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Reconstruction of Multi-channel ECG using Compressive Sensing based Emperor Penguin Colony in WBSN

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Abstract

Nowadays, Wireless body sensor networks (WBSNs) have recently been increasingly used for remote healthcare monitoring, where base station or remote hospitals continuously receives the electrocardiogram (ECG) signals for storage and analysis. In the diagnostic point of view, more information are provided by multichannel ECG (MECG) than single channel ECG. The major challenging task in WBSN is to transmit the signal of MECG without compromising on energy consumption. Therefore, effective compression of data is required, where simultaneous compression and data can be recovered with minimal loss of diagnostic information can be carried out by Compressed Sensing (CS). In addition, CS has emerged as a new signal receiving technology that can increase time for monitoring, reduce costs of equipment and power consumption. This paper proposes a low-ranking CS-based method for efficient data collection and signal reconstruction (SR) in the low-energy WBSN. In addition, we used Kroneker's sparse bases for the usage of spatio-temporal correlations (STC) in MECG signals and its compression. The scarcity limit is represented by the minimization of the l1 norm, where an efficient optimization algorithm called Emperor Penguin Colony (EPC) is developed to reconstruct MECG signals that more efficiently solve the resulting optimization problem. Simulation experiments confirm that the EPC-based algorithm provides higher recovery accuracy with less required transmissions and less computational complexity, when compared with existing recovery methods.

Keywords: Compressed Sensing; Electrocardiogram; Emperor Penguin Colony; Recovery Algorithm; Sparsity Constraint; Wireless Body Sensor Networks.

1.Introduction

Low-cost and high-quality monitoring system of WBSN-based ECG technologies are rapidly increasing in the upcoming days. However, one of the major challenges is the continuous and long-term ECG monitoring, since biosensors are battery powered [1-4]. Researches are conducted on current surveys [5-7] to prove that the above stated issues can be resolved by using the CS method [8-9] that uses the ultra-low coding complexity for compressing the node's ECG, so that power consumption in wireless data transmission is reduced. Using the sparsity function of the considered signals, the CS performs signal acquisition and compression at the same time using a simple linear projection of the conventional signals. During this time, the unit of complex data compression can be saved and there is no need for high-frequency Nyquist sampling. On the other hand, complex optimization algorithm is used for recover the signal during decoding. Normally, powerful servers are used for performing the recovering operations, where WBSN is a critical case. There are limited memories, power and computing resources are presented in the bio-sensors, however, they must done long-term wireless communication and detecting the signals. In contrast, the signals' analysis and reconstruction are normally performed at the data center, which is considered as extremely powerful.

The qualities of signals in terms of reconstruction and compression ratio are determined by using the reconstruction algorithm in CS. There are two categories in the reconstruction algorithm that are adopted in the existing CS-based ECG schemes, where first one is signal sparsity includes orthogonal matching pursuit (OMP), basis pursuit (BP) and finally Bayesian CS [10-12]. BP is used as reconstruction algorithm in [13] for extending the biosensor lifetime and achieved competitive compression ratio. The author from [14] reviews the various reconstruction algorithms and suggests that OMP is best for monitoring the ECG signals for CS in WBSN due to its computational time and reconstruction accuracy[38]. The other algorithms use additional prior information and standard sparsity. Figure 1 shows the model of WBSN.

