two bounds such as UB and LB values are attained. In order to fix both bounds the process is stated as follows:

a) As stated in Eq. (22), the RF LB is the least amount of RF value (RF_{min}), which is "multiplied with - $\hat{q}$ % of default value" (q is an arbitrary number).

b) Likewise, as stated in Eq. (23), RF UB is the utmost RF value (RF_{max}) multiplied "with $+\hat{q}$ % of default value". A similar process is repeated for DF.

The lower and upper bound evaluation to tune the bi-orthogonal wavelet 3.1 scaling filters is expressed as follows:

For design: in wavelet 3.1

$$\text{LB of RF} = \mathrm{RF_{min}} \times (-\hat{q}\%) \tag{8}$$

$$= 0.1250\times \text{(-5\%) ('5')}$$

$$\text{UB of RF} = \mathrm{RF_{max}} \times (+\hat{q}\%) \tag{9}$$

$$= 0.3750\times \text{(-5\%) ('5')}$$

Thus the fine-tuning values may fall in amid these bounds. Finally, the reconstruction process experiences normalization, and the compressed signal and the results attained are recorded.

4.2 Signal Reconstruction Model of Adopted Compressed Sensing Technique

A) Signal Reconstruction

By exploiting the RIP, for CS the theoretical guarantees or K-sparse are entirely explained in c using W measurement. It is a reconstruction step requirement, to consider sparsifying basis Ψ, measurement c, random measurement metric Φ, and the length regeneration - G or its same sparse coefficient vector D. The $\mathrm{W} < \mathrm{G}$ value there subsist enormous numbers of $\mathrm{D'}$ to assure $\mathrm{D'} = \mathrm{c}$ in $(\mathrm{G}-\mathrm{W})$-dimensional hyper-plane $\mathrm{H} := \mathrm{N}(\Theta) + \mathrm{D}$ in null space $\mathrm{N}(\Theta)$ in $\Re^{N}$, in that Θ is converted to true sparse solution D in Eq. (3). For any vector r, the aforesaid condition is fulfilled, while $\Theta\mathrm{D} = \mathrm{c}$ as well as this turns out to be $\Theta(\mathrm{D}+\mathrm{r}) = \mathrm{c}$ in null space.

Therefore, the major contribution of this paper is too protect signals is a sparse coefficient vector D in translated null space. Moreover, ℓ_{w} norm value is stated as $\left(\|\mathrm{D}\|_{\mathrm{P}}\right)^{\mathrm{P}} = \sum_{\mathrm{v}=1}^{\mathrm{G}} |\mathrm{D_v}|^{\mathrm{P}}$ for vector D. In addition, ℓ_0 norm, that is able to compute the number of non-"0" entries in attendance in D is obtained at the time, when $P = 0$. In K -sparse vector, this is the motivation over non-availability of ℓ_0 norm K.

Minimum ℓ_2 norm reconstruction: To resolve the inverse issues, many traditional techniques used the least square. In eq. (10), the vector is chosen with minimum ℓ_2 norm energy it is shown in Eq. (10) the translated null space H. Moreover, there is a suitable closed-form solution $\overset{\Lambda}{\mathrm{D}} = \Theta^{\mathrm{T}}(\Theta\Theta^{\mathrm{T}})^{-1}\mathrm{c}$. Despite this, when the vector D exists in its minimization of ℓ_2 can by no means be established in K-sparse. Rather than this, non-sparse $\overset{\Lambda}{\mathrm{D}}$ is established with ample ringing.

$$\overset{\Lambda}{\mathrm{D}} = \arg\min \|\mathrm{D'}\|_2 \;;\; \Theta\mathrm{D'} = \mathrm{c} \tag{10}$$

Minimum ℓ_0 norm reconstruction: Eq. (24) equivalent ℓ_2 does not imitate signal sparsity, therefore it is necessary to possess substitute logic to explore the sparsest vector in translated null space N as exhibited in Eq. (11).

$$\overset{\Lambda}{\mathrm{D}} = \arg\min \|\mathrm{D'}\|_0 \;;\; \Theta\mathrm{D'} = \mathrm{c} \tag{11}$$

Furthermore, while $\mathrm{W} = \mathrm{K}+1$ iid Gaussian measurements; this optimization will get a K-sparse signal with maximum superior probability. Since resolving eq. (11) generates an NP-complete as well as numerically unstable issue, for all the localizations compared with nonzero entities in S, needs complete details for all the probable integrations of $\binom{\mathrm{G}}{\mathrm{K}}$.