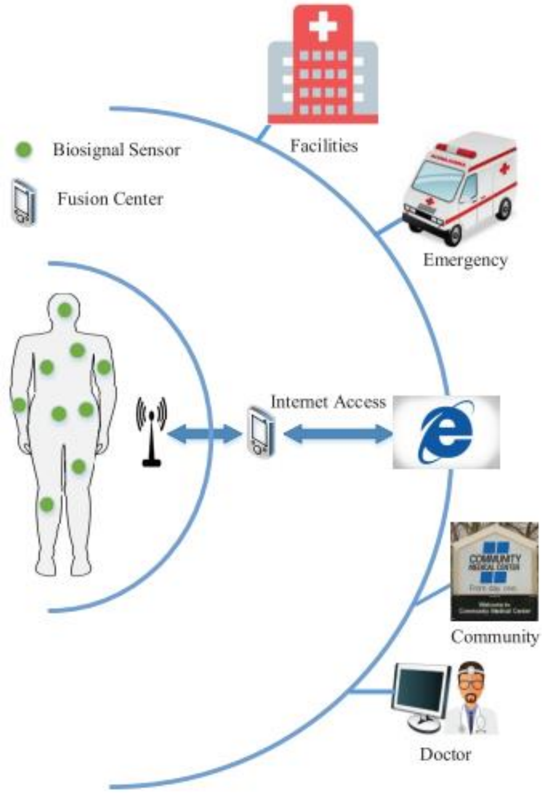


Figure 1: WBSN's Model

In the time domain analysis, the block-sparsity signals is exploited by using the reconstruction algorithm called block sparse Bayesian learning (BSBL), which was developed by the author Zhang et al. [15]. In the wavelet domain, ECG data signals has effective sparse representation, therefore, weighted l1 minimization (WLM) is used in the [16]. The decay characteristics of wavelet coefficients is incorporated between different levels in WLM, i.e. according to the wavelet decomposition levels, weight factors are choosen in the multisource. However, less reconstruction performance is achieved in this WLM, because more prior knowledge is required in terms of reconstruction quality and compression ratio.

The human heart's electrical activity can be measured simultaneously with several biosensors [17]. In CS, even though, inter-channel correlation has been broadly considered [18], [19] none of the works examines the benefits of combining inter-channel correlation with multi-priori of source in wavelet domain. Therefore, a structure of sliding data window is developed in this paper, where the STC of ECG signals are received by the sensors and current ECG signals are reconstructed by the fusion center, which is obtained from CS measurements. The following two points summarize the major contribution of the research article:

- ❖ The accuracy of the reconstructed ECG signals are affected by the dependencies of both temporal and spatial extraction, therefore the paper uses the Kronecker sparse bases for improving the recovery performance effectively by using small number of CS measurements.
- ❖ The sparsity constraint is solved by defining the optimization formula in the proposed reconstruction algorithm. Therefore, EPC based algorithm is developed in this research work to solve the issues of formulated cost optimization problem.

This research article is developed as: Section 2 provides the study of related works, where the 3rd Section briefly described the EPC-based methodology along with optimization problem formulation. Section 4 provides the simulation results of ECG-based technique with existing techniques. Finally, the scientific contribution with future work is presented in Section 5.

2. Related works

The dictionary atoms are updated by using Orthogonal Procrustes analysis that are used in the R-singular value decomposition (R-SVD). While comparing with the traditional methods such as OSDL, K-SVD, ILSDLA for dictionary updating, the R-SVD provides effectiveness and robustness on ECG and EEG data based that are verified by Grossi et al. [20].

According to the correlation between the channels of wavelets, a multi-lead ECG reconstruction method is designed by Zhang et al. [21]. This method minimized the information of weighted multi-source prior and the performance gain of the model is theoretically analyzed. From this result, it is proved that the designed model is robust in the SR from noisy environment.

Rakshit et al. [22] proposed two CS-based ECG reconstruction algorithms that combined the advantages of a rhythmic-type vocabulary with a heterogeneous random sensory matrix, and also used a patient-based special over-full vocabulary design that implemented the unknown signals recovery. Below CR, the complexity of the calculations has been significantly reduced 20% and 44%. All of the above methods use the sparsity of the post-conversion ECG or add appropriate a priori information to recover the signal. Moreover, these methods are repetitive and have high complexity and computational time.

In the different areas of auscultation, the collection and compression of CS at various intensity is parallely occurred in the multi-channel models that are developed by Cheng et al. [23]. The results of numerical experiments have shown that the model proposed in [23] can achieve a speed 9-10 times faster than the BSBL algorithm, and at the same time obtain a better reconstruction quality. However, a comprehensive study of HS signal reception by CS with a common basis for fragmentation and reconstruction algorithms has not yet been carried out.

In [24], joint-CS recovery algorithm based weighted mixed norm (WMNM) minimization algorithm is developed for the reconstruction of CS-MECG signals. The WMNM method increases the performance of recovery and significantly minimized the difference of RMS and improves the SNR. In [25], the authors use space-time correlations using a sparse approach of Bayesian learning based on basic space-time learning (STL-BL). The STL-BL has good SR quality with less computational load on the MECG signal encoder. However, it is difficult to recover the signal with the CS method due to dense.

In [26], a combined STC sparse reconstruction based on a model with a training approach (STSRM-TA) was reported. According to the STSRM without vocabulary learning and sparse blocks, while comparing with optimization of learning, the STSRM-TA provides better improvement in the MECG signal's reconstruction quality. The authors in [27] present a previous WMNM as PWMNM for recovering a JCS-MECG signal with the help of information of added priori and STC about the signal. PWMNM method improves recovery performance, lowers PRD, and improved SNR.

3. Proposed Model

In sliding window of data, the capable of reading, transmitting and sensing the ECG signals are carried out by N sensors in a single-fusion centre hop of WBAN with L as constant length. The size of the data window is described as $F(\tau) \in \mathbb{R}^{N\times L}$, which should be $L \geq 1$ at time instant τ. This window is expressed in Eq. (1) that has sequential data readings of N sensors as$\{\tau - L + 1, \dots, \tau\}$.

$$F(\tau) = \begin{bmatrix} f_1(\tau - L + 1) & \cdots & f_1(\tau - 1) & f_1(\tau) \\ \vdots & \ddots & \vdots & \vdots \\ f_N(\tau - L + 1) & \cdots & f_N(\tau - 1) & f_N(\tau) \end{bmatrix}$$

(1)

Where, sensor (i.e. $n \in N$) reads the data is denoted by$f_n(\tau)$at time instant τ. Consider that sparse approximation is presented in each sensor signal of dictionary $\Omega \in \mathbb{R}^{N\times L}$, where $\Omega f_n(\tau)\ \forall\ n \in N$. Then, measurement matrix $\Phi_n \varepsilon R^{m(\tau)\times L}$ as $y_n(\tau) = \Phi_n(\tau) f_n(\tau) \varepsilon R^{m(\tau)}$sense the readings of sensor and it will be forwarded to the fusion center.

At time instant τ, sensor's original reading reconstruction is the major problem in the fusion center end, which can be solved by the minimization problem shown in Eq. (2):

$$\min_{f} ||\Omega \mathrm{f}||_{l_0} subject\ to\ y_n(\tau) = \Phi(\tau) f(\tau)$$

(2)

The NP- hard problem is the l_0 minimization, many researchers tries various combination of optimization algorithms for solving the norm l_0. In general, norm l_1 is used to replace the norm l_0. The quadratic penalty term is used to convert the unconstrained form from the constrained norm, which is shown in Eq. (3).

$$\min_{f} ||\Omega \mathrm{f}||_{l_1} subject\ to\ y(\tau) = \Phi(\tau) f(\tau)$$

(3)

$$\min_{f} \frac{1}{2} ||\, y(\tau) - \Phi(\tau) f(\tau)||_{l_2}^2 + \eta ||\Omega f(\tau)||_{l_1}$$

(4)

Where, in this problem of minimization, the trade-off between two various terms are controlled by the parameter called η. The Eq. (1) can be rewritten as Eq. (5), where the sliding data window with L are used to attain the readings of data such as current (f) and prior $(\mathcal{F}^{\mathcal{H}})$ from the data.

$$\begin{bmatrix} f_1(\tau - L + 1) & \cdots & f_1(\tau - 1) & f_1(\tau) \\ \vdots & \ddots & \vdots & \vdots \\ f_N(\tau - L + 1) & \cdots & f_N(\tau - 1) & f_N(\tau) \end{bmatrix} = \begin{bmatrix} \underline{\mathcal{F}^{\mathcal{H}}} & \underline{f(\tau)} \end{bmatrix}$$

(5)

The matrix $\begin{bmatrix} \underline{\mathcal{F}^{\mathcal{H}}} & \underline{f(\tau)} \end{bmatrix}$ is a low-rank, when the neighboring sensors' information in a WBSN is correlated with each sensor's information. Finally, the formation of reconstruction of original signal is carried out by low-rank features. The matrix rank reduction in a direct way is the considered as NP-hard problem, hence nuclear norm must be reduced for the matrix instead of focusing on minimizing the matrix rank directly. Eq. (6) shows this conversion process.

$$\min_{f} \left| \left\| \begin{bmatrix} \mathcal{F}^{\mathcal{H}} & f(\tau) \\ - & - \end{bmatrix} \right\| \right|_{*} \text{subject to } y(t) = \Phi(\tau) f(\tau) \quad (6)$$

Where, sum of matrix's eigen values is equalized by the matrix of nuclear norm $||.||_{*}$. Therefore, this norm can be minimized by considering the combinatorial optimization problem with sparsity constraint. In a single formulation, minimization of the nuclear norm $||.||_{*}$by low-rank constraint is described as follows:

$$\underset{f}{argmin} \frac{1}{2} ||y(\tau) - \Phi(\tau) f(\tau)_{l_2}^2 + \eta_1 ||_{l_2}^2 + \eta_1 ||\Omega f(\tau)||_{l_1} + \eta_2 \left\| \begin{bmatrix} \mathcal{F}^{\mathcal{H}} & f(\tau) \\ - & - \end{bmatrix} \right\| \quad (7)$$

Where, weighting parameters is represented asη_1 and $\eta_2$that are used to balance the trade-off between the sparsity constraint of the various data such as error square term, whole data of prior and data of present time with low-rank.