Minimum ℓ_1 norm reconstruction:

By means of estimated compressible vectors stably "K-sparse vector is reconstructed" directly with enormous viewpoint. Eq. (12) explains the mathematical formulation of while $\mathrm{W} \geq \mathrm{c_{const}}\mathrm{K}\log(\mathrm{G}/\mathrm{K})$ i.i.d Gaussian measurements in ℓ_1 optimization. $\mathrm{O(G)}^3$ referred to as basis pursuit computational complexity. CS data acquisition system is referred to as the signal reconstruction which has arbitrary measurements on the basis of Φ and this purses reconstruction of linear programming to attain reconstructed signal $\mathrm{In_{rec}}$.

$$\overset{\Lambda}{\mathrm{D}} = \arg\min \|\mathrm{D'}\|_1 \;;\; \Theta\mathrm{D'} = \mathrm{c} \tag{12}$$

5. Proposed CSA Based Levy Flight Algorithm For Scalar Coefficient Optimization

5.1 Objective Model

The primary objective of this paper is to reduce error amid the original signal In as well as the reconstructed signal In_{rec}. Eq. (13) indicates the formulation of the objective model O_{fun}.

$$O_{fun} = \min(\mathrm{In} - \mathrm{In}_{rec}) \tag{13}$$

The values of Decomposition Filter (DF), as well as Reconstruction Filter (RF), produced amid values of LB as well as UB for every equivalent "bi-orthogonal wavelet 3.1, 3.3, 3.5 as well as 3.7" is subjected as input to developed optimization algorithm to fine-tuning with the deliberation of objective aforesaid.

5.2 Proposed CSA based Levy Flight Algorithm

The CSA in [9] is used to model litter cuckoo birds' parasitic nature as they aspire to assure that their eggs are produced by other host birds. The achievement of this nature-enthused procedure hands out to inspire CSO model construction for optimization purposes. Thus, in the CSO approach the metaphoric connection of terminologies to known variables generally optimization phrasing is stated as below:
A nest or an egg indicates an individual solution regarding solving single-objective model issues. An individual (nest) can comprise numerous solutions that are multiple eggs to solve the multi-objective function issues. Nevertheless, the single objective function issue is considered in this paper. A group of nests stands for candidate solutions populations.
Here, the continuous-based CSO approach identifies novel and superior solutions.

$$x_p^{t+1} = x_p^t + \alpha \otimes \mathrm{levy}(\lambda) \tag{14}$$

x_p^t attained in the preceding iteration t, x_p^{t+1} indicates a new solution attained in a new iteration $t+1$ from a previous solution for a cuckoo p. "The $\mathrm{levy}(\lambda)$ represents levy flight distribution function is exploit to update previous solutions, wherein α indicates step size related with the scale of the issue of interest, as well as λ indicates the Levy walk parameter, $\otimes$ indicates entry wise multiplication. The Levy flight function presents an arbitrary walk as well as arbitrary step length is obtained from a Levy distribution";

$$\mathrm{levy}(\lambda) \sim \frac{u}{v^{-\lambda}} \tag{15}$$

wherein u and v are exploited from normal distributions stated as

$$\begin{aligned} u &\sim N\left(0, \sigma_u^2\right) \\ v &\sim N\left(0, \sigma_v^2\right) \end{aligned} \tag{16}$$

Whereas,

$$\sigma_u^2 = \frac{\Gamma(1+\lambda) * \sin\left(\frac{\pi\lambda}{2}\right)}{\Gamma\left(\frac{1+\lambda}{2}\right) * \lambda * 2^{\left(\frac{\lambda-1}{2}\right)}} \tag{17}$$

$$\sigma_v^2 = 1 \tag{18}$$

Where in Γ indicates Gamma function and $1 < \lambda \leq 3$.

The CSO algorithm description is as stated as below:

a) Initialize all parameters values, such as the probability of abandoning the nest P_a
b) Generate solutions initial population
c) While stopping condition is not met do
   i. Get cuckoo phase: Get new solutions by exploiting Levy flight walk based on the Mantegna approach via eq. (15) - (18).
   ii. To attain the global optimal solution evaluate the new solutions
   iii. Empty nest phase: Abandon the reduced solutions on the basis of the P_a and replace them with novel solutions
   iv. To attain a new global optimal solution, re-evaluate the new population of solutions
d) Carry on iteration until the stopping condition is fulfilled.
e)

6. Result and Discussion

In this section, experimental analysis of the adopted model over the conventional model experimented. Here, the ECG signal and EEG signals were input signals. Moreover, the performance measures such as **Mean Error Percentage(MEP), Mean Absolute Scaled Error (MASE), Root** Mean Squared Error (RMSE) and **Mean Absolute Error (MAE).**

Fig 2 and 3 reveal the error analysis of an adopted model for bior 3.1, 3.3, 3.5 and 3.7 over numerous error measures for ECG and EEG Signal. The overall analysis exhibit that the proposed CSA-based levy flight algorithm is better as it has the minimum errors within it.