3.1. Simultaneous extraction of the STC

In order to find how to use the dictionary for optimization problem in Eq. (7) and find out how to extract the sensor signal's STC by using suitable dictionary (Ω) are find out by developing a mathematical way in this section. By referring Eq. (1), STC consists of data window $F(\tau)$ with a window size. Hence, Eq. (1) can be described in the form of Eq. (8):

$$F(\tau) = [f_1(\tau - L + 1) \ldots \underset{-}{f(\tau)}] = [f_1(\tau) \ldots f_N(\tau)]^T \quad (8)$$

Accordingly, $F(\tau)$ can be expressed as follows:

$$\begin{aligned} F(\tau) &= [f_1(\tau - L + 1) \ldots \underset{-}{f(\tau)}] \\ &= \Omega_s^{-1} [\xi_s(\tau - L + 1) \ldots \xi_s(\tau)] \\ &= \Omega_s^{-1} \xi_s(\tau) \end{aligned} \quad (9)$$

Similarly, to perform the sparse representation, i.e. $f_n(\tau) = \Omega_T^{-1} \xi_{T,n}(\tau)$,temporal dictionary $(\Omega_T \varepsilon R^{L\times L})$is used that has $F(\tau)$ rows, where the coefficient temporal transform of sensor is inclusive by $\xi_{T,n}(\tau) \varepsilon R^L$. Hence $F(\tau)$ can be stated as

$$\begin{aligned} F(\tau) &= [f_1(\tau) \ldots f_N(\tau)] \\ &= (\Omega_T^{-1} [\xi_{T,1}(\tau) \ldots \xi_{T,N}(\tau)])^T \\ &= \Omega_T^{-1} \xi_{T,n}(\tau) \end{aligned} \quad (10)$$

The Kronecker sparse base [28-29] is used for extracting both dependencies and the spatio-temporal dictionaries [28-29]. Therefore, single formulation is obtained by merging the Eq. (9&10) to describe the $F(\tau)$ as follows:

$$\begin{aligned} f(\tau) &= vec(F(\tau)) = vec(\Omega_T^{-1} \xi_{T,n}(\tau)) \\ &= vec(\Omega_s^{-1} \xi_s(\tau) \Omega_T^{-T} \Omega_T^{-T}) \\ &= (\Omega_s^{-1} \otimes \Omega_T^{-1}) vec(\xi_s(\tau) \Omega_T^T) \\ &= (\Omega_s \otimes \Omega_T)^{-1} \xi_{S.T}(\tau) \end{aligned} \quad (11)$$

Where, window vector of data is represented as $f(\tau)\ \varepsilon\ R^{NL}$, product dictionary of STC of proposed Kronecker sparse base is described as $\Omega_s \otimes \Omega_T R^{NL\times NL}$, and the coefficient of joint transformation (JT) is depicted as $\xi_{S.T}(\tau) = vec(\xi_s \Omega_T^T) \varepsilon R^{NL}$. Moreover, the interpretation of JT is occurred as spatial coefficients representation $(\xi_s(\tau))$, in temporal basisΩ_T. Hence, the optimization problem is described in Eq. (12) by substituting the Eq. (11) with (7):

$$\underset{f}{argmin} \frac{1}{2} ||y(\tau) - \Phi(\tau)||_{l_2}^2 + \eta_1 ||\Omega_s \otimes \Omega_T) f(\tau)||_{l_1} + \eta_2 \eta_2 \left| \left\| \begin{bmatrix} \mathcal{F}^{\mathcal{H}} & f(\tau) \\ - & - \end{bmatrix} \right\| \right| \quad (12)$$

The excessive computation complexity is obtained by the non-smooth regularization of various norms with convex optimization problem, even though the constraints applied to the Eq. (12). Therefore, this research work applies the EPC algorithm to solve the above stated issue.

3.2. Emperor Penguins Colony (EPC) Optimization algorithm

Each penguin's cost and location are calculated. Penguins are priced against one another. Penguins will always choose a penguin with a low absorption cost (high heat intensity). The cost is influenced by the temperature and the length of the journey involved. During the attraction process, a brand-new option will be reviewed, and the heat strength will be adjusted as necessary. The best answer is chosen after all others have been sorted. Heat radiation, association, and heat absorption are all subjected to a damping ratio. In algorithm 1, pseudo code for the EPC algorithm is described. The following are the rules that apply to this algorithm:

- ❖ Every penguin in the original population radiates heat and is drawn to others with a similar thermal absorptivity.
- ❖ All penguins are thought to have the same body surface area.
- ❖ The influence of the earth's surface and atmosphere are not taken into account when the penguin absorbs all of the thermal radiation.
- ❖ Penguin heat radiation is a straight line.
- ❖ The attraction between two penguins is determined by the quantity of heat that separates them. Longer distances receive less heat, while shorter distances receive more heat.
- ❖ There is a variation with a consistent distribution in the spiral movement of the penguins during the absorption process.

Heat radiation:

The heat radiation transfer must be computed in order to determine the intensity and attractiveness of the heat. Each penguin's body surface area must be calculated in order to determine how much heat it radiates.

$$Q_{penguin} = A\varepsilon\sigma T_s^4 \quad (13)$$

Where, heat transfer is defined as $Q_{penguin}$ that will be calculated for unit time (W), total surface area 0.56 m^2 is denoted as A that are computed in the previous section. T_s^4 is the absolute temperature in Kelvin (K) and 35 degrees Celsius (°C) is equal to 308.15 K according to [30], emissivity of bird plumage is ε. The Stefan–Boltzmann constant is also known as σ (5.6703×108 W/m2K4).

Attractiveness:

$$Q = A\varepsilon\sigma T_s^4 e^{-\mu x} \quad (14)$$

Algorithm 1: EPC algorithm's Pseudo code.

```
generate initial population array of EPs (Colony Size);
generate position of each EP;
generate cost of each EP;
determine initial heat absorption coefficient;
for It = 1 to MaxIteration do
generate repeat copies of population array;
for i = 1 to n population do
for j = 1 to n population do
i  costj < costi then
calculate heat radiation (Eq.13);
calculate attractiveness (Eq.14);
calculate coordinated spiral movement (Eq.15);
determine new position # As mentioned in the above part;
evaluate new solutions;
end
end
end
sort and find best solution;
update heat radiation (decrease);
update mutation coefficient (decrease);
update heat absorption coefficient (increase);
end
```

The data window is moved to one step forward, when the signals are reconstructed and all parameters with variables are obtained after certain number of iterations, then the recovery algorithm is reworked again. For each initialization, global convergence can be provided by EPC and solves the problem of convex optimization that is defined in Eq. (12). To better visualize the quality of the reconstruction of the EPC-based method, Table 1 shows the reconstructed signals with original signals from the PTB dataset. The whole x-axis determines the number of samples, and the whole y-axis determines the amplitude.

Spiral movement:

$$x_k = ae^{b\frac{1}{b}In\{(1-Q)e^{b\,tan-i\frac{yj}{xi}}\}}cos\{\frac{1}{b}In\,\{(1-Q)e^{b\,tan-i\frac{yj}{xi}} + Qe^{b\,tan-i\frac{yj}{xi}}\}$$

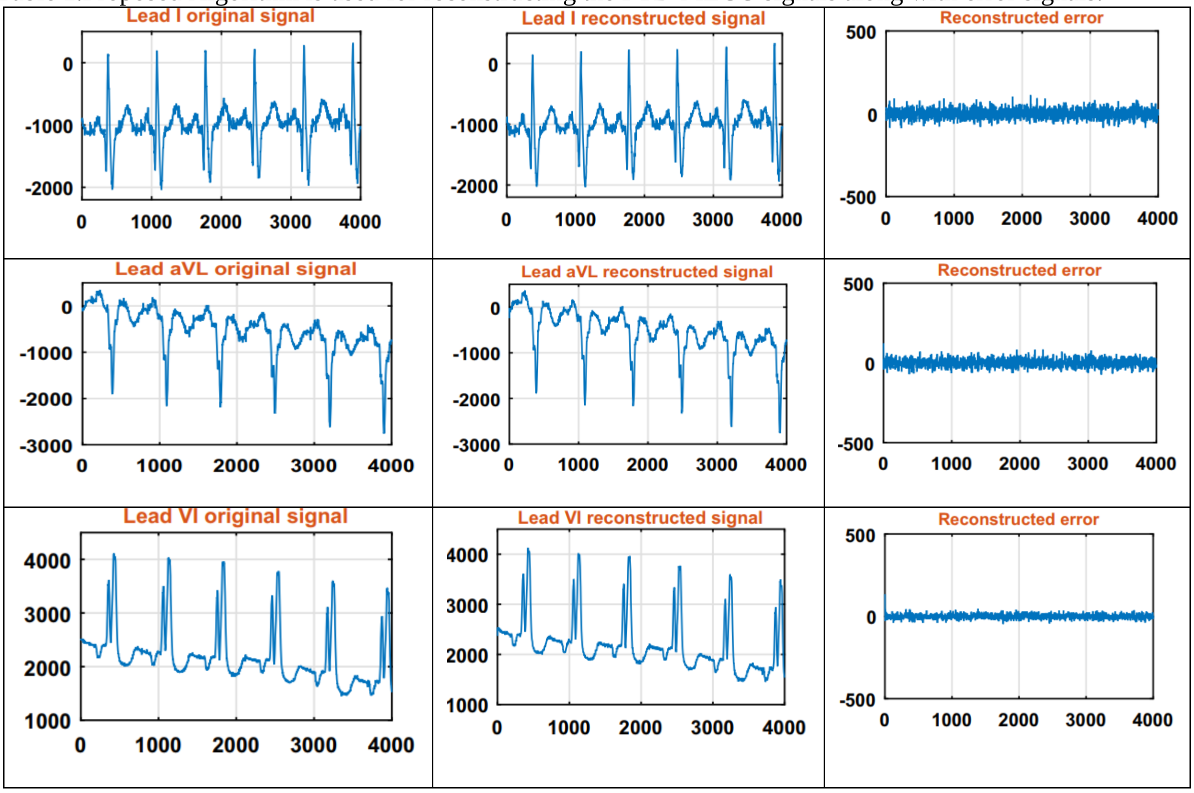
$$y_k = ae^{b\frac{1}{b}In\{(1-Q)e^{b\,tan-i\frac{yj}{xi}}\}}sin\{\frac{1}{b}In\,\{(1-Q)e^{b\,tan-i\frac{yj}{xi}} + Qe^{b\,tan-i\frac{yj}{xi}}\}$$