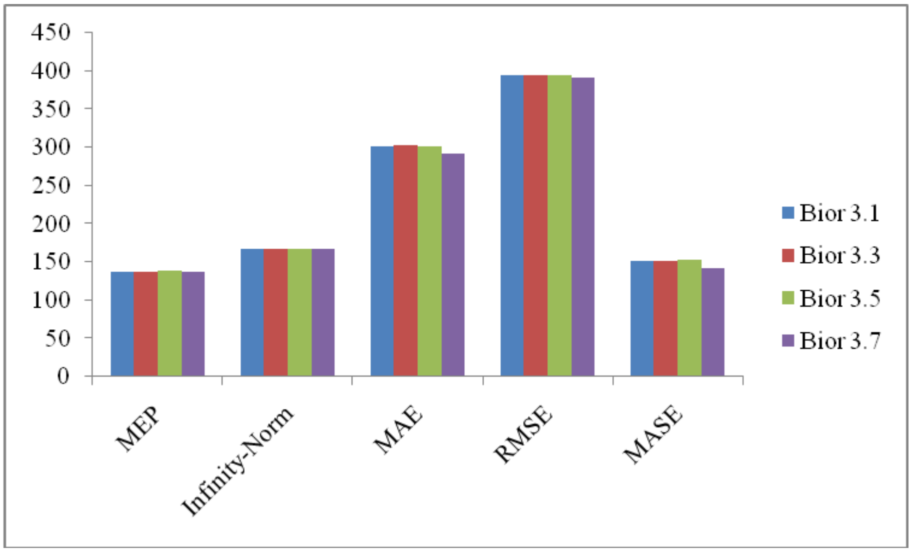

Fig.2. *Error analysis of the proposed CSA based levy flight algorithm under EEG Signal*

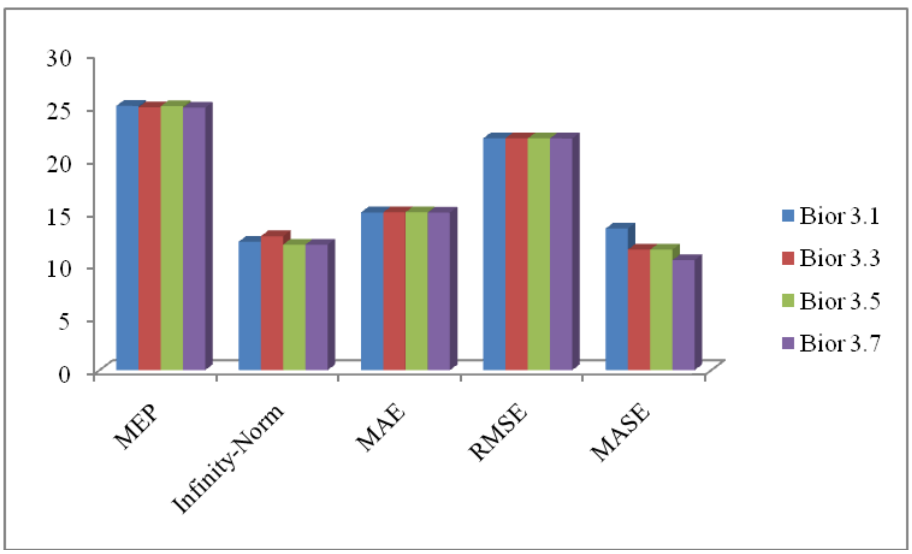

Fig.3. *Error analysis of adopted CSA based levy flight algorithm under ECG Signal*

7. Conclusion

In this work, a novel compressed sensing method was formulated by performing three important states namely signal compression, stable measurement matrix design, and signal reconstruction. At first, stable measurement matrix operation was carried out; subsequently, compression procedure was attained by exploiting like evaluation Θ, signal transformation, as well as normalization. Here, the Θ value was calculated using a novel improved "bi-orthogonal wavelet filter", in that improvement was performed by appropriate of the scaling coefficients at the time of the compression procedure. This challenging manner of optimal tuning scheme was attained by exploiting a metaheuristic model, indicated as CSA-levy flight. Furthermore, the adopted CSA-levy flight model was evaluated with the conventional techniques regarding diverse error analysis for both the ECG and EEG signal to reveal the improvement of the developed ones.

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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