(15)

New position:

Equation (15) is used to calculate the new position, and it is multiplied by the mutation factor and by a random vector, respectively, to arrive at the new position. The random vector's coefficient is tacked on in this fashion. There are three types of distributions for I uniform, normal, and Lévy. A Uniform distribution is utilized for distribution in the EPC algorithm [31]. The following is the EPC algorithm:

Table 1.Proposed Algorithm is used for reconstructing the PTB-MECG signals along with error signals.



4. Results and Discussion

The experiments are carried out in MATLAB (R2018a) on an HP computer equipped with an Intel i7 core 3.40 GHz processor and 10 GB RAM. The EPC-based method is validated by using three available online databases such as PTB, MIT-BIH dataset collected from Beth Israel Hospital of Massachusetts Institute of Technology [32] and OSET fetal ECG [33]. The percentage difference between root mean square (PRD) is the important quality metrics to measure the reconstruction efficiency. The equation for PRD is given as below:

$$PRD(\%) = \frac{||x_{orig} - x_{rec}||_2}{||x_{orig}||_2} \quad (16)$$

Where, the original data is described as x_{orig} and the reconstructed signal is defined as x_{rec}, respectively. We choose a binary perception matrix of random sparse for Φ, where only 0 are presents in each column except 4 entries in random locations. The Daubechies-6 wave ("db6") is used as a diluent Ψ for ECG signals. Here, the wave has a good results in terms ECG signal's sparse representation, hence we considered this wave for the study. After the 20th tests, the results provide average with different sparse binary sensor matrix realizations. The existing techniques called Simultaneous Orthogonal Matching Pursuit (SOMP) and Multichannel Basis Pursuit (MBP) are considered, where they are implemented with software used in [34-37].

4.1. Performance of Proposed Method on PTB-ECG Database

The subjects of 290 patients is used to collect the 15-channel ECG signals for forming the PTB-ECG database, and each waveform is sampled at fs = 1 kHz with 16-bit resolution in the <16.384 mV range. To assess the effectiveness of the EPC-based method, a database was built containing 10 ECG records such as s0014lrem to s0017lrem, s0027lrem to s0031lrem, s0020arem, s0021arem are present in every recording of our experiments. Several modern multichannel CS algorithms were selected for performance comparison, including SOMP, MBP [22], and tMSBL. According to CS algorithm, the fastest algorithm is SOMP, then MBP is a classical convex CS algorithm based on optimization with good and high recovery accuracy, and improved version of MSBL as tMSBL, respectively. Figure 2 shows the averaged PRD results for different users with various number of measurements.

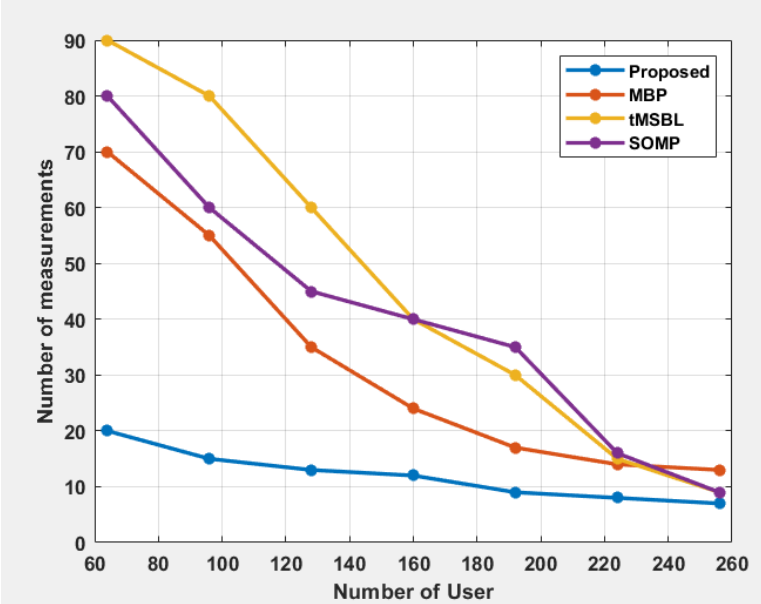


Fig. 2. Graphical Representation of average PRD for proposed algorithm with existing on PTB diagnostic ECG records.

As shown in the above figure, the average PRD results in the proposed algorithm provides better performance than those of other existing algorithms. The average PRD value of the proposed algorithm is about 8.5% with the m = 94 (i.e. number of measurements). In order to achieve the same reconstruction quality, other algorithms must have the range with m = 192. From this we can conclude that the compression ratio is improved without minimizing the quality of reconstruction signals by the proposed EPC-based technique. In most of the situations, the validated result proved that the proposed method is better than the conventional techniques such as SOMP, MBP and tMSBL algorithms.

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4.2. Performance of Proposed Method on MIT-BIH ECG Database

There are two-channel arrhythmia ECG data are presented in this dataset that are collected from 47 subjects. At a sampling speed of fs = 360 Hz, each signal is taken and a resolution of 11 bits. The X ∈ R^ modelling ECG matrix is taken from 2 channels in each database entry for our simulations. Among other things, we evaluate the data entry "419" from the database for ventricular arrhythmias of the MIT-BIH (VFDB) which shows ventricular fibrillation (VF). The results of the reconstruction (superimposed on the original signal) are presented in Figure 3 for channel 1

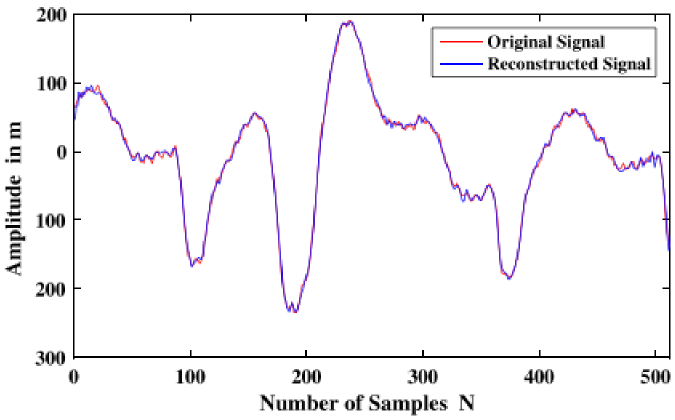

Fig.3. Therecord “419” of MIT-BIH database that are reconstructed by the proposed method.

Here, Table 2 and Figure 4 presents the average PRD values for two channels for a fixed M = 192.

Table 2: Validated Results of proposed methodology in terms of Average PRD (%)on MIT-BIH dataset

Channel	**Methods**			
	Proposed	**MBP**	**SOMP**	**tMSBL**
1	4.62	5.00	5.04	7.33
2	7.34	7.57	8.04	8.80

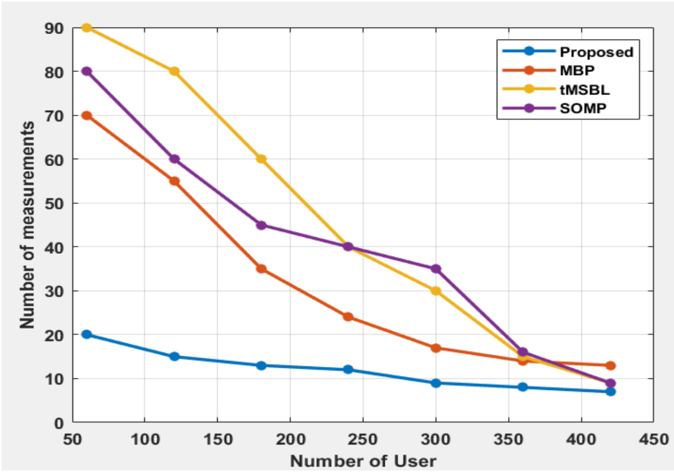

Fig. 4. Graphical Representation of average PRD for proposed algorithm with existing on MIT-BIH diagnostic ECG data.

From above table and figure analysis, it is clearly stated that the SOMP, tMsBL and MBP achieved less PDR value than the proposed algorithm.

4.3. Performance of Proposed Method on OSET FECG Database

In order to validate the proposed method's performance in worst case condition, the study uses the real time ECGs data. It has 8 channels and evaluates the OSET signal01 dataset, which are acquired at 1000 Hz and contains large baseline deviations and poor signals obscured by noise or intrinsic ECG. Here, the extraction of ECG matrix is carried out from those 8 channels during each recording of our experiments. For M = 128, the mean PRD of 8 abdominal images is shown in Figure 5, where the proposed method clearly allows the database to be reconstructed with the least distortion for almost all channels.

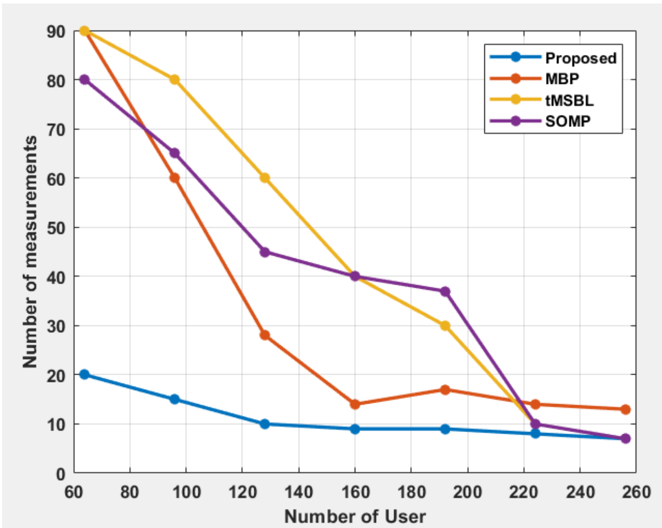

Fig. 5. Graphical Representation of average PRD for proposed algorithm with existing on OSET FECG.

The proposed model reconstructed the dataset with the least distortion of all channels. However, in this dataset, MBP algorithm has less average PRDs than the existing algorithm called SOMP algorithm. Thus, the experimental results show that it is necessary to use inter-channel correlation, which can improve the performance of the reconstruction. Therefore, these results show that due to the inclusion of both inter-channel correlation and direct transmission of several sources in the domain of wavelet, the reconstruction quality of this OSET-FECG is significantly improved by EPC-based method with low rate of measurement.

4.4. Analysis of CPU for proposed Reconstruction Algorithm over Existing Techniques

In this section, CPU calculation time for both existing and proposed algorithms is compared to find out the complexity of the calculations. System configuration used: Intel i7 processor clocked at 3.40 GHz, 10 GB RAM on 64Bit with Matlab R2018a platform. In this regard, the operating time of the projected algorithm is compared with SOMP, MBP and tMSBL for various compression rates. Table 3 provides the experimental results.

Table 3: Time of CPU (second) for the ECG SR algorithms on overall data sets at various compression ratios

	Methods	2	3	4	5	6	7	8
CPU Time (second)	SOMP	0.615	0.569	0.512	0.486	0.451	0.364	0.325
	tMSBL	0.595	0.549	0.501	0.478	0.401	0.340	0.302
	MBP	0.610	0.445	0.323	0.275	0.252	0.226	0.212
	Proposed	0.215	0.145	0.112	0.098	0.086	0.073	0.061

The operating times of the existing algorithms are partially close to each other, but the EPC-based algorithm works well even at less coefficient of compression. These results throughout the database show that the projected method has satisfactory computational complexity compared to classical algorithms.

5. Conclusion

This article discusses CS acquisition and JT of STC-MECG signals in the WBSN. The Kronecker sparse bases is used to exploit the relationships between space and time by designing the sequential frame data window for effectively returning the sensor signals positions to the windows of CS measurements. To obtain a more reliable and efficient SR, an EPC-based analytical solution was developed to efficiently solve the presented optimization problem by minimizing the l1 norm. Validated results confirm that our EPC algorithm provides a higher recovery accuracy, low computational costs and high PRD with fewer required transmissions, when compared to those with classical CS methods. However, the process of CS reconstruction takes time, which limits the use of CS in ECG monitoring systems. Hence, future work requires the development of a unique fast reconstruction algorithm according to deep learning with CS.

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